

**DESIGNING ACCURATE AND EFFECTIVE MEANS FOR
MARINE ECOSYSTEM MONITORING INCORPORATING
SPECIES DISTRIBUTION ASSESSMENTS**

BY

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*Te Whare Wānanga
o te Ūpoko o te Ika a Māui*



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Abstract

Monitoring marine ecosystems is essential for the conservation and management of marine biodiversity as it is central to the development of sustainable management practices and for assessing the effectiveness of the increasing number of marine reserves (MR) globally. Monitoring data are often collected in MRs to assess the state of natural marine systems in the absence of anthropogenic disturbance or to assess recovery of previously impacted species. In recent years, MR designation has attempted to move away from *ad hoc* approaches to MR establishment and towards using existing species distribution and abundance data to define protected areas. Given the logistics and cost of collecting biological data in the marine environment, effective methods are required to successfully demonstrate changes associated with MRs and to identify the spatial distribution of organisms and habitats for the planning of further MRs. The aim of this thesis was to identify effective protocols for the monitoring of fish and invertebrate species inside MRs in New Zealand, and to develop and apply methodologies to identify spatial distribution patterns relevant to marine spatial planning.

Using baseline data of fish and invertebrate species abundances for the Taputeranga MR I performed prospective power analyses to identify the most cost-effective monitoring approach for subsequent monitoring. Based on before-after-control-impact (BACI) tests the power to conclude statistically that abundances were higher at MR sites was low for even large simulated changes in abundance (two-fold or four-fold increases) for most species. Due to differences in baseline abundance and spatio-temporal variance terms, power varied considerably among species, highlighting the difficulty of monitoring all species to the same degree, whilst also remaining cost-effective. Furthermore, the results highlight the need for temporally replicated survey designs as “one-off” surveys had much lower power than those that were temporally replicated.

Longer term monitoring effectiveness was analysed using three long-term datasets from MRs in the South Island of New Zealand. I analysed the power of alternate underwater visual census (UVC) monitoring configurations to conclude statistically that there were increasing/decreasing trends in abundance, as well as the precision and accuracy of trend estimates. Overall even the highest replication designs considered had low power (< 80%) to conclude there was a non-zero trend even when simulated data represented trends equivalent to the population doubling or halving over ten years. The most cost-effective monitoring

design varied among species and MRs, further highlighting that monitoring choices need to be location- and species-specific. A general finding, however, was that increasing the number of sites was almost always more beneficial than increasing the number of transects per site. Based on these results, I recommend that monitoring design planning focuses more specifically on assessments of precision and accuracy of estimated parameters, with less focus on power, as this places greater emphasis on interpreting monitoring data in terms of potential biological significance rather than testing for statistical significance.

Monitoring can never achieve complete coverage of large areas therefore methods for extrapolating or predicting species or habitats to un-surveyed locations are necessary for evaluating large-scale spatial distributions. To address this I used modelling techniques to identify the spatial variation in species and habitats along the Wellington south coast, with a particular focus on elucidating the potential and realised effects of wave exposure. A wave simulation model (SWAN) was used to identify the spatial variation in wave exposure relevant to intertidal and subtidal communities. In particular the spatial variation in wave forces was compared to the distribution of two subtidal macroalgal species, *Macrocystis pyrifera* and *Ecklonia radiata*, taking into consideration the biomechanical thresholds of damage for these plants. Despite considerable wave forces during winter storms, healthy *E. radiata* is unlikely to be damaged, whilst larger (>15 m stipe length) *M. pyrifera* plants are likely to be damaged in certain locations dependent on local sheltering effects. Furthermore, the distribution of *M. pyrifera* from aerial imagery coincided with areas that were predicted to have lower wave forces, suggesting that the distribution of *M. pyrifera* may be related to wave exposure.

I subsequently constructed species distribution models revealing the relationship between intertidal species distributions and environmental factors, as a predictive baseline of the current distributions of species. The abundances of *Chamaesipho* barnacle species were found to be best described by wave exposure, with increased cover correlated with increasing wave exposure, while contrasting patterns were observed for *C. brunnea* and *C. columna* with respect to distance from the harbour entrance, suggesting differential larval supply or differential responses to changing water column characteristics. Macroalgal assemblage composition was explained predominantly by wave exposure, with a rich macroalgal assemblage at the less exposed locations, and more exposed locations exhibiting a community consisting of coralline algal species and the large brown alga *Durvillaea*

antarctica. The predictive models were then used to predict species distributions for a section of coastline demonstrating how this form of modelling can be used to maximise the potential of monitoring data.

Finally, a literature keyword search along with methodological developments and results from previous chapters are used in the final chapter to develop a framework for the collection of data from the planning phase all the way through to long-term monitoring of MRs.

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Contributions

All fieldwork, analyses and writing were carried out by the author with the following exceptions:

Chapter 2

Study design: Author

Data collection: Data sourced from separate studies performed by Tyler Eddy, Tamsen Byfield, Anjali Pande, Melanie Russell and Jonathan Gardner

Analyses: Author

Writing and editing: Author with editing by Dr. James Bell and Dr Jonathan Gardner

Chapter 3

Study design: Author

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Chapter 1 - Introduction

1.1 – Marine ecosystem monitoring

In light of the increasing number of Marine Protected Areas globally and the importance of developing sustainable marine exploitation practices and the protection/conservation of biodiversity, it is essential to monitor marine ecosystems. Ecological and environmental monitoring can be broadly defined as the systematic acquisition of biotic or abiotic data at various locations and/or times (Kremen *et al.* 1994). The reasons for collecting monitoring data usually fall into one of two main categories. The first is to record changes in the abundance of a species or the biodiversity of a region (Maher *et al.* 1994; Nichols & Williams 2006) either because of environmental impacts (Green 1993) or because of recent changes to the level of protection, or ongoing protection, afforded to the region (Edgar & Barrett 1997; 1999; Pande & Gardner 2012). The second is to determine spatial variation in species abundances or biodiversity for conservation planning and management (Ward *et al.* 1999; Aïramé *et al.* 2003; Pande & Gardner 2009) or to help establish further protected areas, for example in a network (Rice & Houston 2011; Di Franco *et al.* 2012). In the case of Marine Reserves and MPAs (the term Marine Reserve, shortened to MR, will be used to indicate areas where extractive use of any kind is prohibited and Marine Protected Area, MPA, will be used as an umbrella term, indicating areas of restricted harvest, mixed harvest and/or full no-take areas) (National Center for Ecological Analysis and Synthesis 2001; Agardy *et al.* 2003) monitoring data are often collected to assess the state of natural marine systems in the absence of anthropogenic disturbance or to assess recovery of impacted species (Allison *et al.* 1998; Kelly *et al.* 2000; Pande *et al.* 2008; Diaz Guisado *et al.* 2012). Increasingly marine reserve designation has also attempted to move away from *ad hoc* approaches to marine reserve designation (Stewart *et al.* 2003; Lundquist & Granek 2005) towards utilising prior monitoring data of species distributions and abundances for defining protected areas (Ward *et al.* 1999; Aïramé *et al.* 2003; Roberts *et al.* 2003; Stewart & Possingham 2005; Leslie 2005) and therefore baseline data are vital for determining the best way to distribute protected areas.

1.2 – Monitoring to quantify change

Monitoring to demonstrate changes in abundance or other ecological parameters (biodiversity, species richness, and mean size) is vital in demonstrating the effectiveness of protected areas and subsequently for advocating for further protected areas. Continual MR monitoring should therefore have pre-specified goals, whether it is to record the changes in

abundance of a previously impacted species (such as blue cod and rock lobsters in New Zealand) (Kelly *et al.* 2000; Pande *et al.* 2008), or to record the ecosystem-wide impacts that may result from the recovery of one or more impacted species (Edgar & Barrett 1999; Shears & Babcock 2003). Therefore monitoring programmes should be capable of demonstrating these effects as well as having sufficient statistical power to inform decision making and further management actions (Field *et al.* 2004; Pullin *et al.* 2004). Many monitoring schemes, however, are poorly designed for achieving these goals (Peterman 1990; Maxwell & Jennings 2005). When not designed carefully, sampling may be inappropriate to assess the extent of change, lacking sufficient spatial and temporal replication to truly assess the state of the system and how it is changing (Ward & Jacoby 1992; Possingham *et al.* 2001). Furthermore, if the monitoring scheme has low statistical power, incorrect conclusions about an ecosystem or population state might be reached, which can lead to inappropriate and possibly harmful management recommendations (Hayes 1987).

Type II statistical errors occur when an effect, whether it is a long-term trend or difference between regions or areas, exists but upon analysing the data no significant effect is detected, either due to variability in the system and/or low statistical power of the sampling design (Gerrodette 1987). Type II errors are potentially costly in ecosystem monitoring as they may lead to the conclusion that a population is stable, when in reality it may not be, or that a potentially harmful effect, such as pollution, is having no effect on the study population. Very few monitoring schemes account for the potential cost of making a Type II error (Nichols & Williams 2006). However, this should be a significant consideration when designing any monitoring programme, otherwise there is potential for wasted time, money, and possibly most importantly the continuation of a detrimental effect to a population, due to low power to detect such an effect (Mapstone 1995; Reed & Blaustein 1997).

1.2.1 – Power analysis

Power analysis is a statistical technique that permits quantification of the power of a survey or monitoring design. By increasing the statistical power the probability of making a Type II error is reduced and so ideally a monitoring or survey design should be established to have high statistical power. The statistical power of a survey design depends on the magnitude of the effect being investigated, the system's variability, the sample size and the stringency of the test, i.e. the Type I error rate, α (Toft & Shea 1983). Power analysis can be used in several different ways. It can be used in a prospective way to judge the statistical

power of sample designs with different levels of sampling effort, for a range of plausible effect sizes (Maxwell & Jennings 2005; Sims *et al.* 2006). In these cases the variability is often estimated from pilot scheme data, or from studies with data from a similar species or system. It can also be used in a retrospective way to judge retroactively the power of surveys to detect effects of biological significance, given the observed variance (Reed & Blaustein 1997; Thomas 1997). Power analysis has also been used in other applications, such as in analysing the probability of species extinction (Reed 1996), in assessments of a precautionary approach to conservation (Peterman & M'Gonigle 1992) and fisheries management (Peterman 1990).

Performing a power analysis during the planning stages of ecological monitoring can be invaluable as it can lead to more effective monitoring designs (Taylor & Gerrodette 1993; Steidl *et al.* 1997). Prospective power analysis involves estimating the statistical power of a sampling design to detect a given effect size or for a range of effect sizes (Morrison 2007). Comparing the prospective power of different monitoring designs, one can identify an optimum or most suitable monitoring design to achieve the specified goal of monitoring (Hoenig & Heisey 2001). In most cases it is applied in order to define an adequate sample size that would be capable of detecting an effect that is deemed biologically significant for a given level of statistical power. In other cases it has been used to define the amount of spatial replication at different spatial scales (Sims *et al.* 2006) as well as the timescale over which sampling should be performed in order to detect an effect with a given level of power (Urquhart & Kincaid 1999).

1.2.2 – Applying power analysis in ecological and conservation studies

The power of tests to identify statistically significant changes in abundance is primarily affected by the degree of variation exhibited by the data to the extent that monitoring is often confounded by natural variation on a variety of spatial and temporal scales (Larsen *et al.* 2001). Thus, determining the optimal number of sites (in the case of MPAs, this includes the number of sites within and outside of the MPA), replication within sites, and replication through time should be a vital part of the planning stages of any monitoring scheme (Larsen *et al.* 2001; Sims *et al.* 2006). In order to achieve maximum power, monitoring schemes should be designed so that the overall variance is minimised by minimising, or controlling for, the largest components of variation. For a multi-site long-term survey, variability among sites, within sites and among survey intervals all contribute to the

overall variance (Sims *et al.* 2006). The size of each contributing factor depends on the system and species being studied, but the importance of each factor can be controlled by the amount of replication performed at that spatial or temporal scale. Consequently optimal survey designs will vary from species to species and place to place (Hartnoll & Hawkins 1980). Identifying an optimal sampling design should also take into account the relative time and effort required to perform each configuration of the sampling design. It is often the case that increasing the replication within sites, either by increasing the number of quadrats, transects or counts is less costly and less time consuming than increasing the number of sites. However, increasing the number of sites may yield the greater increase in statistical power because between-site variance can often be the largest source of variability. In a study of Common Guillemots, Sims *et al.* (2006) found that the largest component of variation was the between-plot variance, with smaller contributions from between sampling occasion variation. To maximise statistical power, for a minimum of additional cost, it was concluded that increasing the number of plots would provide a greater decrease in overall variance than an increase in temporal replication by re-sampling the same plots on separate occasions within each season. By increasing the number of plots the survey design would have had 90% power to detect a 1.5% annual decline over a period of 12 years, 2 years less than the original sampling design and 1 year less than by increasing the amount of temporal replication.

Outside MRs, and from a management perspective, the goal of monitoring is often to identify whether or not a change in some environmental or physical variable is having an effect on a species and if so, management or preventative actions can be applied (Thompson *et al.* 2000; Nichols & Williams 2006). The drawbacks of such an approach are that depending on the length and the power of the monitoring programme, it may take a long period of time to detect any effect, and furthermore, it will take time to initiate a management scheme to control the source of the problem. Maxwell & Jennings (2005) state that with regards to rare and vulnerable species, conservation prioritisation and management actions should not wholly depend on the statistical significance of population changes, as these surveys will often have low power to detect any change. This highlights the importance of performing a power analysis on the data to determine whether the conclusion of no effect was due to low statistical power. This has led to suggestions that a precautionary approach may be more appropriate in these situations (Lauck *et al.* 1998; Thompson *et al.* 2000; Cole & McBride 2004). This is especially applicable to rare species or for small isolated populations where the power to detect a decline in the population is limited. Taylor & Gerrodette (1993)

noted that the ability to detect a change in a population and thus the power of any monitoring scheme will rely somewhat on the abundance of the species. In particular they highlight the problem that the ability to detect declines in abundance becomes increasingly small for rare or low abundance species, as they will be present in only a small fraction of surveys. Maxwell & Jennings (2005) found that the power for detecting declines for vulnerable fish species was significantly lower than for more abundant species. Furthermore, they argue that the species that should be monitored, i.e. those that are naturally rare, uncommon or that have undergone historical depletion, are those for which the survey is least effective. As such, it would be unfeasible and possibly detrimental to the population to prove a decline was occurring before the implementation of a management plan (Peterman & M'Gonigle 1992; Taylor & Gerrodette 1993).

Thompson *et al.* (2000) took this argument one step further and applied power analysis and population viability analysis to the monitoring of a small isolated population of Bottlenose Dolphins (*Tursiops truncatus*). These authors compared a traditional approach to monitoring, where proof of effect is required before management action can be taken, to a precautionary approach, where the management action is applied at the earliest possible time, regardless of the state of the population. They proposed several hypothetical rates of decline for the population and then calculated the number of years of annual monitoring it would take to detect a decline of this magnitude with 95% power. Based on the population size after this length of time they performed a population viability analysis enumerating the percent chance of extinction over a hundred-year period. It was found that a traditional approach to monitoring and management would significantly increase the probability of extinction when compared to a precautionary approach, due to the extended period of time needed to identify the decline. They also suggested that the combination of power analysis and population viability analysis be used to estimate the degree to which a precautionary approach can be taken. For example, this could be used to determine the proportion of an area that should receive protection, which would be useful when defining MRs as a tool in fisheries management (Lauck *et al.* 1998).

The vast majority of work involving power analysis has focussed on detecting changes for a single species (Nichols & Williams, 2006), with little to no work involving power analysis for detecting community wide changes. In addition, monitoring often focuses on rare enigmatic species (Peterman 1990; Taylor & Gerrodette 1993; Maxwell & Jennings

2005), or those that are commercially valuable (Peterman 1989) and very little attention is paid to the full spectrum of species that are present. An alternative approach, as employed by Nielsen *et al.* (2009) and Manley *et al.* (2004, 2005), uses power analysis to optimise large-scale biodiversity monitoring schemes based on species' prevalence across a landscape-scale setting. The monitoring scheme described in Nielsen *et al.* (2009) was designed with the aim that an annual decline in prevalence of 3%, across all the surveyed sites, would be detected with 90% power for all species of songbird, vascular plants and bryophytes over a sampling period of 20 years. The power of monitoring designs with different numbers of sites and frequencies of surveys was tested to ascertain the achievable power for the array of recorded species. It was possible to reach these goals for 27%-65% of all species, for an achievable level of sampling effort. The rest of the species, however, would require unrealistically large sample sizes, or monitoring over a longer period of time. These authors highlight the problem that differences in species abundance and detectability make it difficult to accommodate all species adequately and inevitably the ability to detect declines for some species was not possible. In another approach, Nicholson & Jennings (2004) applied power analyses to fish assemblage metrics, combining length, mass and trophic level information from numerous fish species, in order to determine the power for detecting a change in fish assemblages. They concluded that in the short term (less than ten years of monitoring), power for detecting changes in these metrics is low, and so the use of such metrics should not be advocated for setting short-term management goals.

1.2.3 – Biological significance and type I and type II errors

An important component of performing power analysis is the identification of what effect size should be considered biologically significant. In most cases a biologically significant effect is set as the minimum effect size that can be permitted, without being considered harmful to the population. This is often based on scientists' best judgment of the situation (Toft & Shea 1983; Nielsen *et al.* 2009). Furthermore, an important distinction to make when performing power analysis is that of the difference between biological significance and statistical significance (Yoccoz 1991; Cole & McBride 2004). A small effect may be deemed statistically significant given a large enough sample size, but may not have any real biological importance (Fairweather 1991). Conversely, a large biologically significant effect may be deemed not statistically significant due to high variance or small sample size (Hayes & Steidl 1997). These problems highlight the need to perform power

analyses to identify whether a non-significant conclusion is due to no effect or just the result of low power.

This raises a further issue regarding Type I and Type II error rates. In nearly all cases the Type I error rate α is set at 0.05. This may be widely applicable in the fields of experimental biology, but can be potentially harmful when applied to conservation monitoring (Taylor & Gerrodette 1993; Steidl *et al.* 1997), or the detection of environmental impacts (Peterman & M'Gonigle 1992; Mapstone 1995; Cole & McBride 2004). Many authors have suggested using a less stringent α in order to reduce the probability of making a Type II error (Toft & Shea 1983; Steidl *et al.* 1997), but ideally the respective Type I and Type II error rates should be based on the potential costs of making each error (Peterman & M'Gonigle 1992; Mapstone 1995; Steidl *et al.* 1997). Table 1.1 illustrates four possible outcomes of a monitoring programme, with the aim that if a detrimental effect is detected a management plan to control the effect will be applied.

Table 1.1. Possible outcomes and potential costs of Type I and Type II errors. The probabilities of each are given in brackets.

Measured effect	True Effect	
	Population is Stable	Population is Declining
No significant effect ($p > \alpha$)	Conclusion is correct, no further action ($1 - \alpha$)	Type II error (β), no further action, with potential cost of D due to the decline of this population
Significant decline ($p < \alpha$)	Type I error (α), management action is incorrectly applied, with cost M.	Conclusion is correct ($1 - \beta$), management action is applied with cost M.

If the perceived cost of making a Type II error (D) is much larger than the cost of incorrectly applying the management or preventative action (M), a less stringent α would be advisable in order to increase the power for detecting such an effect. Mapstone (1995) suggested setting the ratio of Type I to Type II error probabilities based on their perceived costs in an environmental impact study. Based on this ratio the actual error rates are set such

that the monitoring programme would be capable of detecting an effect that is deemed to be the minimum permissible effect, at significance level α with power $1-\beta$. However, identifying what effect constitutes the minimum permissible effect, and also the related costs of Type I and Type II errors can be an overwhelming task due to the number of factors and considerations that need to be taken into account.

1.2.4 – Retrospective power analyses

Thus far discussion of power analysis has been limited to the planning aspect of monitoring schemes, or so called prospective power analyses. Retrospective power analyses can also be useful, but they have come under a considerable amount of criticism, mainly due to misuse, or misunderstanding of what can be gained from performing additional power analyses (Hoenig & Heisey 2001). The major criticism has been that of performing retrospective power analyses based on the measured effect size, when they were unable to conclude that there was a significant effect. This analysis yields no new information because it is already known that for this effect size the power of the experimental or survey design must be low (less than 50%) as it failed to give a significant result (Hayes & Steidl 1997; Thomas 1997). When applied correctly however, retrospective power analyses can be particularly useful. Reed & Blaustein (1995) and Hayes & Steidl (1997) applied retrospective power analyses to multiple long-term datasets of amphibian abundance where no statistically significant effect was found. The former incorrectly calculated the power for the effect sizes determined in the studies themselves and showed that power was universally low. The latter study showed that for the datasets concerned, power was low for detecting all reasonable rates of decline, and that power is only sufficient (80%) when the effect is either extremely large, or the survey is carried out for a much longer period of time. Thus they concluded that the results presented in the amphibian surveys they examined were not proof of population stability, but should rather be considered inconclusive and inadequate to determine the true rate of change. Many ecological studies would benefit from this type of analysis, as failure to reject the null hypothesis is too often associated with no effect, without any consideration of how effective the experimental or monitoring design was.

1.2.5 – Criticism of point-null hypothesis testing in ecological studies

Thus far this review has mainly considered power analyses as a means of judging monitoring design effectiveness. Power analysis is an extension of the zero point null-hypothesis significance testing framework, and as such is also subject to the considerable

criticism that has been levelled at this testing framework (see Gerrodette 2011). The major criticism is that statistical significance and biological significance are unrelated concepts and while a study may be able to demonstrate statistical significance, this does not imply biological significance (small effect size, with low variability) and similarly biologically significant effects may be overlooked in the quest for statistical significance (large effect, but demonstrating this may be confounded by variable data) (Gerrodette 2011). In addition, many have argued that the rejection of a null hypothesis of no-effect is meaningless because it was never a valid hypothesis (outside of experimental studies where the null hypothesis may be an entirely valid proposition given adequate controls) as even the smallest deviation away from equivalence would negate the hypothesis (Anderson *et al.* 2000; Gerrodette 2011).

Despite these criticisms power analysis is still a useful tool for evaluating monitoring programme effectiveness (Seavy & Reynolds 2007). There have, however, been several recommendations for expanding the utility of monitoring design assessments and statistical reporting in general. The vast majority of these recommendations include the reporting of estimated effect sizes and their confidence intervals as a measure of precision (McBride *et al.* 1993; Anderson *et al.* 2000; Nakagawa & Cuthill 2007; Gerrodette 2011). This incorporates a measure of the biological significance of the effect being reported (its magnitude and direction) and the range of values the effect is likely to have (how certain are the results). Expanding this into the arena of monitoring programme design highlights that there are two aspects of monitoring programme design that are often emphasised - the accuracy and precision of resulting estimates of ecological parameters (e.g. abundance, change in abundance) (Tyre *et al.* 2003). Statistical bias is concerned with how much the estimate differs from the true population value, which may result from sampling too few sites, or sites that are not representative of the population as a whole (Olsen *et al.* 1999; Vos *et al.* 2000) with several studies focussing on bias reduction by altering monitoring programme design (Tyre *et al.* 2003; Wintle *et al.* 2004). Precision is associated with the range of the estimated parameter and is a measure of the uncertainty of statistical estimates. Both aspects are important to ecological reporting but it is worth noting that whilst a monitoring design may be precise in the determination of ecological parameters, this does not guarantee that the estimated parameters are accurate, and so consideration of both bias and precision are important in monitoring programme assessments (Wintle *et al.* 2004; Nakagawa & Cuthill 2007; Seavy & Reynolds 2007).

1.3 – Monitoring to quantify spatial and temporal variability

Identifying the spatial and temporal variability that exists in an area prior to protection is an important consideration both for setting baselines of abundance (Edgar *et al.* 2004; Pande & Gardner 2009) and for defining where best to place protected areas with regard to the spatial distribution of biodiversity (Roberts *et al.* 2003; Stewart & Possingham 2005; Leslie 2005). However, due to the expense of performing replicated ecological monitoring over wide enough areas and because of *ad hoc* establishment decisions (e.g., marine reserve boundaries may change as a result of negotiations between different stakeholders) (Pande & Gardner 2009), baseline surveys are often not carried out. In addition, for exploratory surveys for MR planning there may be a lack of incentive to provide funds to perform this kind of work, perhaps due to the perception that surveillance data is not immediately useful or urgent as MR planning may take years (Pande and Gardner 2009) and may never come to fruition (Wood *et al.* 2008). Thus, alternative methods of assessing spatial variability in abundance and/or species distributions (e.g. species distribution models) (Elith & Leathwick 2009) are likely to aid both in determining baselines of spatial and temporal variation as well as MR planning and designation.

1.3.1 – The importance of spatially and temporally replicated baseline data

The collection of baseline data is vital in order to make strong assertions about the effects of protection (Ward & Jacoby 1992; Edgar *et al.* 2004; Pande & Gardner 2009). Without prior knowledge of the spatial variation exhibited both within and among designated reserve and control sites, observed differences may be attributable to pre-existing spatial variation, which is likely to confound control-impact studies (Edgar *et al.* 2004; Pande & Gardner 2012). The few examples of baseline data collected prior to reserve establishment have illustrated the utility of performing baseline surveys. Edgar *et al.* (2004) performed extensive surveys of marine areas designated for conservation, tourism only, fishing only and multi-purpose areas in the Galapagos Marine Reserve prior to the enforcement of these boundaries. Their findings were indicative of considerable bias in the placement of these designated areas, with areas open to fishing containing the highest abundance of sea cucumbers (the most valuable fishing resource in the region), compared to conservation units which had sea cucumber densities three times lower. In addition, the magnitude of spatial variation was comparable with the size of previously demonstrated protected area effects, and thus the effects of reserve designation could easily be masked through selective site placement. Therefore, without baseline data from these sites it would be difficult to confirm

(through a control-impact analysis) that the conservation units were effective, but with baseline data the effects of fishing exclusion can be more readily demonstrated. Pande & Gardner (2009) collected a spatially and temporally replicated baseline dataset for the Taputeranga Marine Reserve in Wellington, New Zealand. The resulting surveys revealed a gradient among sites in fish abundance and macroalgal composition moving from East to West, with reserve sites in the centre. In addition, several surveyed species exhibited significant temporal variation among years and seasons. Acknowledging that this spatial and temporal variation exists gives not only a baseline against which to compare future survey data, but also gives a measure of the variation through time that would be naturally expected and thus provides a background for separating MR effects from natural variation (Ward & Jacoby 1992).

1.3.2 – Adapting monitoring data beyond “Site”

Baseline data are vital for informed management and conservation actions, including the effective designation of MPAs (Roberts *et al.* 2003; Lundquist & Granek 2005; Leslie 2005), mapping of invasive species distributions (Delaney *et al.* 2008), and also for increasing the efficiency and effectiveness of future monitoring by identifying specific habitat units that exist in an area (dit Durell *et al.* 2005). Many, if not all monitoring programmes focus sampling effort within specific locations, either due to specificity of the habitats within these sites, but more often due to logistical and time limitations. However, with a location-specific approach (i.e. monitoring within sites) changes that occur elsewhere are likely to be missed, or at least baseline data for these locations will not exist making it difficult to assess the degree of localised changes. One approach would be to increase the number of sites to achieve greater coverage. However, this is often not feasible due to escalating costs. In the terrestrial realm much has been achieved by using predictive models relating species’ distributions to the environment (Guisan & Zimmerman 2000; Rodriguez *et al.* 2007; Elith & Leathwick 2009; McMahon *et al.* 2011). Establishing predictive baselines of species’ distributions can be useful from a monitoring and management perspective because it allows inferences (with a given level of certainty) to be made about what species (or species groups) should have been in a given location that may have been previously unsampled. This widens the scope of the monitoring programme beyond the realm of the sites sampled and can increase the applicability of monitoring data in making inferences about whole marine areas. The numbers of predictive species’ distribution models applied in marine studies are however, considerably less than in terrestrial applications, but of the models

developed the vast majority have been for the purpose of aiding marine conservation planning (Robinson *et al.* 2011). Leathwick *et al.* (2006) used a predictive modelling approach to identify the variation in demersal fish species richness in the oceans around New Zealand. In a later paper, Leathwick *et al.* (2008a) built upon this knowledge and mapped the predicted distributions of 96 fish species, and used this information to evaluate alternative offshore marine reserve configurations, and highlighted the utility of adapting quantitative data beyond patchy trawl data to provide recommendations over a much wider area. Furthermore, Maxwell *et al.* (2009) used a predictive modelling approach to define the spatial distribution of three fish species in response to environmental factors in order to define management and protection areas. Predictive modelling can therefore increase the usefulness of collected baseline data, in collaboration with relevant environmental factors, by providing information regarding the surrounding areas that were un-surveyed.

1.4 – Marine reserve monitoring in New Zealand

The primary purpose of MRs in New Zealand is for scientific study and as such there have been many studies documenting changes within MRs and the recovery of species. However, much of the monitoring is focussed on commercially valuable species such as snapper (*Pagrus auratus*) (Willis *et al.* 2003a; Denny *et al.* 2004), blue cod (*Parapercis colias*) (Davidson 2001; Stewart & MacDiarmid 2003; Davidson *et al.* 2001; 2007; 2009), rock lobster (*Jasus edwardsii*) (Kelly *et al.* 2000; Davidson & Abel 2003; Haggitt & Kelly 2004; Haggitt & Mead 2007), paua (abalone species, *Haliotis iris* and *Haliotis australis*) and kina (sea urchin species: *Evechinus chloroticus*) (Davidson & Abel 2003; Davidson *et al.* 2001; 2007; 2009). The motivation to monitor these species is understandable in that these species experience the largest fishing pressures, both commercially and recreationally, and thus are most in need of monitoring. In the case of MR monitoring these species are most likely to have the strongest and most rapid response to reserve status (Battershill *et al.* 1993; Shears 2007; Pande & Gardner 2012) and so are most likely to provide a good indication that marine reserves ‘work’ (i.e. achieves the conservation goals explicit in their design and establishment), and as such much of the Department of Conservation’s monitoring programmes are focussed on these few species.

Marine reserve monitoring in New Zealand has been criticised for being too short-term to truly assess the changes that are occurring within them (Cole 2003). The Cape Rodney to Okakari Point Marine Reserve (Leigh) was the first to be established in NZ and

considerable research and monitoring has been performed there, including the documenting of increases in abundance of rock lobster and several fish species in the early years after reserve establishment (Cole *et al.* 1990), and the quantification of long-term changes to subtidal habitats in the reserve (Shears & Babcock 2003). In addition, the Department of Conservation has a few extended monitoring programmes, in particular at the Long Island-Kokomohua Marine Reserve (Davidson *et al.* 2009) and the Tonga Island Marine Reserve (Davidson *et al.* 2007) where monitoring of reef fish, rock lobster, paua and kina has been ongoing for 15 years or more, and also at the Te Whanganui-A-Hei Marine Reserve, where reef fish populations have been monitored for more than ten years (Taylor *et al.* 2006). The vast majority of other work carried out by DOC in marine reserves involves smaller, one-off surveys assessing mainly the status of rock lobster populations inside and outside several marine reserves (Haggitt & Kelly 2004, Haggitt & Mead 2007), and of common reef fish (Shears & Usmar 2006). Such one-off focussed surveys are informative to a point, but are lacking in that they are unable to assess how abundances or communities are changing. Furthermore, with one-off surveys such as these it is impossible to separate the MR effect from spatial variability in abundances, highlighting the need for baseline data or extended datasets in which trends in abundance can be identified. Cole (2003) recommends that marine reserves be monitored over a period of decades to truly assess any changes occurring and to determine that populations have become stable. In some cases changes in MRs may not become apparent for 20 years or more after reserve establishment (Shears & Babcock 2003). For example, changes in macroalgal abundance at the Leigh were still being observed up to 25 years after reserve establishment due to the slow recovery of carnivorous species controlling grazers (Shears & Babcock 2003). When interactions such as these occur, the expected time scale of monitoring is recommended to be twice the length of the longest lived species involved (Connell & Sousa 1983; Cole 2003) in order to truly assess that the reserve site has returned to a stable state. However, the cost of performing such a long-term monitoring programme is often prohibitive, and with the number of MRs in New Zealand, it would be not feasible to establish a long-term monitoring programme for each due to spiralling costs.

Another area that has thus far been largely ignored in MR monitoring in New Zealand is the intertidal zone. Marine reserves may have a possibly detrimental effect on the mid to upper intertidal and of rock pool communities due to increased trampling as a result of increased visitor numbers (Brown & Taylor 1999). For example, the effects of trampling

have been shown to affect animals inhabiting coralline algal turf at the Cape Rodney to Okakari Point Marine Reserve (Brown & Taylor 1999), and have been shown to detrimentally affect algal assemblages of rocky intertidal platforms (Schiel & Taylor 1999). This may have wide ranging impacts, such as a reduction in biodiversity, and a noticeable reduction in larger branching species of algae and an increase in ephemeral species (Pinn & Rodgers 2005). Brown & Taylor (1999) argue that because of the possible damage caused by human visitation that in some cases marine reserves should be entirely closed off to the public to fully protect the flora and fauna present. However, without any form of intertidal monitoring it is difficult to assess the effects of reserve designation on intertidal assemblages, and so intertidal monitoring should be incorporated into MR monitoring plans.

1.5 – Aims and thesis structure

The first aim of this thesis is to analyse various marine monitoring methods, current monitoring programmes and baseline surveys to assess the statistical power associated with the specific method or monitoring approach. For each methodology, an assessment of their effectiveness will be carried out, and recommendations will be given for improvements that will increase their statistical power.

Chapter 2 focuses on a traditional power analysis approach applied to a multiple species (reef fish and invertebrate species) baseline data set collected within the Taputeranga Marine Reserve, Wellington. This extensive baseline dataset is one of the few datasets that includes information regarding species abundances prior to marine reserve establishment. This dataset is used to identify the optimal approach for subsequent marine reserve monitoring, both in terms of statistical power and also including an analysis of the monetary costs of the alternative monitoring approaches. The aim of this chapter is to present the statistical power attributable to each methodology for each species and consequently provide recommendations for establishing a multispecies monitoring programme that has high statistical power for detecting changes that may occur as a result of reserve status. Chapter 3 builds on this, incorporating measures of precision and accuracy, as well as power, in order to identify the best monitoring approach. Monitoring designs should provide both accurate and precise measures of the changes in abundance through time of the monitored species. A large part of this chapter assesses whether a focus on power analyses alone can identify an accurate and precise monitoring programme. The aim of this chapter was therefore to analyse the accuracy, precision and power of alternative monitoring approaches to identify the best

monitoring approach for monitoring reef fish within New Zealand. This was achieved by analysing data collected from three marine reserves in New Zealand, and comparing and contrasting the efficacy of the different monitoring approaches across species, but also among reserves. This also allowed for a comparison among the different metrics that are used to define what constitutes an effective monitoring programme (power, precision and accuracy), and which aspects of a monitoring design are emphasized by each of these measures.

The second aim of my thesis is to highlight uses of monitoring data beyond identifying changes through time, and incorporating the development of species distribution models into a baseline monitoring framework. In Chapter 4 I develop a wave model (Simulating WAVes Nearshore – SWAN) for Wellington’s South Coast to predict the wave forces experienced by subtidal and intertidal organisms at various locations. The variation in wave exposure across the south coast is used to predict potential disturbance rates for two species of canopy forming, and therefore habitat modifying, macroalgae, *Ecklonia radiata* and *Macrocystis pyrifera*. This information is also used in Chapter 5 where I utilise these predictions of wave exposure and relate them to biological data collected from the intertidal zone over a two year time period to identify predictive species distribution models relating species presence/absence and abundance to a range of physical forces, including wave action. The primary aim of this chapter was to develop a predictive model baseline for the current distribution of intertidal species across Wellington’s south coast. In Chapter 6 I draw together all of my findings from the four previous chapters and include a survey of the marine monitoring literature in order to develop a framework for MR baseline data collection, establishment using spatial and temporal data complemented by species distribution model predictions, and subsequent monitoring protocols.

Overall the aim of this thesis is to provide an assessment of commonly employed methodologies for monitoring marine species, and to provide an assessment of specific analysis methods for analysing and utilising these data to develop predictive baselines that expand the utility of monitoring data. The outcomes are to provide a series of recommendations and proposals for future monitoring and data analysis, specific to New Zealand, but that may be applied globally.

Chapter 2 - Evaluating marine reserve monitoring programs using baseline data: A case study from the Taputeranga Marine Reserve, New Zealand

2.1 – Introduction

The increasing international trend to create marine reserves (MRs - usually defined as full no-take areas) and marine protected areas (MPAs - usually defined as an area providing partial but not full protection from anthropogenic disturbance) has focused the attention of marine scientists and government agencies on the need to develop cost-effective and powerful monitoring strategies to quantify the benefits of such protection (e.g. Lubchenco *et al.* 2003; Gerber *et al.* 2005; Grorud-Colvert *et al.* 2010; Gaines *et al.* 2010; Roberts *et al.* 2010; Ban *et al.* 2011). Monitoring is the systematic acquisition of biotic or abiotic data, which are used to inform management, to aid further monitoring decisions, or to help establish further protected areas, for example in a network (Rice & Houston 2011; Di Franco *et al.* 2012). In the case of MRs or MPAs such data may be used to assess the state of natural marine systems in the absence of anthropogenic disturbance or to assess recovery of impacted species (Allison *et al.* 1998). MR monitoring often focuses on the abundance of fish or invertebrate species, and involves an assessment of MR “effects”. These range from direct effects, such as an observed increase in the size and/or abundance of previously targeted or harvested species (Russ *et al.* 2005; Pande *et al.* 2008; Diaz Guisado *et al.* 2012) or changes in community level metrics, such as species richness and diversity (Micheli *et al.* 2004; Molloy *et al.* 2010). The design and application of monitoring programs in and around MRs is therefore now recognised as being important in terms of informing managers, scientists and the public about the real and perceived costs and benefits of establishing and maintaining various types of MPAs (Cole 2003; White *et al.* 2011; Pande & Gardner 2012).

Since such quantifications began, most studies have reported that MR sites have an increased abundance and/or size of targeted species compared to non-reserve sites (Pande *et al.* 2008; Lester *et al.* 2009; Watson *et al.* 2009; Diaz Guisado *et al.* 2012). However, the effects may be extremely variable from one reserve to another (Lester *et al.* 2009). The variability of the responses is not surprising given the considerable differences in habitat type and distribution, environmental condition, enforcement and prior level of anthropogenic impact at different MR sites (Mosqueira *et al.* 2000; Kelly *et al.* 2000; Micheli *et al.* 2004). To control for this, monitoring requires significant amounts of planning and effort to obtain reliable estimates of abundance. MR monitoring, however, has been subject to considerable criticism because the data quality is highly variable (Edgar & Barrett 1999; Willis *et al.* 2003b), with studies being criticised for inadequate spatial and temporal replication (Molloy *et al.* 2010; Kelly *et al.* 2000; Field *et al.* 2007) and lack of adequate controls (Jones *et al.*

1993; Russ 2002; Denny *et al.* 2004). The main criticism, however, is that MR studies are largely comprised of one-off comparisons of reserve sites versus non-reserve sites (Russ 2002; Willis *et al.* 2003b; Denny *et al.* 2004). As such, the effect observed between reserve and non-reserve areas cannot wholly be attributed to a MR “effect” because such studies fail to account for differences that may have existed prior to reserve establishment (Côté *et al.* 2001; Claudet *et al.* 2006). This criticism pertains to the lack of adequate baseline data both within and outside MR sites (Mosqueira *et al.* 2000; Micheli *et al.* 2004; Claudet *et al.* 2006, but see Russ & Alcala 1996; Edgar & Barrett 1999; Parsons *et al.* 2004). Without baseline data, identifying the rate of response to protection (Denny *et al.* 2004) and distinguishing between the effects of natural variation among sites and over time from the effects due to reserve protection are impossible (Claudet *et al.* 2006; Pande & Gardner 2012).

The concept of a Before-After-Control-Impact (BACI) statistical testing regime (now modified to include multiple site or region comparisons, and known as “beyond BACI”) (Underwood 1992; 1994; Benedetti-Cecchi 2001) has been used extensively in environmental monitoring situations because it is capable of distinguishing between natural variability and the effect of a certain treatment (Underwood 1994; Benedetti-Cecchi 2001; Skilleter *et al.* 2006; Di Carlo *et al.* 2011). This is the most appropriate form of test for determining MR effects because it is capable of identifying effects independent of general temporal changes and pre-existing spatial differences between sites (Allison *et al.* 1998; Fraschetti *et al.* 2002; Benedetti-Cecchi *et al.* 2003; Claudet *et al.* 2006). However, due to the paucity of studies that perform monitoring prior to reserve establishment there are few published examples of its use in a MR context (however, see Lison de Loma *et al.* 2008).

The aim of this study was to evaluate the performance of a range of sampling designs for monitoring a newly established marine reserve for which baseline data had been collected. The Taputeranga Marine Reserve (TMR) was officially gazetted in 2008 and is situated on the south-coast of the North Island of New Zealand (Figure 2.1). TMR is located in the highly dynamic Cook Strait, which separates the North and South islands of New Zealand (Pande & Gardner 2009). The surrounding area supports a commercial rock lobster (*Jasus edwardsii*) fishery and is subject to high recreational fishing pressure. Densities of targeted species, mainly blue cod (*Parapercis colias*), blue moki (*Latridopsis ciliaris*) collected by line fishing, butterfish (*Odax pullus*) collected by spearfishing, rock lobster, abalone (paua - *Haliotis iris*, *Haliotis australis*) and to a lesser degree sea urchin (kina - *Evechinus*

chloroticus) collected by recreational divers, are likely to change at reserve sites as a result of the cessation of fishing activity (Pande *et al.* 2008; Pande & Gardner 2009; Diaz Guisado *et al.* 2012). The baseline abundances of fish and invertebrate species were collected from multiple sites within and outside the future TMR (Figure 2.1), thereby providing valuable information as to the pre-existing natural variation along this coastline. Furthermore, this baseline sampling was replicated over several years, giving an indication of the variation over temporal, as well as spatial scales, relevant to the design of future sampling protocols (Pande & Gardner 2009).

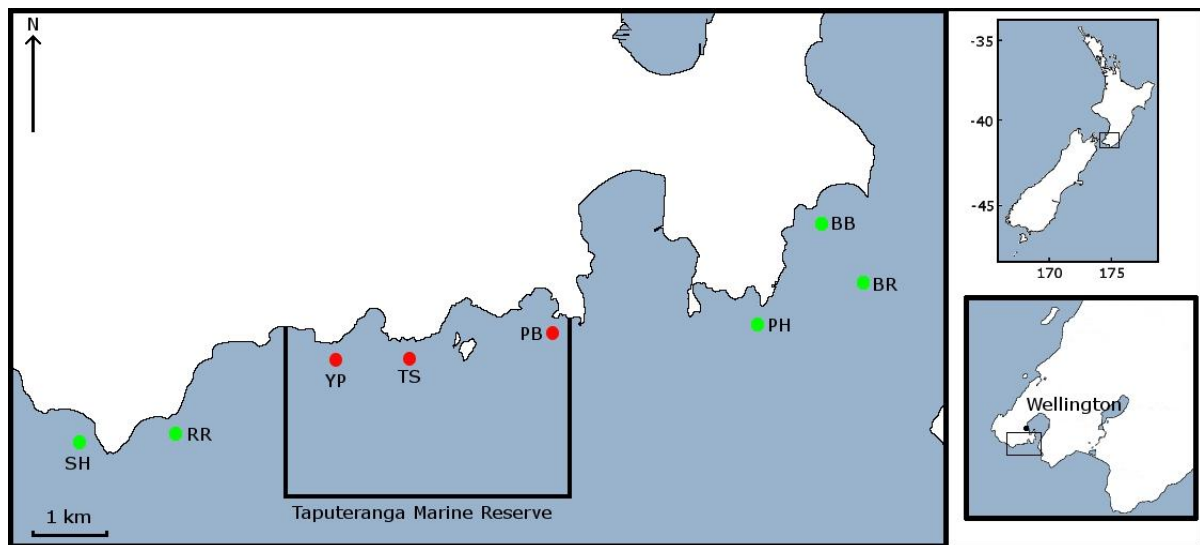


Figure 2.1. Location of the Taputeranga marine reserve and the study sites located within and outside of the marine reserve. Site codes are BR-Barrett Reef, BB-Breaker Bay, PH-Palmer Head, RR-Red Rocks and SH-Sinclair Head for control (non-reserve) sites (●) and PB-Princess Bay, TS-The Sirens and YP-Yungh Pen for reserve sites (●).

This multi-site, multi-year baseline data-set is used to evaluate a series of monitoring programs to test their ability to identify biological change and also measure their cost-effectiveness for survey work. Specifically, the statistical power for detecting changes in the abundances of several fish and invertebrate species was obtained in order to identify a monitoring design that is capable of detecting biologically significant changes in abundance. The statistical power of several monitoring designs incorporating different amounts of spatial and temporal replication were evaluated and the costs and the benefits of each design are discussed in order to identify an optimum monitoring design for the different species considered. In a wider context, the general process outlined here of evaluating monitoring program design with regard to decisions pertaining to sampling effort provides a guide for

establishing future monitoring protocols and highlights the importance of acquiring baseline data.

2.2 – Methods

2.2.1 – Data collection

Data were collected using standardised methodologies between 1998 and 2010 at 8 sites (Table 2.1, Figure 2.1), as described by Pande and Gardner (2009). Briefly, sites were located in coastal reef areas with no defined shelf or slope. Data were collected from a standardised depth range (8-15 m) to avoid confounding effects of depth. Fish counts were obtained by underwater visual census (UVC) performed along 25 m belt transects. Transect tapes were tied off in an initial start position and one diver would swim in a random direction from the start point and the other diver, after indicating the start of the transect at 5 m, would follow behind with the transect line, so as not to scare the fish away before the diver counting the fish could record them. All fish encountered within a 2.5 m distance either side of the transect tape were counted and identified to species level (125 m² surveyed per transect x 9 replicates per site). Invertebrate abundances were also estimated using UVC. A 25 m transect line was laid down haphazardly in the defined area and each diver would swim along the transect whilst intensively searching a one metre strip on their side of the tape counting all abalone, urchins and rock lobsters encountered (50 m² per transect x 6 replicates per site). The analysis was restricted to data collected during the Austral summer season (December-March) for all of the species listed in Table 2.1.

2.2.2 – Preliminary analyses and summary statistics

The data-set was composed of individual counts which are likely to follow an overdispersed poisson distribution (White & Bennetts 1996; Dennis *et al.* 2010), with varying degrees of overdispersion among species. In addition, the data exhibited temporal variability among survey years, as well as variability within and between-sites. Due to the non-gaussian nature of the error distributions and the number of variance components, a Monte-Carlo simulation approach was adopted to assess statistical power. This involves generating data that has the same characteristics (i.e., spatial and temporal variability) as the observed data, but where some inherent difference between treatments/time periods is included (Sims *et al.* 2006). The analyses are focussed specifically on determining the power for detecting changes in abundance of three targeted fish species, blue cod (*Parapercis colias*), blue moki (*Latridopsis ciliaris*) and butterflyfish (*Odax pullus*), and three non-targeted fish species,

banded wrasse (*Notolabrus fucicola*), scarlet wrasse (*Pseudolabrus miles*) and spotty (*Notolabrus celidotus*). Similarly four targeted invertebrate species were included for analysis, rock lobster (*Jasus edwardsii*), blackfoot paua (*Haliotis iris*), yellowfoot paua (*Haliotis australis*) and kina (*Evechinus chloroticus*).

To aid with comparing these results with data of other species in other systems, a range of simple summary statistics were calculated from the observed data. Observed abundances were summarised by calculating the average abundance (ind/125m² for fish, and ind/50 m² for invertebrates) across all sites, as well as identifying the site-specific maximum and minimum densities across all surveys. To give a representation of the variability exhibited by the data, the maximum and minimum survey specific mean densities (averaged across the nine or six replicate counts at each site and each survey period for fish and invertebrates, respectively) were calculated, as well as the variance of mean densities across all surveys. Finally, to represent the variability among replicate transects (i.e. among the nine, or six, replicate counts), the ratio of the variance among replicate counts to the mean density was calculated for each survey (ratio's equal to one indicate poisson distributed counts whereas greater than one indicates overdispersion and clumping of counts). The variance:mean ratios averaged across all surveys, as well as the maximum and minimum ratios are presented. These statistics were calculated separately for reserve and non-reserve designated sites.

Table 2.1. Species and datasets included in the analysis along with the time period data was collected and the number of replicate transects per site.

Species	Common Name	Dataset	Time Period	Sample Size per Survey
Fish				
<i>Notolabrus fucicola</i>	Banded wrasse	Pande & Gardner 2009	1998-2000	9 transects (25m by 5m)
		Eddy 2011	2008-2010	
<i>Parapercis colias</i>	Blue Cod	Pande & Gardner 2009	1998-2000	
		Eddy 2011	2008-2010	
<i>Latridopsis ciliaris</i>	Blue Moki	Pande & Gardner 2009	1998-2000	
		Eddy 2011	2008-2010	
<i>Odax pullus</i>	Butterfish	Pande & Gardner 2009	1998-2000	
		Eddy 2011	2008-2010	
<i>Pseudolabrus miles</i>	Scarlet Wrasse	Pande & Gardner 2009	1998-2000	
		Eddy 2011	2008-2010	
<i>Notolabrus celidotus</i>	Spotty	Pande & Gardner 2009	1998-2000	
		Eddy 2011	2008-2010	
Invertebrates				
<i>Evechinus chloroticus</i>	Kina	Pande & Gardner 2009	1998-2000	6 Transects (25m by 2m)
		Byfield 2012	2008	4 Transects (25m by 2m)
<i>Jasus edwardsii</i>	Rock Lobster	Pande & Gardner 2009	1998-2000	6 Transects (25m by 2m)
		Byfield 2012	2008	4 Transects (25m by 2m)
<i>Haliotis iris</i>	Blackfoot Paua	Pande & Gardner 2009	1998-2000	6 Transects (25m by 2m)
		Russell 2004	2003	4 Transects (25m by 2m)
		Byfield 2012	2008	
<i>Haliotis australis</i>	Yellowfoot Paua	Pande & Gardner 2009	1998-2000	6 Transects (25m by 2m)
		Russell 2004	2003	4 Transects (25m by 2m)
		Byfield 2012	2008	

2.2.3 – Decomposition of variance

Four variance components were identified as important contributors to the overall variance, (i) within-site, (ii) between-site and (iii) between-survey temporal effects that were the same across sites (synchronous temporal variation), and (iv) different between sites (interaction temporal variation) (Larsen *et al.* 2001). Quasipoisson generalized linear mixed effects models (GLMER with log link in R package lme4) (Bates & Maechler 2010) were applied to the data for each species to quantify the magnitude of each of these variance components. In this assessment a fixed factor describing the differences between the different datasets (e.g. between datasets from Pande & Gardner 2009 and Eddy 2011 for fish) was included so that variation due to different teams of people collecting the data were not misinterpreted as random variation through time. The magnitude of the synchronous and interaction temporal variability terms were quantified by including random effects of “Year” and “Site:Year”, respectively, into the mixed effects model. The standard deviations σ_Y and σ_{YS} of these random effects were taken to be representative of the magnitude of variation

attributable to synchronous and interaction temporal variability, respectively. Because between-site differences are likely to be maintained in future surveys, and all future surveys are likely to be carried out at the original sites, “Site” was incorporated as a fixed factor and the site averages from the data were used as the starting point for simulating future counts from these sites. Within-site variance was modelled based on a negative binomial distribution to generate counts with similar dispersion as the observed data (the negative binomial distribution is often used to model overdispersed counts) (White & Bennetts 1996; Link & Sauer 1998; Dennis *et al.* 2010). The negative binomial model has two parameters, the mean μ and a dispersion parameter ν , and has variance according to equation 2.1

$$Var = \mu + \frac{\mu^2}{\nu}$$

eqn. 2.1

As ν tends towards high values the negative binomial distribution tends toward a poisson distribution with variance equivalent to the mean. However, as ν tends to zero the generated counts become overdispersed compared to a poisson distribution, exhibiting a high degree of clumping (White & Bennetts 1996). Negative binomial distributions were fitted to replicate counts obtained at each site on each survey date (year) and the dispersion parameter was recorded for each model fit. These were averaged and the resulting parameter was used to model the dispersion in the simulated data. This was applied to the data separately for each species.

2.2.4 – Data simulation

The simulation process was split into two parts. The mean values for each site i in each year t , denoted by $\mu_{i,t}$, were constructed according to equation 2.2

$$\ln(\mu_{i,t}) = \eta_i + A_t + B_{i,t}$$

eqn. 2.2

where η_i is the log-average abundance at site i , A_t is the random effect of year and $B_{i,t}$ is the random effect of year specific to each site. Values for A_t and $B_{i,t}$ were generated as normal random variables drawn from distributions with means equal to zero and standard deviations equal to σ_Y and σ_{YS} , respectively. The average value is expressed as a logarithm because a logarithmic link function was used in the GLMER fit to the baseline data. Individual counts

$Y_{k,i,t}$, with transect number denoted by subscript k were then generated from a negative binomial distribution with mean $\mu_{i,t}$ and dispersion parameter ν for each site i and time t .

$$Y_{k,i,t} \sim NB(\mu_{i,t}, \nu)$$

eqn. 2.3

For control sites, η_i was taken to be constant, such that abundances were the same as in the baseline data. As such, any observed changes would be due to random variation in the number of individuals observed rather than due to any consistent changes over time. To simulate different MR effects, η_i was set to different values according to different hypothetical scenarios whereby the abundance is 2, 4, 6 or 8 times greater within reserve sites in the after period compared to the baseline data (Table 2.2). Such changes in abundance are consistent with actual recorded changes (e.g. Pande *et al.* 2008, Diaz Guisado *et al.* 2012). Three temporal monitoring design choices were considered. The first (hereafter referred to as design 1) consisted of generating data for a single surveyed year. This is representative of a one-off survey where data from a single surveyed year are compared to the baseline data. The second (design 2) consisted of generating data that corresponds to a sampling design that is replicated over two consecutive years. The third (design 3) consisted of generating data that correspond to a sampling design that is replicated over three consecutive years (Table 2.2). For each of these designs three levels of within-site replication were simulated, giving a total of nine competing monitoring designs (Table 2.2).

Table 2.2. Effect sizes investigated and the level of replication in terms of replicate transects and number of consecutive years surveyed.

Species	Transects	Years/Designs	Proportional increase in abundance
Fish	6,9,12	1,2,3	2
	6,9,12	1,2,3	4
	6,9,12	1,2,3	6
	6,9,12	1,2,3	8
Invertebrates	4,6,8	1,2,3	2
	4,6,8	1,2,3	4
	4,6,8	1,2,3	6
	4,6,8	1,2,3	8

2.2.5 – Testing procedure

To test the combined simulated and baseline data for a significant MR effect a BACI testing procedure was performed. The simulated data set (1, 2 or 3 years depending on design – Table 2.2) was combined with the baseline data set so that a full before-after data scenario

was created. Two quasipoisson GLMER models were fitted to the combined dataset. The first model consisted of fixed factors for Treatment, Period and random factors for Site, Year and Site:Year to account for spatial and temporal variability. The second model was the same, but with the inclusion of the Treatment:Period term. The two models were then compared using a likelihood ratio test (aov in R) based on AIC and log-likelihood values to determine the best model fit to the data (Pinheiro & Bates 2000). A p -value of less than 0.05 from the likelihood ratio test was interpreted as an indication that the interaction term was a significant addition to the model and thus constituted a MR effect. The simulation procedure was run 1000 times, and the power to detect a reserve effect was interpreted as the proportion of these simulations where the second model was a statistically significant improvement on the first model. All simulations and tests were performed in R version 2.12 (R Development Core Team 2011).

2.2.6 – Monitoring design costs

The costs of the competing monitoring designs were calculated based on the time required to conduct the surveys. Based on field experience, it was assumed that three dives could be carried out each day, with each dive lasting 40 min for minimal replication (invertebrates – 4 transects, fish – 6 transects) and 60 min for medium replication (invertebrates – 6 transects, fish – 9 transects), carried out by two experienced scientific divers. In order to carry out the maximum replication (invertebrates – 8 transects, fish – 12 transects) it was assumed that dives lasted 40 min and were carried out by 4 experienced scientific divers with the workload split evenly between the two pairs of divers. A surface interval of three hours between dives was assumed for safety purposes. Based on local experience, an hourly rate of \$130 (NZD) for the scientific divers was assumed, and daily boat and skipper hire were estimated at \$1500 (NZD). Although costs are not specific to any agency or operator they are indicative of the costs required for this kind of work. Based on these costs the power to detect a four-fold increase in abundance divided by the costs was calculated as an indication of the cost-effectiveness of the competing monitoring designs.

2.3 – Results

Summary statistics regarding species abundances within and outside of marine reserve sites and simulation parameters are given in Table 2.3

Table 2.3. Parameters estimated from the mixed effects models that were used to perform the simulations and summary statistics regarding abundance within and outside reserve designated sites, survey specific abundances, and variance estimates with respect to the variance among survey means, and the ratio of within survey variance to the within survey mean as a measure of the among transect variability. Densities are ind/125m² for fish, and ind/50 m² for invertebrates.

Species	Area	Density				Within survey var:mean ratio		Parameters		
		Average	Site Specific (min, max)	Survey Specific (min, max)	Var of survey means	Average	Survey specific (min, max)	σ_Y	σ_{YS}	ν
Banded Wrasse	R	0.38	(0.33, 0.44)	(0.00, 0.89)	0.10	0.96	(0.69, 1.40)	0.24	0.32	3.86
	C	0.85	(0.40, 1.63)	(0.11, 4.11)	0.95	1.48	(0.50, 5.10)			
Blue Cod	R	0.31	(0.19, 0.52)	(0.00, 0.88)	0.10	1.35	(0.95, 3.20)	0.00	0.42	0.31
	C	0.18	(0.00, 0.33)	(0.00, 0.77)	0.08	1.37	(0.90, 3.20)			
Blue Moki	R	0.17	(0.11, 0.22)	(0.00, 0.55)	0.03	1.01	(0.88, 1.40)	0.00	0.34	4.16
	C	0.27	(0.04, 0.67)	(0.00, 0.89)	0.09	1.17	(0.57, 2.00)			
Butterfish	R	0.36	(0.00, 0.85)	(0.00, 2.11)	0.46	2.06	(0.50, 11.3)	0.09	0.47	0.41
	C	0.24	(0.07, 0.48)	(0.00, 1.33)	0.13	1.20	(0.75, 2.00)			
Scarlet Wrasse	R	0.19	(0.11, 0.33)	(0.00, 0.66)	0.05	1.07	(0.76, 2.00)	0.00	0.39	0.78
	C	0.08	(0.00, 0.15)	(0.00, 0.33)	0.01	1.04	(0.76, 2.00)			
Spotty	R	0.85	(0.33, 1.41)	(0.33, 2.22)	0.41	2.60	(0.76, 8.90)	0.00	1.20	0.81
	C	2.37	(1.15, 5.30)	(0.44, 12.00)	7.80	4.02	(0.54, 14.00)			
Blackfoot Paua	R	2.3	(1.71, 3.43)	(0.00, 11.50)	8.92	2.89	(0.80, 8.00)	0.30	1.20	1.01
	C	2.61	(0.79, 5.43)	(0.00, 8.17)	7.74	2.74	(0.66, 8.55)			
Rock Lobster	R	0.26	(0.14, 0.50)	(0.00, 2.25)	0.40	1.24	(1.00, 2.00)	0.27	0.43	1.75
	C	0.35	(0.09, 0.86)	(0.00, 3.25)	0.63	2.17	(0.66, 13.00)			
Kina	R	2.06	(1.30, 2.45)	(0.00, 8.17)	5.70	4.80	(0.66, 32.00)	0.08	0.96	0.86
	C	3.29	(0.50, 7.04)	(0.00, 15.50)	18.70	3.52	(0.60, 19.5)			
Yellowfoot Paua	R	1.93	(0.93, 3.11)	(0.00, 11.00)	8.70	1.62	(0.53, 4.30)	0.00	0.96	1.20
	C	1.11	(0.57, 1.90)	(0.00, 4.17)	1.17	1.93	(0.66, 7.00)			

Differences in power among monitoring designs were considerable (Tables 2.4 and 2.5). For fish, design 2 had 15% (range 0-36%) greater power than design 1, and design 3 had 6% (range 0-19%) greater power (averaged over species and effect sizes) than design 2. In both cases there were differences between species, with considerable increases in power to detect change in abundance of three species – blue cod, blue moki and scarlet wrasse, but smaller increases in power to detect changes in abundance of spotty (Table 2.4). For invertebrates, design 2 had 20% (range 0-43%) greater power (averaged over species and effect sizes) than

design 1, and design 3 had 8% (0-16%) greater power than design 2, with the largest increases in power to detect change for rock lobsters and yellowfoot paua (Table 2.5).

Changing the within-site replication had a much smaller effect on power than changing the replication over years (Tables 2.4 and 2.5). Designs with the highest replication had the highest power, but there were differences among species as to how power changed with design choice. When averaging differences in power across temporal designs and species, increasing the replication from six to nine transects for fish increased power by 4.4% (range 0-12%) for a four-fold increase in abundance, and by 3.1% (range 1-6%) for a six-fold increase. Further increasing the replication from six to twelve transects increased power by 6.1% (range 1-13%) for a four-fold increase in abundance, and by 5.25% (range 1-10%) for a six-fold increase. This was consistent across species but was most notable for blue cod, blue moki and butterfish (Table 2.4). Averaging differences in power across temporal designs and invertebrate species indicated that increasing replication from six to eight transects increased power by 1.1% (range 0-5%) for a four-fold increase, and by 1.8% (range 0-7%) for a six-fold increase in abundance. Decreasing replication from six to four transects decreased power by 4.8% (range 0-11%) for a four-fold increase in abundance and by 2.9% (range 0-9%) for a six-fold increase in abundance. These increases were most notable for rock lobster and kina (Table 2.5).

Table 2.4. Power to detect different proportional increases in abundance of fish species for the different monitoring design choices. The final two columns give a comparison of the difference in average power between different levels of spatial replication (differences averaged across temporal designs) and between different temporal designs (differences averaged across replication levels).

Species	Proportional increase in abundance	Power ($\alpha=0.05$)									Power		Power	
		Design 1			Design 2			Design 3			compared across replication		compared across designs	
		Transects			Transects			Transects						
		6	9	12	6	9	12	6	9	12	6-9	9-12	1-2	2-3
Banded Wrasse	2	35	39	40	46	51	54	50	59	65	+6	+3	+12	+8
	4	88	93	94	99	99	100	100	100	100	+2	+1	+8	+1
	6	98	100	99	100	100	100	100	100	100	+1	0	+1	0
	8	100	100	100	100	100	100	100	100	100	0	0	0	0
Blue Cod	2	3	3	3	5	4	4	7	4	5	-1	0	+1	+1
	4	10	11	11	25	27	26	33	39	39	+3	0	+15	+11
	6	20	22	23	44	49	54	61	66	71	+4	+4	+27	+17
	8	24	33	36	60	70	72	80	86	90	+8	+3	+36	+18
Blue Moki	2	3	4	4	6	7	10	6	8	11	+1	+2	+4	+1
	4	17	18	24	42	49	55	61	68	73	+5	+6	+29	+19
	6	43	45	50	79	84	84	91	94	95	+3	+2	+36	+11
	8	62	65	67	94	96	97	99	100	100	+2	+1	+31	+4
Butterfish	2	12	11	13	13	14	16	17	18	14	0	0	+2	+2
	4	40	46	49	56	67	69	67	79	78	+10	+1	+19	+11
	6	62	67	71	84	87	91	93	97	97	+4	+3	+21	+8
	8	80	83	82	95	96	97	99	100	100	+2	0	+14	+4
Scarlet wrasse	2	10	10	8	16	18	16	21	20	21	0	-1	+7	+4
	4	40	39	40	68	73	75	84	88	90	+3	+2	+32	+15
	6	62	68	71	93	93	95	97	98	98	+2	+2	+27	+4
	8	75	81	82	98	98	99	100	100	100	+2	+1	+19	+2
Spotty	2	19	20	20	16	16	18	13	14	12	+1	0	-3	-4
	4	48	50	52	53	53	56	60	61	62	+1	+2	+4	+7
	6	64	68	68	75	78	80	84	85	87	+3	+1	+11	+8
	8	77	79	83	88	91	94	95	96	97	+2	+3	+11	+5

Table 2.5. Power to detect different proportional increases in abundance of invertebrate species for the different monitoring design choices. The final two columns give a comparison of the difference in average power between different levels of spatial replication (differences averaged across temporal designs) and between different temporal designs (differences averaged across replication levels).

Species	Proportional increase in abundance	Power ($\alpha=0.05$)									Power		Power	
		Design 1			Design 2			Design 3			compared		compared	
		Transects			Transects			Transects			across		across	
											replication		designs	
		4	6	8	4	6	8	4	6	8	4-6	6-8	1-2	2-3
Blackfoot paua	2	8	8	7	9	7	6	9	6	7	-2	0	0	0
	4	22	22	23	32	32	33	37	41	42	+1	+1	+10	+8
	6	35	35	36	54	57	58	67	67	70	+1	+2	+21	+12
	8	45	46	51	71	73	76	82	87	86	+3	+2	+26	+12
Yellowfoot paua	2	16	14	17	26	25	27	32	32	35	-1	+3	+10	+7
	4	42	44	44	73	74	74	87	88	90	+1	+1	+30	+15
	6	61	64	66	91	92	92	97	98	98	+2	+1	+28	+6
	8	76	76	78	98	98	98	100	100	100	0	+1	+21	+2
Kina	2	5	8	7	7	8	9	6	10	8	+3	-1	+1	0
	4	23	27	28	32	43	45	46	55	53	+8	0	+14	+11
	6	39	42	46	61	69	69	76	85	85	+7	+1	+24	+16
	8	57	59	62	79	82	85	92	94	96	+2	+3	+23	+12
Rock lobster	2	7	8	7	21	23	30	33	39	51	+3	+6	+17	+16
	4	30	40	41	72	82	87	90	96	97	+9	+2	+43	+14
	6	59	65	72	95	96	99	99	99	100	+2	+4	+31	+3
	8	71	84	89	98	100	100	100	100	100	+5	+2	+18	+1

2.3.1 - Costs and cost-effectiveness

There was very little difference in cost between the minimum replication and the medium replication designs (Table 2.6) because only an additional hour each day (assuming 3 dives per day) was required to complete the additional transects. However, maximum replication designs were considerably more costly because twice the number of experienced scientific divers will be required to carry out the work (Table 2.6). Designs 2 and 3 were two and three times more costly, respectively, than design 1 because consecutive annual surveys were required. Design 1 with minimal replication was most cost-effective for the monitoring of banded wrasse, scarlet wrasse, spotty, blackfoot paua and yellowfoot paua (Figures 2.2 and 2.3), whereas design 1 with medium replication was most cost-effective for butterflyfish and kina. Design 2 with medium replication was most cost-effective for blue cod, blue moki and rock lobster (Figures 2.2 and 2.3).

Table 2.6. Costs (NZD) of the invertebrates/fish surveys in terms of the temporal design and the number of replicate transects per site.

		Design		
		1	2	3
Transects	4/6	11325	22650	33975
	6/9	12018	24036	36054
	8/12	18150	36300	54450

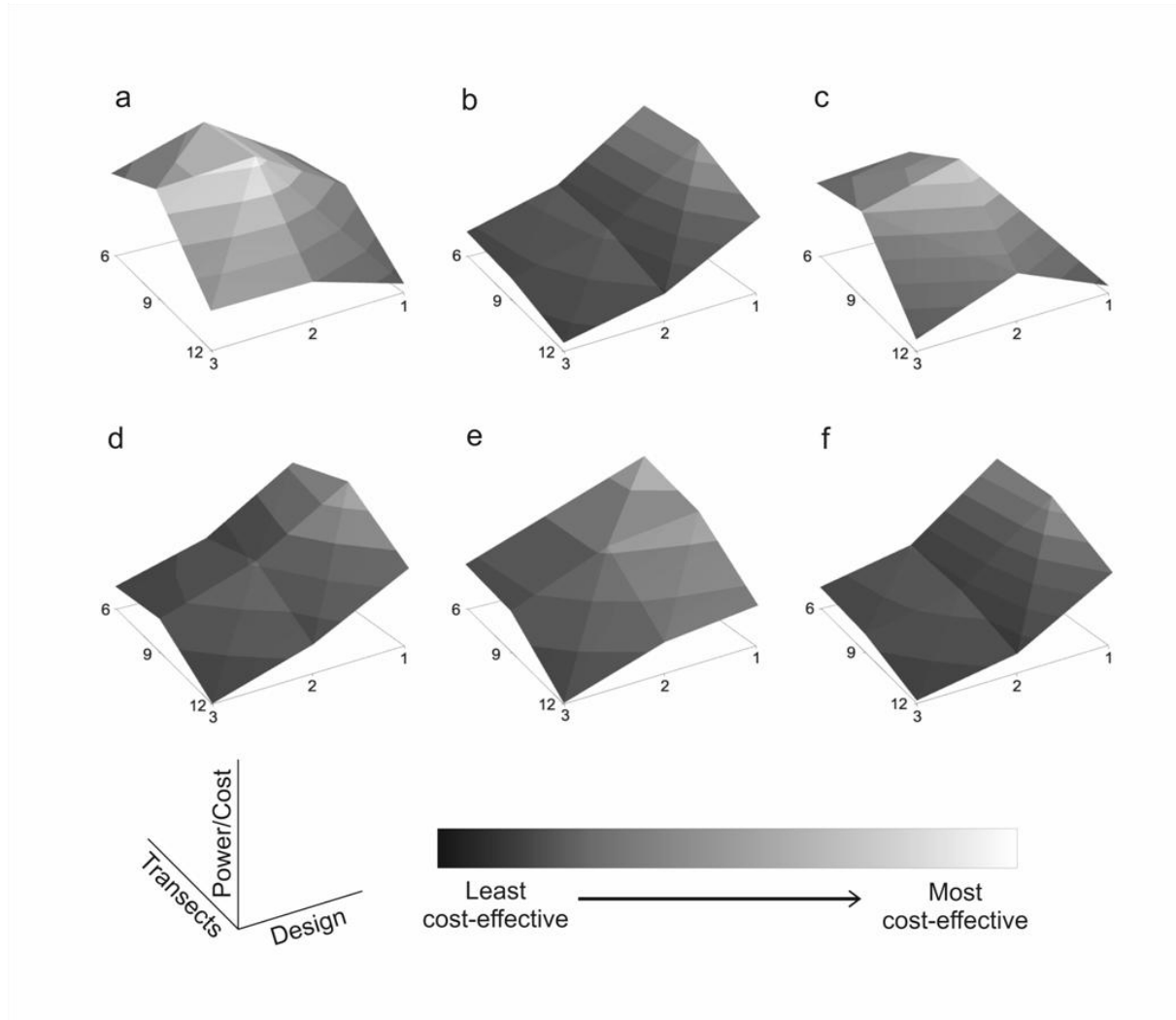


Figure 2.2. Surface plot illustrating the power to detect a four-fold increase in abundance divided by the cost for each of the monitoring design choices for (a) blue cod, (b) banded wrasse, (c) blue moki, (d) butterfish, (e) scarlet wrasse and (f) spotty.

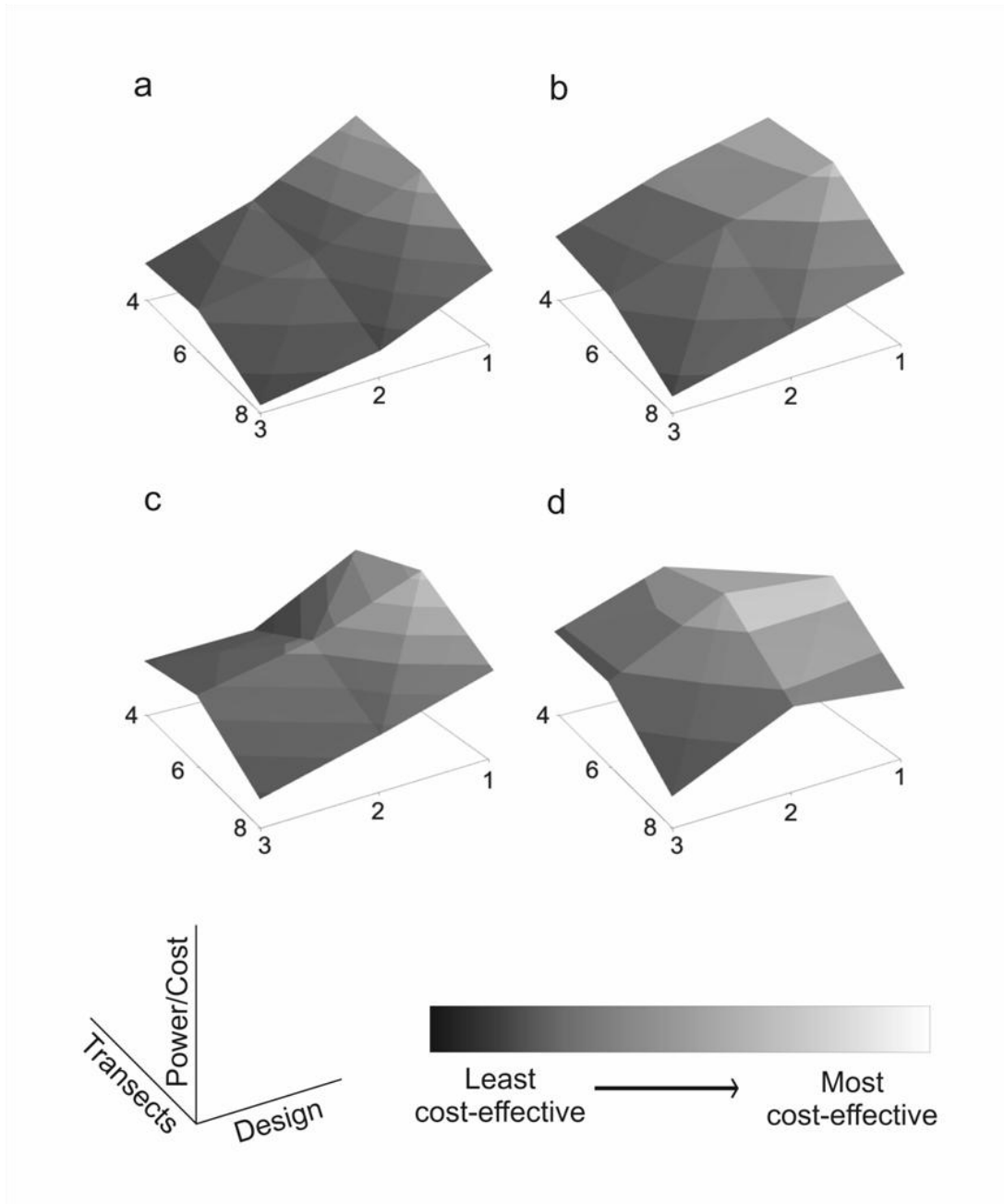


Figure 2.3. Surface plot illustrating the power to detect a four-fold increase in abundance divided by the cost for each of the monitoring design choices for (a) blackfoot paua, (b) yellowfoot paua, (c) kina, (d) rock lobster.

2.4 – Discussion

This evaluation of different monitoring programs highlights a particular problem associated with assessing MR effects: many studies may be unable to demonstrate small but meaningful effects due to the low power of the sampling designs to detect such effects (Battershill *et al.* 1993; Kelly *et al.* 2000; Pande & Gardner 2012). Thus, smaller effects may be overlooked due to inadequate or inappropriate monitoring survey design and the

subsequent inability of statistical analysis to prove that a small but biologically significant change has occurred. Notably, many studies of MRs lack the requisite duration of data collection or the replication necessary to identify smaller effects that are nonetheless biologically significant. In particular, data collected by underwater visual census (UVC) methods have been criticised because of their low precision and high variability (Thresher & Gunn 1986; Edgar & Barrett 1999). However, this is not only a limitation of the data collected but also of the statistical measures that are commonly employed to test these data. The reliance on null hypothesis significance testing has been criticised in the literature with regard to the testing of an *a priori* trivial null hypothesis (specification of no difference between levels and time periods are almost never going to be true and so the rejection of the null hypothesis is trivial) (Anderson *et al.* 2000; Cole & McBride 2004; Gerrodette 2011). Many authors criticising null hypothesis significance testing suggest that there should be greater emphasis on the presentation of effect size and precision in the form of confidence intervals (Gerrodette 2011; Nakagawa & Cuthill 2007) or credible intervals in a Bayesian framework (Wade 2000). However, this does not imply that the approach adopted here is without merit, given that power is directly related to the precision of the effect size estimates (high power requires high precision) and is therefore still useful when designing a monitoring program (Nakagawa & Cuthill 2007; Seavy & Reynolds 2007). Null hypothesis testing still remains the dominant paradigm of statistical testing employed throughout the marine ecology literature and therefore a monitoring program design based on power is still the most easily recognisable and accessible means of comparing monitoring design choices.

This study highlights the difficulties of identifying an adequate single design for a multi-species monitoring program. Power to detect biological change (in this case, abundance) varies considerably among species, with some designs being entirely adequate for one species (e.g. low replication is adequate to detect change in abundance of banded wrasse) but inappropriate for others (e.g. low replication is inadequate to detect change in abundance of blue cod). Overall, power was low to detect changes in abundance corresponding to a two-fold increase in abundance for all species and for all sampling designs considered, but particularly so for design 1. Power to detect change in abundance of banded wrasse was considerably higher than for all other species simply because banded wrasse were abundant and observed consistently throughout the baseline surveys. During the baseline surveys, spotty and blackfoot paua were also particularly abundant, but in contrast to banded wrasse they displayed high levels of among-site and within-site variation due to

schooling/aggregating behaviour. This additional dispersion likely reduced our power to detect changes in their abundances. In contrast, during the baseline surveys blue cod, blue moki and rock lobster were observed at very low abundances with the data consisting mostly of zeros. Analysis of data of this kind has low power to detect change because seemingly large changes in relative abundance manifest as small changes in observed abundance. For example, if on one occasion one individual was observed over 9 transects and on a subsequent occasion two individuals were observed, i.e. a doubling in observed abundance, there is a high probability that this difference could have occurred by chance alone resulting in low power to detect these changes unless spatial and temporal replication is considerable (Table 2.4). The use of larger sampling units (i.e. wider or longer transects) in these cases would likely help to address these issues. However, there would also be a likely tradeoff with increasing transect size in terms of the replication achievable in a given time (i.e. longer transects are likely to take longer) and the accuracy of the resulting data (i.e. wider transects are more prone to error in judging whether fish were or were not on the transect). Longer transects are also more likely to cover multiple habitat types and/or depths depending on the transect orientation. This could potentially lead to greater heterogeneity in the resulting counts and may in fact reduce power if not adequately accounted for. In these instances, depths, habitat type and other potential explanatory variables could potentially be used as a covariate in any statistical analyses to explain some of the variation in fish counts (Shears *et al.* 2008a). This would counter the increased variation and may make it more likely to detect changes in abundance through time, particularly where larger sampling units are required to account for species that occur in low densities. This may be particularly important in the initial stages of an MPA where species may occur in low densities as a result of historical depletion.

Although perhaps not explicitly stated in most cases, the design of many monitoring programs assumes a reasonably uniform environment across and within the monitored area. However, it must often be the case that environmental heterogeneity exists at various spatial scales across and within the monitored area, and that such heterogeneity must be taken into consideration. This extra level of complexity adds substantially to the difficulty and cost of designing a monitoring program that has power to detect change in abundance of focal taxa in an environment that is characterised by patchiness or a gradient. In the present study, the observed high among-site variability for many species is attributable in large part to the existence of a natural environmental gradient along the south coast (Pande & Gardner 2009).

Considerable differences exist in the abundances of fishes, invertebrates and macroalgae among the eight sites, with eastern sites (e.g., Barrett Reef and Breaker Bay) having greater abundance on average than western sites (e.g., Red Rocks and Sinclair Head), and the Taputeranga Marine Reserve (TMR) being located in between (Pande & Gardner 2009). As a consequence, the variability in the control “Treatment” level is large because it consists of two distinct groups (east and west, either side of TMR). This combination of overall low abundance, coupled with high variability in the abundance estimates, reduces the ability to detect changes in taxon abundance. Nonetheless, as outlined below, it is still possible to design and implement a monitoring program that can detect change in abundance of some, but not all, species along the natural environmental gradient.

Design and replication issues can often be secondary to logistical and cost restraints (Molloy *et al.* 2010). In the present context for TMR, the design of the monitoring protocol for the baseline survey (Pande & Gardner 2009) was driven more by what could reasonably be achieved on a very limited budget and within a tight time frame, rather than by what was biologically desirable or statistically robust (Pande 2008). The costs of employing designs 2 or 3 were two or three times greater than design 1, which may be prohibitive depending on the monitoring budget. Consequently design 2 was only cost-effective for blue cod, blue moki and rock lobster, whereas design 3 was the least cost-effective for all species examined because of its greater costs (Figures 2.2 and 2.3). Although design 1 was the most cost-effective for most species and is comparable in design to surveys actually carried out in temperate MR studies (Jones *et al.* 1993; Kelly *et al.* 2000) the results presented herein reveal that the power to detect even large changes in abundance is low for most species (Tables 2.4 and 2.5), highlighting the need for temporal replication to determine if there have been changes in abundances. However, increasing replication across years to the detriment of within-site replication is not recommended given that replication over both spatial and temporal scales is required to control for spatial and temporal variation (Underwood 1992; Underwood & Chapman 2003; Molloy *et al.* 2010). This evaluation of monitoring this marine reserve revealed that medium levels of replication (i.e. 6 transects for invertebrates and 9 for fish) were the most cost-effective for detecting changes in abundance of blue cod, blue moki, butterflyfish, rock lobster and kina. These species were all commercially or recreationally targeted along the entire south coast prior to marine reserve establishment and so were initially observed in low numbers requiring greater replication to get an accurate measure of their abundance.

A major challenge faced by managers and scientists alike is to design and implement a monitoring program that is cost-effective and will answer questions about the magnitude of change that is both detectable and biologically meaningful. Identifying the best overall monitoring program to employ requires the quantification of the adequacy and the costs of several competing choices (in this case the power to detect a change in abundance at reserve sites), but also the specification of definite goals/targets to be achieved by the monitoring design in question (Ringold *et al.* 1996; Vos *et al.* 2000). These goals and targets should incorporate specification of the size of effect that is deemed important, along with the ability to quantify or detect these changes. Most marine reserve monitoring in New Zealand is performed to quantify the change in abundance of commercially or recreationally harvested species once an area has been closed to fishing (Cole *et al.* 1990; Kelly *et al.* 2000; Willis *et al.* 2003a; Pande *et al.* 2008; Diaz Guisado *et al.* 2012; Pande & Gardner 2012). In particular, much research has focussed on changes in blue cod and rock lobster abundance (summarised by Pande *et al.* 2008; Diaz Guisado *et al.* 2012 and references therein). If future monitoring of the Taputeranga Marine Reserve is to focus solely on these two species then the most cost-effective approach is design 2 with six invertebrate transects and nine fish transects. This choice would still be adequate for monitoring all six fish and four invertebrate species considered here (e.g., to assess the broader community response), rather than focussing solely on two particular species. Based on these findings and where costs are limiting monitoring using design 2 with 6 and 9 transects for invertebrates and fish, respectively, is the most cost-effective protocol.

The approach employed here to evaluate different monitoring programs is based on the existence of a spatially and temporally replicated baseline data set. Whilst the recommendations that are proposed are specific to the local situation, all of the focal taxa discussed here are widespread and present throughout New Zealand. Thus, in the absence of baseline data for one or more such species from other sites, it would be reasonable to take the recommendations from this study and use them as a starting point, for example in a pilot study in another area. Beyond this, it would be reasonable to use the monitoring designs and their indicative levels of power that are presented here, for different species in other countries where no baseline data exist. Thus, for species in other parts of the world that possess similar levels of abundance and also distributions (e.g., based on depth, habitat type, etc) recommendations might reasonably be made based on their NZ counterparts as a first step towards achieving a region-specific and species-specific monitoring program. Ultimately, this

study highlights the value of an extensive baseline data set, as well as highlighting the need for such fundamental survey work to be conducted in every region where long term monitoring is to be undertaken.

Chapter 3 - Optimizing monitoring for quantifying change in fish abundance: power, accuracy and precision of visual census methods

3.1 – Introduction

Interest in marine monitoring has risen sharply over the last decade to address the need to understand changes in the marine environment in response to anthropogenic disturbance (Lubchenco *et al.* 2003; Edgar *et al.* 2004). Monitoring is usually used to describe long-term changes in the abundance of specific species, as well as to provide information regarding demographic parameters and ecosystem condition (Seavy & Reynolds 2007). In particular, quantifying abundance trends of many plant and animal species has been vital to their successful conservation and management (Bart *et al.* 2004). In order for a monitoring program to be effective it should provide the best possible information regarding changes in abundance by presenting both accurate (small bias) and precise (smaller confidence intervals regarding trend parameters) estimates of trend parameters (Block *et al.* 2001; Tyre *et al.* 2003). However, estimating change in abundance from survey data poses several logistical and statistical challenges (see Thomas 1996; Willis *et al.* 2003a; McDonald-Madden *et al.* 2010; Molloy *et al.* 2010). Because quantifying trends in ecological studies is so greatly influenced by temporal and spatial variability (Sims *et al.* 2006; Molloy *et al.* 2010) the design of a monitoring program requires considerable planning, field testing and statistical evaluation before implementation (Zielinski & Stauffer 1996). However, *a priori*, researchers often do not know the degree of variability that affects abundance measures (Underwood 1993; Gibbs *et al.* 1998; Willis *et al.* 2003a), which is important considering that decisions pertaining to how to distribute sampling effort will depend on the relative magnitudes of the different components of variation (Urquhart *et al.* 1998; Sims *et al.* 2006). In many cases, resource limitations (e.g. time, monetary cost, availability of trained observers) mean that the chosen survey design may meet some of the requirements by emphasizing replication on specific spatial or temporal scales (e.g. high spatial replication will achieve a greater degree of coverage of the target population), but this may be to the detriment of the other monitoring requirements (resources used to achieve high spatial replication may mean that monitoring can only be carried out infrequently, thus giving a poor indication of changes through time) (Field *et al.* 2005). Given the general lack of resources dedicated to monitoring and the expense of performing large-scale surveys, particularly in marine habitats, there is a danger that sub-optimal monitoring may be performed (Nicholson & Fryer 2002; McDonald-Madden *et al.* 2010). Identifying the best way to distribute effort, through space and time, within financial constraints, is a challenging task (Gibbs *et al.* 1998;

Cabral & Murta 2004; Elphick 2008; McDonald-Madden *et al.* 2010), but one that underpins sound management decisions.

Underwater visual census (UVC) methodologies are used extensively in marine studies (Edgar & Barrett 1997; Paddock & Estes 2000; Willis *et al.* 2000; Denny and Babcock 2004; Edgar *et al.* 2004). These methods have been used for assessing the abundance of invertebrates, macroalgal assemblages, and reef fish (Cole *et al.* 1990; Edgar & Barrett 1997; Samoilys & Carlos 2000; Shears & Babcock 2003; Edgar *et al.* 2004; Stuart-Smith *et al.* 2008; Pande & Gardner 2009; 2012). However, there have been few studies examining the effectiveness (in terms of accuracy and precision) of these studies for determining long-term trends in fish abundance, which is vital considering the reliance on these techniques globally for quantifying the status of fish populations (Buxton & Smale 1989; Dufour *et al.* 1995; Edgar & Barrett 1997; Denny & Babcock 2004). Data collected by UVC techniques are often characterized by high variability and low precision due to the often overdispersed nature of the data (Brock 1982; Samoilys & Carlos 2000; Willis *et al.* 2003a; Pande & Gardner 2009), although little has been done to quantify, let alone attempt to minimize the bias and maximize precision of long-term trend estimates through monitoring design assessments (but see Molloy *et al.* 2010 for an assessment of sample size and detection of particular short-term trends).

Monitoring design assessments often focus on the statistical power to detect trends (Gerrodette 1987; Nicholson *et al.* 1997; Sims *et al.* 2006; Elphick 2008; Molloy *et al.* 2010). Power analysis is the analysis of the probability of a given sampling design being able to provide a statistically significant result, at some significance level α , for an effect of a given size, based on the null hypothesis of no effect (Chapter 2; Thomas 1996). There has however been considerable criticism of the application of point null-hypothesis significance testing within non-experimental ecological approaches (Gerrodette 2011). The major criticism is that a statistically significant result may not be biologically significant and conversely a result that would be considered biologically significant may often not be statistically significant due to the variability of the response being measured (Gerrodette 2011). Many researchers have called for a greater emphasis on effect size estimation plus the inclusion of confidence intervals as a measure of precision (McBride *et al.* 1993; Anderson *et al.* 2000; Nakagawa & Cuthill 2007; Gerrodette 2011) because this approach contains all the relevant information required to assess the biological significance of the results. In this context, the quote of

Nakagawa & Cuthill (2007, pg 595) that “... power analysis was right for the wrong reasons ...” is particularly relevant because monitoring designs that have high power (assuming also that the effect size in question is set at a meaningful level) by definition also provide precise estimates of the parameters being tested and are therefore useful when designing a monitoring program. Power, accuracy and precision, however, are separate concepts and whilst a monitoring design may be precise in the determination of abundance trends, this does not guarantee that the estimated trends are accurate.

In this chapter I describe an approach that may be used to design optimum monitoring programs to identify abundance trends of reef fish species as assessed by UVC. Using data from four temperate New Zealand reef fish species that vary in their abundance both temporally and spatially, the bias, precision and power of multiple monitoring design configurations that incorporate different numbers of sites, transects within sites and monitoring frequencies is defined. The monetary cost of each design is also quantified, in order to identify the most cost-effective approach as the one that gives the highest ratio of precision, accuracy and power in relation to cost. Finally, this chapter aims to provide a general methodology for the identification of a cost-effective monitoring design and illustrate how this varies among species and locations dependent on average abundance, along with spatial and temporal variability in abundance at spatial scales relevant to sampling (~10-100 m²).

3.2 – Methods

3.2.1 – Description of data and summary statistics

Datasets from three marine reserves (MR) were examined: Long Island-Kokomohua Marine Reserve (established 1993, hereafter LIMR), Tonga Island Marine Reserve (established 1993 hereafter TIMR) and Horoirangi Marine Reserve (established 2005, hereafter HMR) in the northern region of the South Island of New Zealand (Figure 3.1). Datasets consisted of the observed abundance of common reef fish collected using the same sampling protocol at each reserve and sampled by the same set of divers trained in the identification of New Zealand reef fish and underwater visual census strip transect methods. The data were collected from sites characterized by boulder or rocky reef substratum devoid of a macroalgal canopy (i.e. rocky barrens), in a depth range of 5-12 m below mean high water springs. At each site, pairs of divers recorded fish abundance by swimming along 30 m transects haphazardly placed at the same designated sites. At the start of each transect a lead

weight was dropped onto the substratum within the depth range. The line was reeled off the spool as the diver swam away from the weight, and starting at 5 m from the weight all reef fish, excluding triplefins (family - Tripterygiidae), within a diver estimated 2 m wide and 2 m high corridor either side of the transect were recorded. Transects were swum at a constant slow speed but fast enough that fish did not overtake the recorder. A total of twelve transects were performed at each site on each sampling occasion. The number of sites within MRs varied. Data for LIMR were collected from 5 sites monitored annually from 1993-2010. Data from TIMR were collected from 7 sites from 1999-2010. Data from HMR were collected over a shorter timescale because monitoring only began in 2006. Six sites were monitored over the full time period, 2006-2010, and two additional sites were monitored from 2007-2010. All observations were performed in the same season (austral summer - February-May) to avoid issues arising from seasonal changes in observed abundance (Davidson 2001; Davidson *et al.* 2007; 2009).

The analysis was limited to four species that were observed at all three MRs. Blue cod (*Parapercis colias*) were commonly observed because this species was the primary target of all three MR monitoring programs. They were particularly abundant at LIMR, but less so at TIMR and HMR. In addition to total blue cod abundance, the abundance of legal-sized (greater than 33 cm) individuals was also analysed. The abundance of legal-sized blue cod has previously been used as an indicator of a MR effect (Davidson 2001; Pande *et al.* 2008). It also may provide a better indication of a MR effect when compared to total abundance as it is less likely to be affected by variable recruitment, which may increase the interannual variability in total fish counts. Spotty (*Notolabrus celidotus*) were the most abundant species observed, consistent with them being the most abundant reef fish species in New Zealand coastal waters (except at the Poor Knights Islands and Three Kings Islands where they rarely occur; Choat & Ayling 1987; Francis 2001). However, due to schooling behaviour they were often observed in quite high numbers (schools larger than 50 individuals were regularly encountered) and displayed quite high variability between replicate transects. Blue moki (*Latridopsis ciliaris*) had the lowest abundance, with the majority of the data consisting of zero counts, or counts in the low figures with few counts greater than five. Tarakihi (*Nemadactylus macropterus*) were infrequently encountered, but as they show schooling behaviour they were recorded in very high abundance when encountered and so the counts for this species were highly variable within sites, between sites, and over time. In addition

blue cod, blue moki, and tarakihi outside of marine reserves are commercially and recreationally targeted whereas spotty are not.

To aid with comparing these results with data of other species in other systems, a range of simple summary statistics were calculated from the observed data. Observed abundances are summarised by calculating the average density (ind/120m²) across all sites, as well as identifying the site-specific maximum and minimum densities across all surveys. To give a representation of the variability exhibited by the data, the maximum and minimum survey specific mean densities (averaged across the twelve or so replicate transect counts at each site and each survey period) were calculated, as well as the variance of mean densities across all surveys. Finally, to give an idea of the variability among replicate transects (i.e. among the replicate counts obtained within each site, each year), the ratio of the variance among replicate counts to the mean density was calculated for each survey (ratio's greater than one indicate overdispersion and clumping of counts). The variance:mean ratios averaged across all surveys, as well as the maximum and minimum ratios are presented.

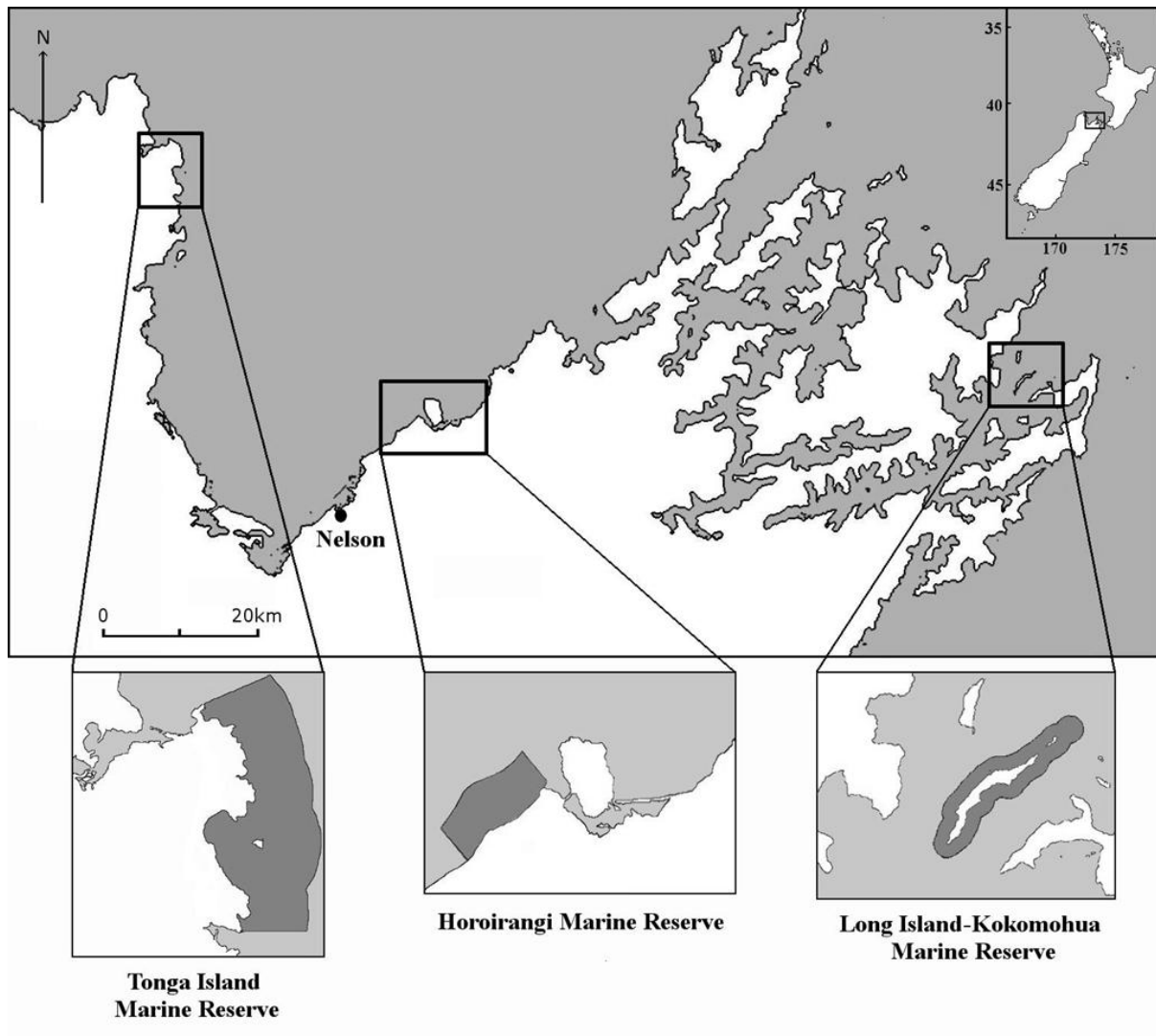


Figure 3.1. Locations of the three marine reserves in the northern part of the South Island of New Zealand used in this study.

3.2.2 – *Modelling the data*

Spatial and temporal variability in the datasets were modelled (after Sims *et al.* 2006) by employing a Monte-Carlo simulation methodology to assess statistical power and the average bias and precision of the trend estimates. Monte-Carlo approaches have been applied in complex power analysis studies (Zielinski & Stauffer 1996; Sims *et al.* 2006), to assess the bias and precision of terrestrial population monitoring (Wintle *et al.* 2004; Freilich *et al.* 2005) and large-scale biodiversity monitoring programmes (Nielsen *et al.* 2009), but have rarely been applied in a marine monitoring context.

Four variance factors were identified as being important contributors to the overall variance of the fish counts. These were: (1) between-site; (2) within-site; and between-survey temporal variability that can be split into two separate components; (3) temporal variability that is the same across sites (synchronous variation); and (4) temporal variability that is unique to each site (interaction variation) (Larsen *et al.* 2001). Count data often violate the assumptions of normality and constant error variance and it is more likely that the variance is related to the mean (Willis *et al.* 2003a; O'Hara & Kotze 2010). Mean count values were usually in the range 0-10 and exhibited a high degree of variability. The data was therefore modelled using a two-stage process. The average values, μ_{ij} , for the counts observed at each site i on each date j were modelled using a log-linear additive model (Millar & Willis 1999) assuming exponential population growth, according to equation 3.1:

$$\log(\mu_{ij}) = \mu_0 + y \cdot \log(\beta) + A_i + B_j + C_{ij}$$

eqn. 3.1

where μ_0 is the log-transformed average population size in year 0, y is the year (starting from year $y = 0$), β is the trend expressed as the proportional increase per year, A_i is the effect of site i independent of date (between-site variation), B_j is the effect of date j independent of site (models synchronous variation) and C_{ij} is the effect of date j specific to each site i (models interaction variation). The second stage in the simulation process involves simulating the actual counts Y_{ijk} that are generated according to equation 3.2:

$$Y_{ijk} \sim g(\mu_{ij}, v_{ij})$$

eqn. 3.2

where g is an integer based statistical distribution, such as a poisson or negative binomial distribution, with arguments μ_{ij} describing the mean, and v_{ij} describing the dispersion or variance of the counts.

3.2.3 – Variance parameter estimation

The distribution of the observed count data was investigated in order to identify the distributional form of the function g . The poisson distribution specifically applies to counts of organisms and classically applies to field transect sampling (White & Bennetts 1996; Dennis *et al.* 2010; O'Hara & Kotze 2010); it also assumes that the variance is equivalent to the mean. However, many ecological studies are characterized by heterogeneous sampling

conditions that can lead to overdispersion in the observations (Dennis *et al.* 2010). When overdispersion is present an appropriate model is the negative binomial model (White & Bennetts 1996; Link & Sauer 1998). The negative binomial model has two parameters; the mean μ and a dispersion parameter v . The dispersion or size parameter in the negative binomial distribution parameterizes the degree of overdispersion in a dataset and acts to model the variance according to equation 3.3:

$$Var = \mu + \frac{\mu^2}{v}$$

eqn. 3.3

As v tends towards high values the negative binomial tends toward a poisson distribution with variance equivalent to the mean. However, as v tends to zero the generated counts become overdispersed compared to a poisson distribution, exhibiting a high degree of clumping (White & Bennetts 1996). As such, it is an ideal distribution for modelling fish counts that are likely to display varying degrees of overdispersion, for example, due to schooling behaviour.

The data were tested to assess if counts were poisson-distributed or overdispersed. Data for each species in each MR were treated separately (12 species-reserve specific datasets) as described below. A generalized linear model was fitted to each dataset using the statistical package R (R Development Core Team 2011) with the interaction term site:date such that the average for each site on each date was modelled. The only remaining variation was therefore due to the variability of the counts within each site on each date. This analysis was performed assuming normal-, poisson- and negative-binomial-based errors. The negative-binomial model was the best fit to the data based on the Akaike Information Criterion (AIC – lower values indicate a better fit of the model to the data) and log-likelihood values (see Appendix 1, Table A1.1). As such the within-site variance was tested for overdispersion by obtaining the variance of the counts at each site on each date and comparing it to the variance that would be expected given a poisson distribution. If the variance was significantly different ($p=0.05$) from that expected given a poisson distribution (using a χ^2 test, with $dof.=n_{transects}-1$, Wetherill & Brown 1991) then the data were considered to be overdispersed. Table A1.2 of Appendix 1 gives the frequency at which site:date combinations were considered to be overdispersed. Overdispersion was prominent (over 50% of all site:date sets of counts were overdispersed compared to a poisson distribution) for blue

cod at LIMR, spotty at LIMR and TIMR, tarakihi at TIMR, but infrequently for blue moki at any of the reserves.

Based on the above findings the function g was modelled as a negative-binomial. Because the species display overdispersion to varying degrees, two values for the dispersion parameter were adopted to assess the effects of overdispersion on the assessment of trends in abundance. Firstly, $v=10,000$ was set so that generated counts followed a poisson distribution, because for high values of v the negative binomial is indistinguishable from the poisson distribution. A value of 10,000 was chosen such that $\frac{\mu^2}{v} \ll \mu$, which ensures that the variance is equivalent to the mean over an approximate range of $\mu = 0-100$ (see eqn. 3.3). This gives a lower limit for the variability within each site. Secondly, $v=0.2$ was set such that the counts were overdispersed, with respect to a poisson distribution, with variance considerably larger than the mean. The specific value of $v=0.2$ was chosen as it conformed to the minimum value of v observed when analyzing the replicate counts across all species. This therefore gives the most variable counts.

To estimate the parameters in eqn. 3.1 a linear mixed effects model was fitted to each dataset (quasipoisson distribution with log-link using glmer in the lme4 package in R, Bates & Maechler 2010). Site, date and site:date were fitted as random effects corresponding to the between-site, synchronous and interaction temporal effects respectively. The standard deviations of the random effects were extracted from the model fit to account for the magnitude of these effects. To remove the possibility of a genuine trend being interpreted as interannual variability, the same model was fitted, but with a continuous fixed effect of date to account for trends in abundance over time. This and the null model were compared based on log-likelihood, and the variance components were extracted from the most likely model. Therefore A_i is the random effect of site with values generated from a normal distribution with mean zero and standard deviation σ_s , i.e. as $\sim N(0, \sigma_s)$, B_j is the synchronous random effect of date with values generated as $\sim N(0, \sigma_d)$ and C_{ij} is the interaction annual variance with values generated as $\sim N(0, \sigma_{sd})$, where σ_s , σ_d and σ_{sd} are the standard deviations derived from the mixed effects model for between-site, synchronous and interaction variance, respectively. Inherent to this simulation process the assumption is made that the estimates of variance will apply in future years and also for additional surveyed sites (Jennings & Dulvy 2005).

3.2.4 – *Simulation and testing procedure*

Data were simulated according to equations 3.1, 3.2 and 3.3 using the parameters estimated from the model fits for each species in each reserve. In order to test for a significant trend and to quantify the statistical power, two glmer models were fitted to the simulated data (quasipoisson-based errors to account for overdispersion, log-link function to account for exponential increase in population size). The two models were identical in having site, date and site:date included as random effects, but the second model had a fixed effect of date to model for a continuous trend in abundance. To quantify power, the two models were compared using a likelihood ratio test (aov in R) (Pinheiro & Bates 2000). This comparison tested if the interannual variation is better described by a continuous trend in abundance with random fluctuations among years or by random fluctuations among years alone, by testing to see how well the data support one model over the other (Hobbs & Hilborn 2006). The comparison produces a p -value to indicate if the model with a fixed-effect of date is a significant improvement over the model with random fluctuations alone. The significance level was set at $\alpha=0.05$. The proportion of simulated datasets that gave p -values less than or equal to this was recorded as the statistical power for detecting a trend of that magnitude given the variability in the dataset. To quantify precision and bias the trend estimate was extracted from the second model along with the 95% confidence interval of the trend estimate. Estimates of precision were taken as the width of the 95% confidence interval and bias was recorded as the absolute magnitude of the difference between the trend estimate produced by the model and the true simulated trend over time. One thousand simulations were performed for each level of monitoring design, species, reserve, and trend combination and the power was estimated as the proportion of simulations where the model with a continuous effect of time was a significant improvement over the model with no continuous time effect. Each simulation and model fit to the simulated data resulted in an estimate of the trend through time. These were treated as alternate realisations of the data that could arise given the observed variability in the data and the monitoring design, and thus the trend estimate from the model fit for each simulation is an alternate realisation of a trend estimate that could be obtained given that monitoring design. Performing 1000 simulations results in 1000 realisations of this trend estimate, and to quantify the performance of each monitoring design the median confidence interval width and median absolute bias from the 1000 simulations were taken as an estimate of the precision and bias of each of the monitoring designs for each species. Medians rather than mean values were used as some simulations

resulted in large confidence interval widths, and/or biases that would skew the mean value. All simulations and testing were performed by a program written in R version 2.10.0 (R development core team 2011).

3.2.5 – *Simulated tests*

Three different approaches to altering the monitoring design were investigated. These consisted of changes to the within-site replication, the number of sites and the frequency of sampling. Monitoring designs with all combinations of 6, 8, 10, 12 and 16 transects at each site and 3, 4, 5, 6 and 8 sites being monitored within each MR were investigated. This level of spatial replication is representative of the monitoring that is currently carried out in New Zealand and covers a range of possible ways to distribute effort. Sampling frequencies of once per year, once every two years and once every three years were also investigated. Datasets representing all possible combinations of these monitoring design choices were simulated (75 combinations for each species) for a ten-year time period. This was performed for both low dispersion and overdispersed counts. A time period of ten years was used because it has been identified as the minimum required for assessing the status of populations and because studies in New Zealand have demonstrated change in this time frame (Zielinski & Stauffer 1996; Cole 2003; Pande *et al.* 2008; Pande & Gardner 2009; 2012; Diaz Guisado *et al.* 2011). Due to the number of scenarios investigated simulations were performed according to two trends through time. It has been suggested that a minimum biologically significant effect might be a doubling or a halving of a population's size given the inherent variability in natural marine systems (Edgar & Barrett 1997). Datasets were therefore simulated consistent with these changes over a period of ten years, corresponding to trends with annual increases/decreases of $\pm 7.7\%$ respectively.

3.2.6 – *Relative costs of competing monitoring designs*

The costs of the various monitoring designs were quantified based on the time requirements of the studies examined. Currently, 12 replicate transects 30 m long and 2 m wide are collected per dive. Additional transects require additional dives at each site. Costs are calculated based on the assumption that three dives could be carried out each day, with each dive lasting 30-60 minutes depending on the amount of replication, with a maximum of 12 transects requiring a full one hour dive. In order to carry out 16 transects, two dives are required at each site and so would require double the manpower per dive or double the number of dives/days. A surface interval of three hours between dives was also assumed for

safety purposes. An hourly rate of \$130 (NZD) for the scientific divers was assumed and daily boat and skipper hire were estimated at \$1500 (NZD). Based on these estimates, plus the time required to carry out the different monitoring designs, the cost incurred for each monitoring design was calculated. For ease of discussion these designs were split into five classes depending on their cost (Table 3.1). The ratio of precision (the inverse of the average confidence interval width), accuracy (the inverse of the average absolute bias) and power for each species and for each monitoring design in relation to the calculated costs for that monitoring design were calculated. The most cost-effective design for each of the measures was defined as the one that has the highest ratio of power:costs, precision:costs, accuracy:costs, respectively and the most cost-effective monitoring approach to achieve specific targets of power (20%, 30%, 40%, at 5% significance) precision (95% CI widths of 0.4, 0.3 and 0.2) and accuracy (bias of 0.05, 0.04, and 0.03) are also identified. Finally the required costs and how the costs change across a continuous range of levels of power, precision and accuracy are plotted. Although costs are not specific to any agency or operator they are indicative of the costs required for this kind of work.

Table 3.1. Number of monitored sites, transects and monitoring frequency for the different monitoring designs considered, along with their associated costs. All costs are in NZD.

	Sites	Transects	Frequency	Cost (×1000 NZD)
Class A (15,000-30,000)	3	6-12	3,2	16,22
	3	16	3	27
	4	16	3	24-27
	5	6-10	3	28-30
Class B (30,000-40,000)	3	16	2	34
	3	6	1	40
	4	6-12	2	31-33
	4	16	3	38
	5	12	3	31
	5	6-12	2	35-38
	6	6-12	3	32-35
	6	6	2	40
Class C (40,000-60,000)	3	8-12	1	41-44
	4	16	2	48
	5	16	3,2	46,57
	6	8-12	2	41-44
	6	16	3	54
	8	6-12	3	44-48
	8	6-10	2	55-58
Class D (60,000-80,000)	3	16	1	67
	4	6-12	1	61-66
	5	6-12	1	70-77
	6	16	2	67
	6	6	1	79
	8	12	2	60
	8	16	3	73
Class E (80,000-182,000)	4	16	1	96
	5	16	1	115
	6	8-16	1	82-134
	8	16	2	91
	8	6-16	1	110-182

3.3 – Results

Summary statistics of species densities and variation among and within surveys are given in Table 3.2, along with the parameters obtained from the mixed effects model fit to the observed data. Data for legal-sized blue cod abundance at HMR were not analysed as abundances were too low (a total of only 23 individuals were observed throughout the entire monitoring) to meaningfully estimate variance parameters.

Table 3.2. Parameters estimated from the mixed effects models that were used to perform the simulations and summary statistics regarding abundance, survey- and site-specific abundances, and variance estimates with respect to the variance among survey means, and the ratio of within survey variance to the within survey mean as a measure of the among transect variability. Densities are ind/120m².

Species	MR	Density			Var among survey means	Within survey var:mean		Parameters			
		Average	Site specific (min, max)	Survey specific (min, max)		Average	Survey specific (min, max)	μ_0	σ_s	σ_Y	σ_{YS}
Blue cod	LIMR	5.60	(5.40, 5.90)	(0.67, 15.25)	5.43	2.92	(0.59, 14.55)	1.62	0.00	0.26	0.41
	TIMR	0.55	(0.22, 1.43)	(0.00, 3.17)	0.36	1.60	(0.73, 12.56)	-1.62	0.61	0.23	0.81
	HMR	0.17	(0.05, 0.38)	(0.00, 0.83)	0.03	1.13	(0.73, 3.00)	-2.63	0.52	0.00	0.69
Blue cod (legal)	LIMR	1.87	(1.74, 1.99)	(0.08, 5.67)	1.15	1.90	(0.29, 10.47)	-0.15	0	0.38	0.36
	TIMR	0.28	(0.15, 0.78)	(0.00, 2.33)	0.13	1.40	(0.69, 5.13)	-2.61	0.51	0.26	0.47
Spotty	LIMR	13.76	(7.00, 21.00)	(0.00, 35.58)	65.19	8.46	(0.44, 56.52)	2.38	0.50	0.25	0.71
	TIMR	4.14	(2.14, 9.40)	(0.00, 24.58)	17.00	3.53	(0.49, 25.09)	0.59	0.51	0.31	0.68
	HMR	4.37	(3.19, 5.23)	(2.25, 7.75)	2.14	1.63	(0.41, 5.32)	1.63	0.11	0.00	0.29
Blue moki	LIMR	0.15	(0.01, 0.43)	(0.00, 1.08)	0.06	1.28	(0.82, 11.00)	-2.41	0.70	0.00	0.77
	TIMR	0.29	(0.20, 0.42)	(0.00, 1.75)	0.09	1.56	(0.55, 10.20)	-1.68	0.00	0.33	0.97
	HMR	0.07	(0.00, 0.23)	(0.00, 0.92)	0.03	1.24	(0.82, 4.45)	-3.00	0.00	0.00	0.72
Tarakihi	LIMR	0.09	(0.01, 0.28)	(0.00, 4.17)	0.21	1.69	(0.09, 50.00)	-2.85	0.12	0.00	0.77
	TIMR	1.00	(0.58, 1.78)	(0.00, 8.51)	1.82	3.36	(0.55, 23.03)	-0.91	0.18	1.06	1.09
	HMR	0.54	(0.10, 2.05)	(0.00, 8.53)	1.91	3.27	(0.75, 43.63)	-1.68	0.25	0.52	1.25

For brevity the results for power focus on the level of dispersion most appropriate for each species in each reserve (blue cod; LIMR - overdispersed, TIMR, HMR - poisson distributed: legal-sized blue cod; poisson distributed, blue moki; poisson distributed: spotty; overdispersed: tarakihi; TIMR – overdispersed, LIMR, HMR – poisson distributed), but all results are available (Appendix 1, Tables A1.3-A1.38).

3.3.1 – Distributing effort spatially

With annual sampling, the power to detect a trend equivalent to the population doubling or halving in a ten-year period was variable among species, and overall it was low. Power was less than 80% for all levels of sampling effort examined (Figures 3.2 - 3.5). In addition, precision was also relatively low with on average 95% CI widths in the range of 0.3-0.6 (~4-8 times the size of the effect) for the lowest replication and 0.15-0.4 (~2-5 times the size of the effect) for the highest replication (Figures 3.2 - 3.5). This coincides with relatively low accuracy with biases of the order of 0.04-0.11 (~0.6-1.4 times the size of the effect) for the lowest replication and 0.02-0.085 (~0.25-1 times the size of the effect) for the highest replication (Figures 3.2 - 3.5).

3.3.2 – *Monitoring blue cod*

For blue cod, the power to detect these trends varied among reserves, but was largely consistent between LIMR and TIMR, with power varying between 15% at the lowest replication and 40-50% for the highest replication (Figure 3.2). This corresponded to similar levels of precision and bias between these marine reserves (Figure 3.2). However, monitoring of blue cod abundance at HMR resulted in lower power, lower precision and greater bias than at either LIMR or TIMR (Figure 3.2). The effects of increasing the number of sites had the largest effect on power, precision and bias at all three MRs, although the extent to which this applied varied among the reserves (Figure 3.2 and Table 3.3). Doubling the amount of spatial replication from three sites and six transects per site to three sites and twelve transects per site increased the power by a smaller factor than when doubling the number of sites (Table 3.3) at HMR and TIMR. A similar, but more pronounced pattern, was seen for precision and bias, where increasing the number of transects within sites had a much smaller effect than doubling the number of sites. However, at LIMR this pattern was not as pronounced, with similar effects being observed for increasing the replication through either the number of sites or replication within sites. A greater benefit was observed when increasing the number of transects per site when the trend was positive than when there was a decreasing trend in abundance (Table 3.3).

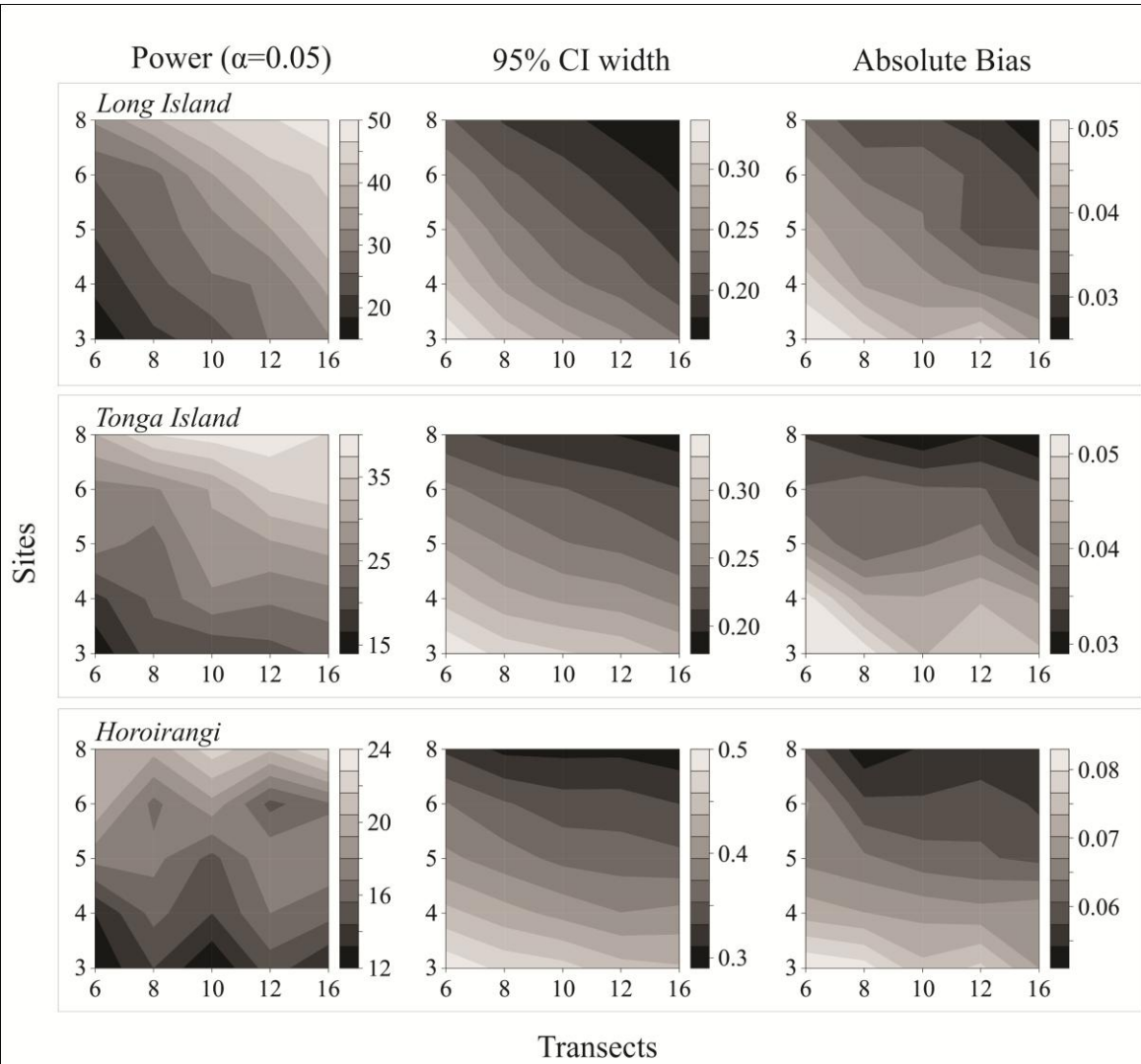


Figure 3.2. Contour plots illustrating power ($\alpha=0.05$), median 95% CI width and median bias relative to the number of monitored sites and transects for blue cod at Long Island, Tonga Island and Horoirangi marine reserves. These results are for a decreasing trend in abundance.

Table 3.3. Power, median 95% CI width and median absolute bias for monitoring designs monitoring 3 sites with 6 transects per site along with monitoring designs that have double the spatial replication, one in terms of the number of sites (6 sites, 6 transects per site) and the other in terms of the number of replicate transects per site (3 sites, 12 transects per site). All results are for monitoring designs surveying on an annual basis.

		3 sites, 6 Transects			3 Sites, 12 Transects			6 Sites, 6 Transects		
		Power	95% CI	Bias	Power	95% CI	Bias	Power	95% CI	Bias
Negative Trend										
Blue Cod	TIMR	14.6	0.34	0.050	20.8	0.30	0.047	26	0.25	0.036
	HMR	12.2	0.49	0.083	15	0.45	0.077	20.2	0.37	0.068
	LIMR	15.6	0.34	0.051	29.2	0.25	0.046	25.8	0.25	0.039
Blue Cod (legal)	TIMR	9.7	0.57	0.082	14.3	0.40	0.061	14.1	0.39	0.052
	LIMR	29.6	0.23	0.038	33.3	0.21	0.035	38.0	0.19	0.034
Blue Moki	TIMR	14.6	0.43	0.073	16.2	0.38	0.065	21.2	0.31	0.049
	HMR	7.6	0.62	0.080	11.4	0.45	0.064	8.6	0.44	0.059
	LIMR	10	0.50	0.068	13	0.40	0.052	18.2	0.35	0.051
Spotty	TIMR	15.6	0.39	0.059	19	0.31	0.050	24.2	0.29	0.047
	HMR	19.8	0.31	0.047	30.8	0.22	0.033	30.2	0.23	0.034
	LIMR	12.2	0.38	0.056	16.8	0.31	0.045	19.6	0.29	0.048
Tarakihi	TIMR	10.2	0.65	0.112	12.4	0.59	0.103	13.8	0.54	0.097
	HMR	10.8	0.62	0.095	11.2	0.52	0.085	13.6	0.45	0.083
	LIMR	8.6	0.62	0.096	9	0.52	0.080	13	0.45	0.075
Positive Trend										
Blue Cod	TIMR	23.6	0.30	0.043	22	0.28	0.045	32	0.22	0.034
	HMR	13	0.45	0.069	14.4	0.43	0.066	19.8	0.34	0.058
	LIMR	15.8	0.34	0.052	28.8	0.25	0.035	25.4	0.25	0.043
Blue Cod (legal)	TIMR	13.2	0.40	0.061	21.2	0.30	0.049	21.9	0.29	0.043
	LIMR	33.5	0.21	0.035	38.4	0.20	0.034	39.2	0.19	0.033
Blue Moki	TIMR	13.6	0.37	0.056	17.6	0.34	0.053	24.2	0.27	0.044
	HMR	9	0.45	0.066	15.6	0.34	0.049	19.8	0.32	0.044
	LIMR	13.4	0.38	0.060	18	0.32	0.050	23	0.27	0.042
Spotty	TIMR	15.4	0.39	0.063	17.6	0.31	0.048	19.2	0.28	0.046
	HMR	17.8	0.32	0.049	32.8	0.22	0.032	27.8	0.23	0.031
	LIMR	15	0.39	0.056	19.8	0.31	0.045	19.6	0.28	0.042
Tarakihi	TIMR	12.6	0.61	0.110	14.2	0.61	0.108	12.2	0.53	0.090
	HMR	9.2	0.57	0.088	11.6	0.49	0.082	13.2	0.42	0.077
	LIMR	11.2	0.56	0.096	9.8	0.50	0.078	18.4	0.41	0.079

3.3.3 – Monitoring legal-sized blue cod

There were noticeable differences in power to detect these trends between LIMR and TIMR, with power being considerably lower at TIMR. At TIMR power varied between 9% at the lowest replication and 33% at the highest replication, whereas at LIMR power varied between 29% and 43%, respectively (Figure 3.3). Similarly precision and accuracy were

similarly higher at LIMR than TIMR (Figure 3.3). However, power, precision and bias at LIMR were far less sensitive to changing replication (range of power: 29-43%, 95% CI width: 0.18-0.24 and absolute bias: 0.029-0.039) than at TIMR (range of power: 9-33%, 95% CI width: 0.22-0.58 and absolute bias: 0.034-0.082). Doubling the amount of replication increased power, precision and accuracy but there was no difference in the results between doubling the number of sites, versus doubling the amount of transects per site, with both monitoring designs (3 sites, 12 transects and 6 sites, 6 transects) achieving similar results (Table 3.3). The one exception was for decreasing trends in abundance at LIMR, where a monitoring design with 6 sites, 6 transects per site achieved higher power than a monitoring design with 3 sites and 12 transects per site (Table 3.3).

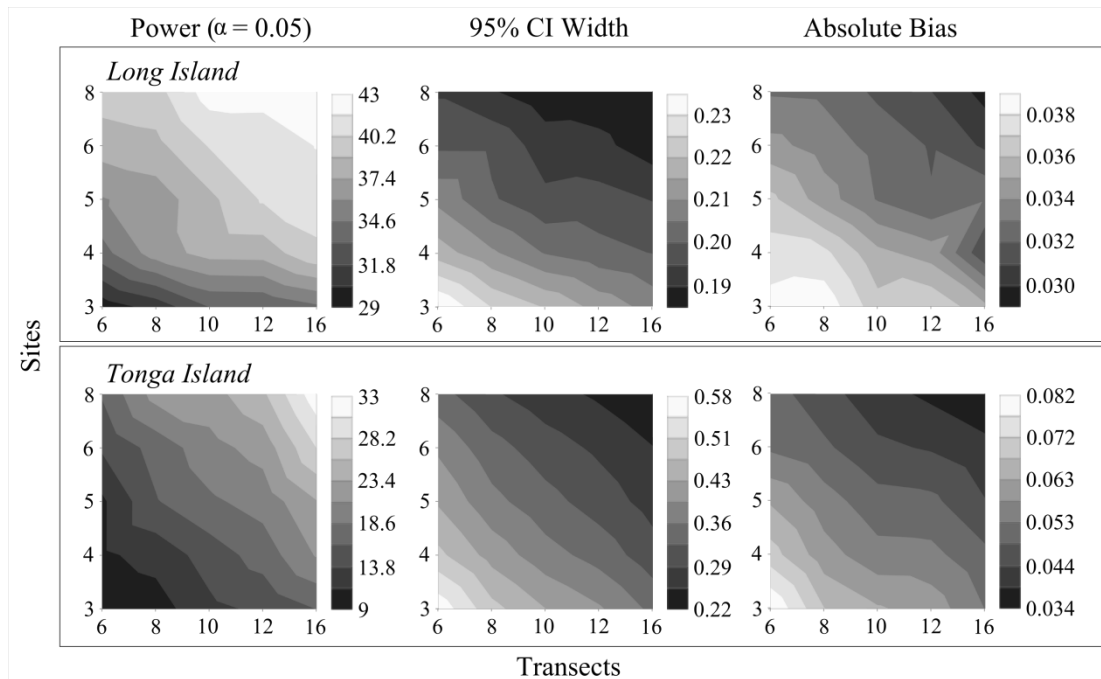


Figure 3.3. Contour plots illustrating power ($\alpha=0.05$), median 95% CI width and median bias relative to the number of monitored sites and transects for legal-sized blue cod at Long Island and Tonga Island marine reserves. These results are for a decreasing trend in abundance.

3.3.4 – Monitoring blue moki

Power, precision and accuracy were similar across the three reserves (Figure 3.4), with slightly lower power, precision and accuracy at HMR at the lowest spatial replication. However, for the highest level of replication all surveys at the three reserves achieved similar levels of power, precision and accuracy. For all three MRs, power, precision and accuracy were more affected by increasing the number of sites than by increasing the number of transects within each site (Table 3.3). In addition, increasing the spatial replication through

increasing the number of sites, rather than replication within each site, resulted in a more pronounced increase in power when trends were positive than negative. This effect was not observed for precision or bias (Table 3.3).

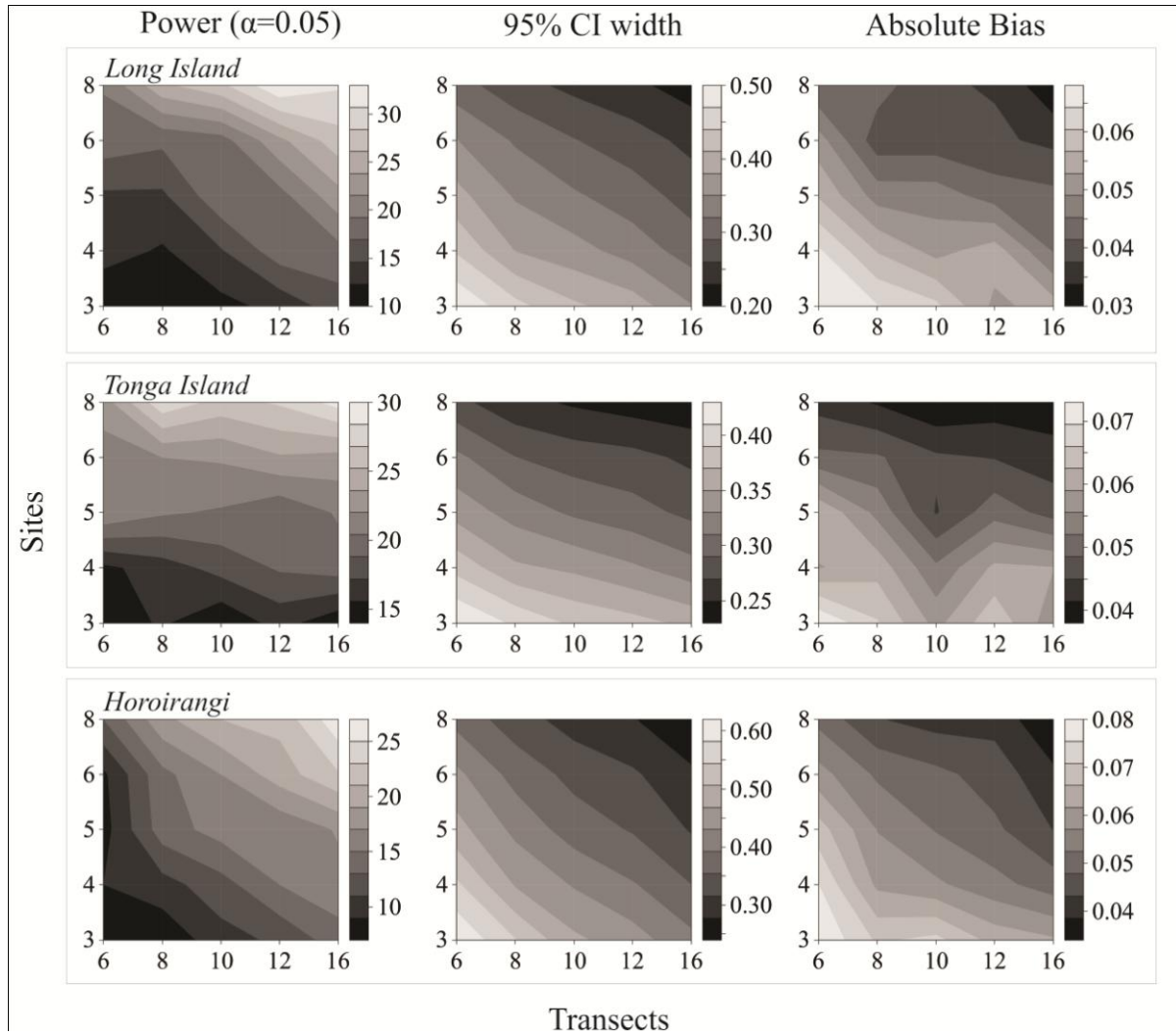


Figure 3.4. Contour plots illustrating power ($\alpha=0.05$), median 95% CI width and median bias relative to the number of monitored sites and transects for blue moki at Long Island, Tonga Island and Horoirangi marine reserves. These results are for a decreasing trend in abundance.

3.3.5 – Monitoring spotty

Power, precision and accuracy were similar between LIMR and TIMR across the different levels of replication, but were markedly different at HMR, which had higher power, higher precision and lower bias, particularly at higher replications (Figure 3.5). In addition, doubling the replication within sites at HMR was more beneficial for power, precision and accuracy than increasing the number of sites, which is in contrast to the situation for TIMR and LIMR where it was more beneficial to increase the number of sites (Table 3.3).

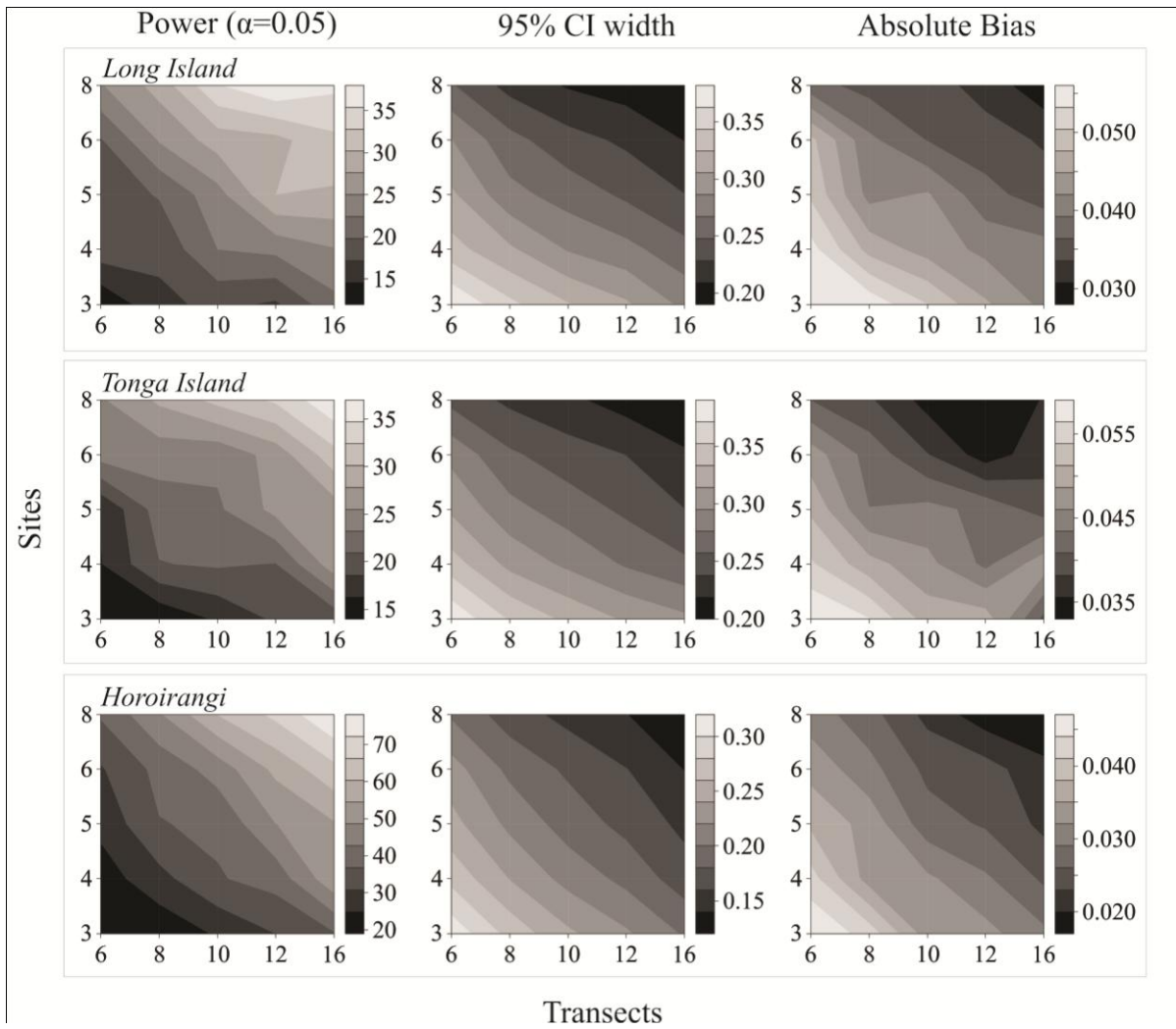


Figure 3.5. Contour plots illustrating power ($\alpha=0.05$), median 95% CI width and median bias relative to the number of monitored sites and transects for spotty at Long Island, Tonga Island and Horoirangi marine reserves. These results are for a decreasing trend in abundance.

3.3.6 – Monitoring tarakihi

For tarakihi, power was low for all levels of replication, which coincided with low precision and high bias. Increasing the number of sites had a greater effect on power, precision and accuracy than increasing the number of transects (Figure 3.6 and Table 3.3).

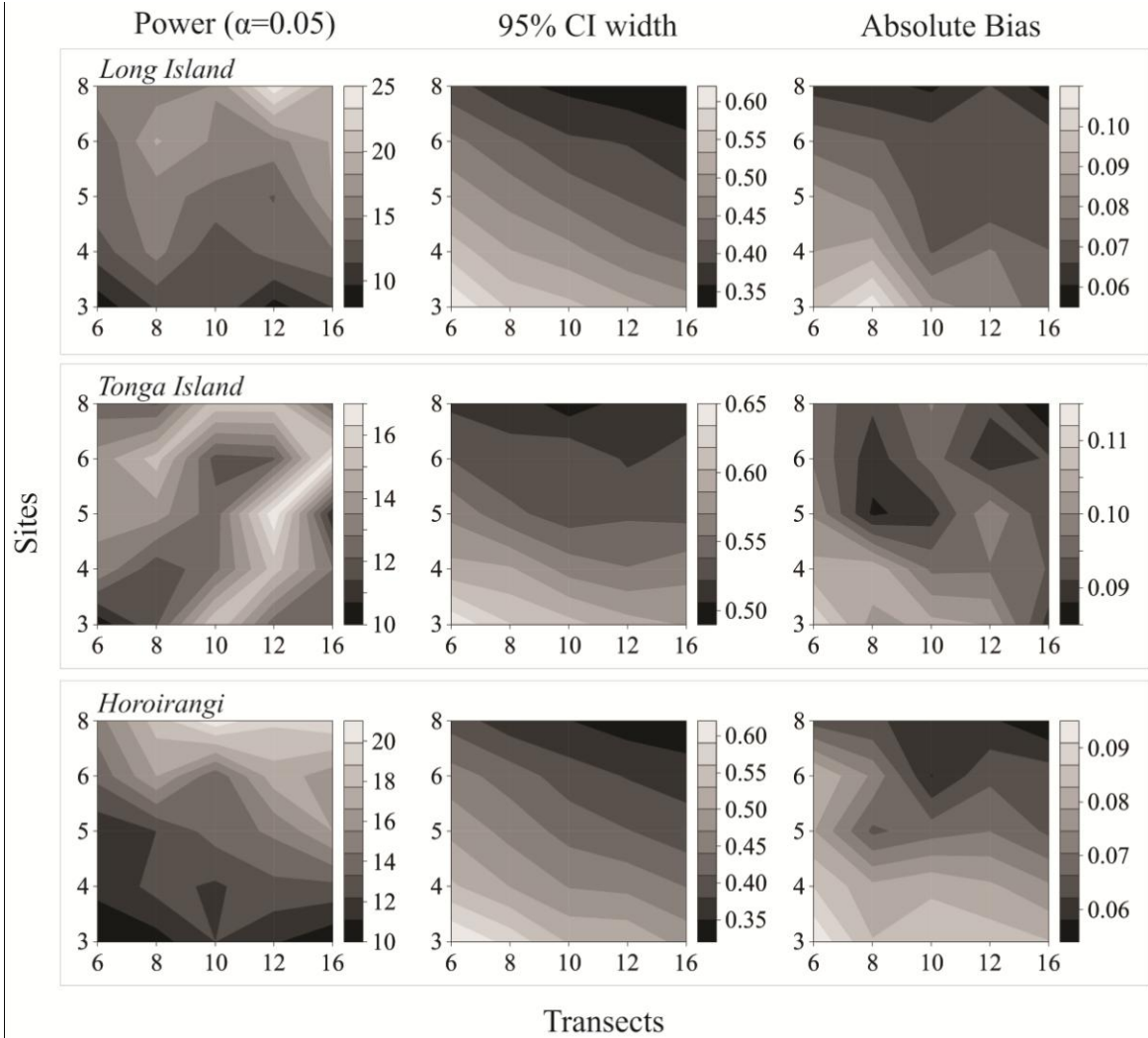


Figure 3.6. Contour plots illustrating power ($\alpha=0.05$), median 95% CI width and median bias relative to the number of monitored sites and transects for tarakihi at Long Island, Tonga Island and Horoirangi marine reserves. These results are for a decreasing trend in abundance.

3.3.7 – Monitoring design costs and cost-effectiveness

The most cost-effective design varied among species and among reserves depending on the specific targets in terms of power, precision and bias (Table 3.4). The lowest targets were achievable in a cost-effective manner by monitoring designs with relatively low spatial or temporal replication for blue cod and spotty, with most designs being in classes A-C (Table 3.4). The exceptions were blue cod at HMR, and legal-sized blue cod at TIMR where much more monitoring is required to reach these goals (Table 3.4). In contrast, monitoring blue moki required a great deal more replication to achieve these targets and would require the maximum replication investigated to achieve the mid level targets. To achieve even the lowest targets in terms of power, precision and bias when monitoring tarakihi, much higher

levels of sampling effort are required, and the mid and higher level targets could not be achieved with the amount of replication investigated (Table 3.4).

Of the most cost-effective designs, over 50% were designs with twelve replicate transects carried out per site (Table 3.4). Overall, six transects per site was the least cost-effective monitoring option, featuring least often compared to all other number of transects per site (Table 3.4). In addition, the maximum number of transects was only cost-effective for the higher targets of power, precision and bias because these monitoring designs were the only ones investigated that were capable of reaching these targets (Table 3.4). Triennial monitoring frequencies were cost-effective only when setting low targets for power and bias and mid level targets where it was more cost-effective to monitor less frequently but with the highest levels of spatial replication (Table 3.4). In most cases, however, monitoring designs with lower spatial replication with annual monitoring were chosen over those that maximized spatial replication but monitored less frequently (Table 3.4). There was no clear optimum number of sites to be monitored when the results were compared across species and reserves, because this varied considerably with the target levels of power, precision and bias (Table 3.4). However, in general, a lower number of sites were required to attain the targets of power, precision and bias for spotty than for blue moki, blue cod and tarakihi (Table 3.4).

Across all species, reserves and targets the different measures tended to trend towards specific design choices. Based on precision, monitoring designs that focused effort on annual sampling but with lower number of sites were most cost-effective (modal number of sites = 3, median number of sites = 4 - Table 3.4), whereas assessments of bias and power tended to select for monitoring designs with more sites (modal number of sites = 8, median number of sites = 6), but monitoring less frequently (Table 3.4).

Table 3.4. Most cost-effective monitoring designs for achieving three levels of power, precision (in terms of 95% confidence interval width) and absolute bias for each species in each reserve for positive and negative trends. The values given are in the format “Sites, Transects, Frequency”, where a frequency of 1 indicates annual monitoring, 2 indicates biennial monitoring and 3 indicates triennial monitoring. / indicates no monitoring design investigated was capable of meeting the relevant target.

Species	Reserve	Trend	Power			Precision			Bias		
			20	30	40	0.4	0.3	0.2	0.05	0.04	0.03
Blue Cod	Tonga	+	6,6,3	6,8,1	8,12,1	3,10,1	3,10,1	8,8,1	5,8,3	3,10,1	8,12,1
	Island	-	6,10,3	6,12,1	/	3,8,1	4,10,1	8,10,1	6,12,3	5,8,1	8,10,1
	Long Island	+	3,10,3	8,12,3	8,10,1	3,12,1	3,12,1	6,12,1	4,12,3	3,12,1	8,10,1
		-	3,12,3	6,12,3	6,12,1	3,12,1	3,12,1	6,12,1	4,12,3	8,10,3	8,12,1
	Horoirangi	+	8,8,3	/	/	4,8,1	8,10,1	/	8,12,1	/	/
		-	8,10,3	/	/	4,12,1	8,16,1	/	/	/	/
Blue Cod (legal)	Tonga	+	5,12,3	5,12,1	8,16,1	3,12,1	4,12,1	8,12,1	6,12,3	6,12,1	8,16,1
	Island	-	8,16,3	8,16,1	/	4,12,1	6,12,1	/	8,16,3	8,12,1	/
	Long Island	+	3,6,3	3,6,3	4,8,1	3,10,3	3,6,1	4,6,1	3,6,3	3,6,1	5,8,1
		-	3,12,3	3,12,3	4,10,1	3,12,2	3,6,1	5,8,1	3,10,3	3,6,1	8,12,1
Blue Moki	Tonga	+	6,8,3	6,8,1	/	3,10,1	5,8,1	/	4,8,1	8,6,1	/
	Island	-	8,12,3	/	/	3,10,1	5,12,1	/	5,10,1	8,10,1	/
	Long Island	+	8,10,3	8,12,1	8,12,1	3,12,1	4,12,1	8,16,1	6,12,3	8,16,3	8,10,1
		-	8,16,3	8,12,1	/	3,12,1	6,12,1	/	8,12,3	6,8,1	/
	Horoirangi	+	8,12,3	8,12,1	/	3,12,1	5,12,1	8,16,1	6,12,3	8,16,3	8,16,1
		-	6,12,1	/	/	4,12,1	8,12,1	/	8,16,3	6,16,1	/
Spotty	Tonga	+	5,10,3	8,10,1	/	3,12,1	4,12,1	/	3,12,1	5,8,1	/
	Island	-	6,12,3	8,12,1	/	3,12,1	4,12,1	/	3,12,1	6,12,1	/
	Long Island	+	3,10,1	8,12,1	/	3,12,1	4,12,1	8,12,1	6,12,3	5,12,1	8,12,1
		-	4,16,3	8,12,1	/	3,12,1	4,12,1	8,16,1	6,12,3	5,16,1	8,16,1
	Horoirangi	+	3,12,3	6,12,3	8,12,3	3,12,1	3,12,1	3,16,1	3,12,3	4,10,3	8,12,3
		-	3,12,3	6,12,3	8,12,3	3,12,1	3,12,1	4,12,1	3,12,3	4,12,3	6,12,3
Tarakihi	Tonga	+	3,16,3	/	/	/	/	/	/	/	/
	Island	-	6,8,3	/	/	/	/	/	/	/	/
	Long Island	+	8,8,1	/	/	6,10,1	/	/	/	/	/
		-	8,12,1	/	/	6,10,1	/	/	/	/	/
	Horoirangi	+	8,16,1	/	/	5,12,1	/	/	/	/	/
		-	8,10,1	/	/	6,12,1	/	/	/	/	/

The overall costs for each of the species for different levels of power, precision and bias show similar patterns of initially flat or slowly increasing costs as power, precision and bias targets increase/decrease respectively, with a sharp rise in costs as these values approach the limits achievable with the monitoring designs examined (Figure 3.7). For similar costs, considerably higher power can be achieved for spotty and blue cod than for blue moki and tarakihi. This difference is most pronounced when examining the precision and bias, which are considerably higher/lower for blue cod and spotty than tarakihi, and marginally higher

than blue moki (Figure 3.7). Based on the data for blue cod from LIMR, similar levels of power, precision and accuracy can be achieved for similar costs between total blue cod abundance compared to the abundance of legal sized individuals (Figure 3.7). However, based on the data from TIMR, the power, precision and accuracy are lower, for similar costs of monitoring, when assessing for trends in abundance of legal-sized individuals compared to total abundance (Figure 3.7). The cost profile for legal-sized blue cod at TIMR is more similar to that of blue moki at TIMR and HMR than it is to total blue cod abundance at TIMR.

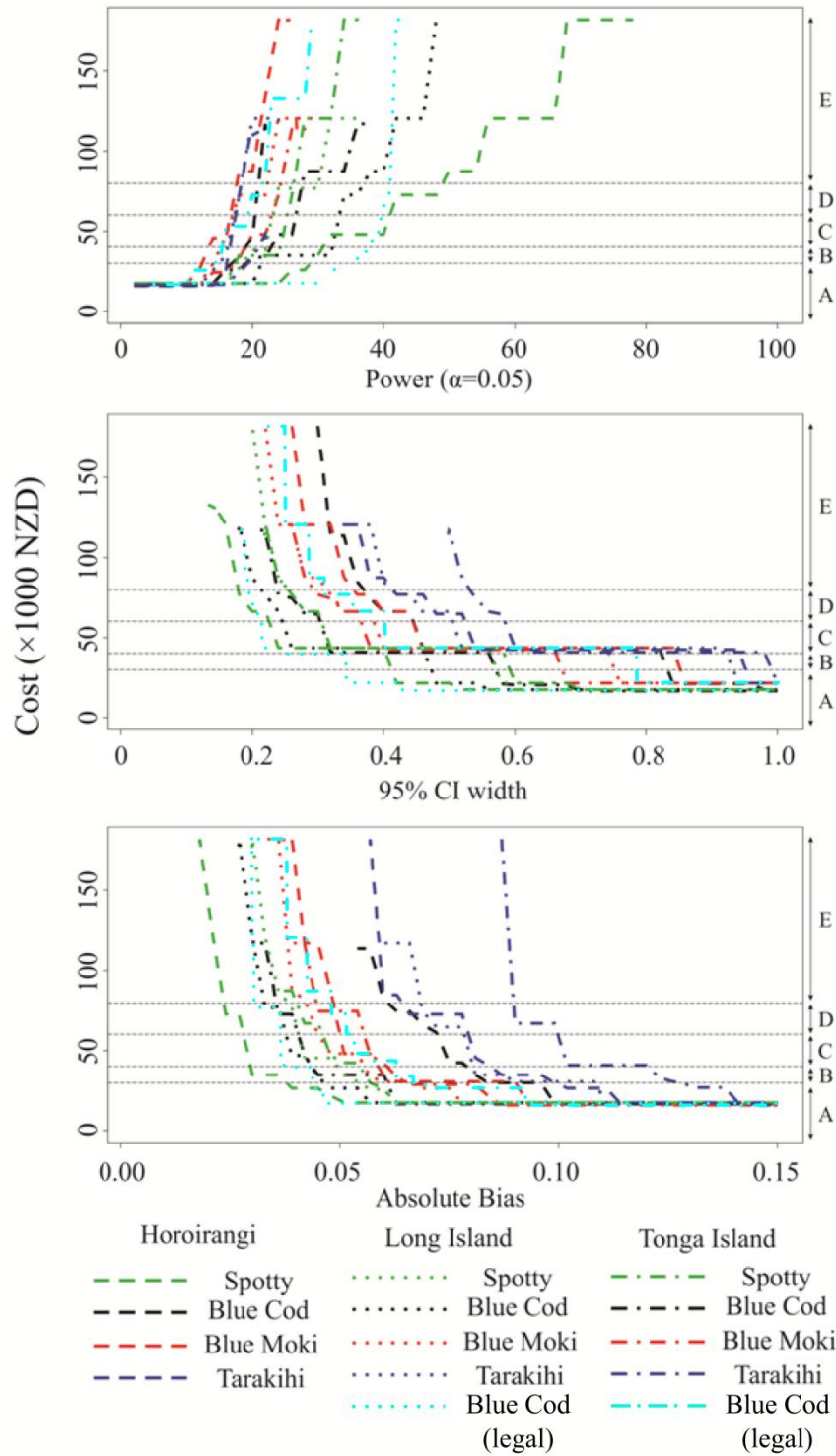


Figure 3.7. Plot giving the cost of the most cost-effective monitoring design for increasing power ($\alpha=0.05$), precision (95% CI width) and absolute bias for each species at each marine reserve. Where the lines stop indicates the maximum/minimum value attained for the monitoring designs considered. This plot is for a decreasing trend in abundance. The letters at the side of each plot indicate the cost class for the range in costs as defined in Table 3.1.

3.4 – Discussion

Designing a monitoring program that is both accurate and precise is a challenge common to ecologists, conservation managers and governmental agencies. The results presented here highlight the relatively low power, low precision and high potential bias of underwater visual census data for determining trends in reef fish abundance in temperate subtidal reefs in New Zealand. Although this study only includes four species, the results are likely to be indicative of the levels of power, precision and accuracy achievable using this methodology for most temperate reef fish species given the range in abundances and variabilities exhibited by the species examined. However given set targets, optimal monitoring designs can be achieved by identifying the most cost-effective monitoring design for achieving these goals.

Previous analyses of monitoring design efficacy (mostly focused on power) have shown that many monitoring designs are limited by the low observed abundances of individuals (fish or otherwise) within many populations (Nicholson & Jennings 2004; Maxwell & Jennings 2005; Freilich *et al.* 2005; Blanchard *et al.* 2008). This is true for the fish species examined here whereby power, precision and accuracy were highest for the more abundant and consistently recorded species, blue cod (total abundance at LIMR and TIMR, and abundance of legal-sized blue cod at LIMR) and spotty. This is to be expected because the original surveys were aimed predominantly at recording the abundance of blue cod, and so surveys were performed in their preferred habitat. In addition, spotty is the most abundant reef fish species at most New Zealand coastal sites (Choat & Ayling 1987; Francis 2001), and so are always recorded in relatively high abundance in these areas. However, for naturally scarce species or heavily fished species whose populations are depleted, abundances are going to be considerably lower, resulting in less precise and accurate assessments of trends in abundance (Blanchard *et al.* 2008) particularly for decreasing trends (Freilich *et al.* 2005). Blue moki at all three marine reserves, blue cod at HMR and legal-sized blue cod at TIMR were observed in low abundance, resulting in low power, precision and accuracy of trend assessments, particularly for decreasing trends in abundance. Unless sampling is extensive (highly replicated in time and space) these changes would likely be attributed to chance rather than to an actual underlying change in population abundance. This is evident for blue moki and blue cod at HMR where optimum monitoring designs tended to require more spatial replication for declining trends in abundance than for increasing trends in abundance (Table 3.4).

The relative effectiveness of monitoring total blue cod abundance versus the abundance of legal-sized individuals was different between LIMR and TIMR. At LIMR the results were similar between monitoring total abundance and legal-sized abundance, with less replication required to achieve set targets for legal sized abundance than total abundance (Table 3.4). Although lower in abundance and displaying similar levels of variability through time and between sites, the abundance of legal-sized individuals at the transect level tended to be less variable than total abundance, perhaps due to aggregations of juvenile blue cod or the influence of territoriality in larger individuals (Francis 2001) that may ensure less clumping of individuals. This may partially explain the slight gains in effectiveness when analysing the abundance of legal-sized blue cod compared to overall abundance. However, at TIMR power, precision and accuracy were all lower for legal-sized abundance compared to total abundance. The abundance of legal-sized blue cod at TIMR was much lower than at LIMR. This coupled with greater variability among sites is likely to be the main reason for the differences in effectiveness among these locations. This also highlights the necessity of not relying on individual metrics as relying on total abundance at LIMR wouldn't have yielded results as quickly as for legal sized abundance, and vice versa at TIMR. Biomass is frequently used in MPA assessments (Edgar & Barrett 1999; Shears & Babcock 2003; Edgar & Stuart-Smith 2009) as increases in average size and abundance combine to make a less variable, and more pronounced response measure than overall abundance that can be affected by many smaller individuals. The estimation of fish sizes would require additional diver training and may be prone to greater observation level error (i.e. differences in size estimation between divers). This however, can be addressed through validation of diver size estimates with targets of a known size as part of the diver training. Although with the data available I was unable to analyse the relative benefits of biomass data over abundance data, there would be a distinct advantage of collecting this additional information as it provide an additional, and potentially more sensitive, metric with which to demonstrate MR effects and would therefore be a valuable addition to any monitoring program. Monitoring, or analysing, alternative metrics, such as those based on size classes, biomass or additional species, maximises the chances that at least one will prove effective, or will be related to the actual response exhibited by the MR, and therefore increases the likelihood of demonstrating MR effects. Variability both among sites and within sites will affect the precision and accuracy of trend assessments. Although spotty were always observed in high abundance, the overdispersed nature of the counts was a limiting factor in the precision and accuracy of trend

assessments. Schools of more than 50 spotty's were regularly encountered, therefore there was considerable variation among transects (e.g., counts >50 versus counts ~2-10). Increasing the within-site replication by surveying a greater number of transects would control for the higher dispersion of counts, resulting in a more accurate assessment of the population abundance. This can be seen in the monitoring design choices, whereby monitoring designs with 12-16 transects at each site were predominantly the most cost-effective designs for spotty. In comparison, optimal monitoring designs for blue cod and blue moki more commonly featured 8 and 10 transects. Also, monitoring spotty tended to require fewer sites than blue cod or blue moki (in particular for measures of precision) as spotty tended to be present in similar abundances at all sites, and therefore required fewer sites to get an accurate and precise measure of their overall abundance than for blue cod or blue moki. Tarakihi abundance was the most variable of the fish species examined. They are predominantly found in soft bottom habitats, but are intermittently observed over rocky reefs (Francis 2001). In the study areas examined, tarakihi exhibited large-scale fluctuations in abundance among years, as well as exhibiting variability in the size classes of individuals present. For example, at TIMR and HMR, tarakihi populations were dominated by small individuals (10-16 cm length), whereas at LIMR this species was dominated by 20-35 cm fish. Furthermore, when present they were often observed in schools and so were observed in great abundance. Given this variability estimates of trends in abundance would be expected to be inaccurate and also imprecise. Even with considerable sampling effort, the precision, power and accuracy of the modelled survey designs are still low. Therefore investing money in the monitoring of tarakihi (at least in the areas/habitats examined) is not as cost-effective to achieve similar levels of accuracy and precision as blue cod, spotty and blue moki. The inclusion in this study of tarakihi data from sub-optimal habitat for this species is informative for two reasons. First, these real survey data provides a case study of a fish species occurring at genuinely low abundance (in this sense, the actual taxon is not important) and contrast that species with others that have higher abundances. Second, while most monitoring focuses on "optimal" habitats it is important to recognize that individuals may exist in areas of sub-optimal habitat for much of their lives. Indeed, for temperate rocky reef fish species that are very heavily targeted, it may be that more individuals now exist outside their optimal habitat than exist inside it because of fishing pressure. Thus, the ability to survey individuals in sub-optimal habitats may be as important and informative as surveys of the same taxon inside optimal habitats. In cases where there are multiple choices of species to focus on, assessments

of this kind can reveal which species are useful as indicator species. In particular, conservation managers may not wish to monitor species where trend estimates are likely to be imprecise or inaccurate and rather use resources to monitor species that are more likely to return accurate and precise measures of changes in abundance (Seavy & Reynolds 2007). This coupled with information regarding the ecological importance of the different species can be utilized to identify an effective and relevant monitoring program.

Deciding on an optimal monitoring scheme is challenging considering the costs and the number of factors that are likely to affect the performance of a given monitoring design (Cabral & Murta 2004). The results presented here also highlight the fact that there can be no “one survey fits all” monitoring design because the choice of optimum monitoring design varies among species and also among marine reserves, depending on the abundance and the degree of variability exhibited by these species in these different areas (Field *et al.* 2005). However, a general finding was that performing 12 transects was optimal in over 50% of cases. These analyses reveal that reducing the number of replicates below 12 would save little time and cost given that one dive would still be required per site. Thus, reducing the number of transects below 12 would have a detrimental effect on the benefits, in terms of power, precision and accuracy without a similar reduction in costs. Performing more than 12 transects would require two or more dives at each site and so would at least double the number of dives, approximately doubling the cost of performing the monitoring. As such, 16 transects were only optimal for the highest targets because this was the only monitoring design capable of reaching these goals and so was the optimal design by default. In addition, in many cases increasing the number of transects did not greatly increase precision, power or accuracy. In nearly all cases increasing spatial replication by increasing the number of sites was more beneficial than increasing the replication within each site. The addition of extra sites will undoubtedly increase the cost of the project because adding additional sites means more dives and greater associated costs. As such, monitoring designs with more sites are penalized in terms of cost when trying to find the most cost-effective monitoring design. Incorporating additional sites may also be problematic in other ways because they need to have the same characteristics in terms of habitat, substratum, depth and distance offshore. There will also be an additional cost of site establishment, through additional dives to locate areas of suitable habitat (Field *et al.* 2005). This in itself may limit the number of candidate sites and highlights the problems faced by researchers in achieving the necessary balance

between quality science, and logistical and cost constraints (e.g., McDonald-Madden *et al.* 2010; Molloy *et al.* 2010).

Deciding on the optimum monitoring design also depends on the measure chosen to judge the monitoring design. In this study three measures for assessing monitoring design effectiveness have been presented that focus on different aspects of the monitoring design. There were subtle differences among the designs that were chosen as the most cost-effective, depending on which measure of monitoring design effectiveness was used. Although the targets set (low, mid and high) by themselves are not directly comparable across measures (power, precision and bias refer to different aspects of the estimated trend parameter, to which there is no common currency) some inferences can be made regarding which aspects of monitoring design are emphasized by each measure. The most cost-effective designs for precision were those that focused effort on higher monitoring frequencies with lower number of sites, whereas those judged on bias tended to emphasize higher numbers of sites to the detriment of monitoring frequency. Sampling more points over time will constrain the trend estimate, and as such, monitoring more frequently will greatly increase the precision of the trend estimate. This would be to the detriment of the number of sites monitored in order to remain cost-effective. On the other hand, monitoring fewer sites encompasses less of the overall population and therefore is likely to be biased more towards the values exhibited by those sites alone, rather than be representative of the whole population. Consequently focusing on more sites should reduce bias, but the trade-off is that monitoring frequency has to be lower in order for the monitoring design to remain cost-effective. Reducing the frequency of monitoring, however, considerably reduced precision of trend assessments. An additional problem when reducing the sampling frequency is that infrequent events such as pulses of recruitment, the first arrival and establishment of invasive species or a decrease in abundance due to poaching or disease, are more likely to be missed. Monitoring more frequently will give better estimates of the rates of these events and can possibly aid in the management of marine reserves, in the form of increased policing or increased scientific understanding of the ecosystem. Ideally, a monitoring design should deliver data that is both accurate and precise and so a careful balance between monitoring frequency and spatial coverage (number of sites) is required. By identifying multiple targets in terms of precision and bias a cost-effective monitoring program can be identified using the procedures outlined and employed here.

There are several aspects of the data collection and the subsequent statistical analyses that require further discussion regarding the influence they may have on the conclusions of this study. The data was collected from a limited number of sites (between 5 and 8) that were of a single uniform habitat type (bedrock/rubble) over a limited number of years (between 5 and 17). One of the assumptions of the data simulation process is that any additional site, or year would conform to (i.e. fall within) the level of variation in abundance exhibited among the prior observed sites and/or years, as observed data was used to parameterise simulations. For the temporal variance component this assumption is unlikely to hold true, as extreme events occur infrequently and are thus unlikely to be evident in the observed datasets, particularly those that are of limited duration (i.e. HMR). As such the interannual variance component may be an underestimate of the true variation through time, which would lead to higher power and precision than would otherwise be expected. However, the assumption of completely random fluctuation in abundance among years is also unlikely to be true as deviations away from a monotonic trend, whether it be increasing, decreasing or flat, are likely to be temporally autocorrelated as a surplus or deficit of individuals (due to recruitment pulses and/or abnormally high mortality) are likely to be observable across multiple years. Accounting for this autocorrelation may reduce the magnitude of the temporal variance term, which would result in higher power and precision due to reduced variation. Incorporating autocorrelation within the simulation and testing process applied here would increase model complexity and the difficulty with which these models can be fit to the data, independent of human intervention (as is required when running thousands of simulations).

The assumption that additional sites fall within the magnitude of variation observed at previous sites may hold true if the proportion of that habitat surveyed within previous sites was a large proportion of the area occupied by this habitat in the entire reserve. However, in most cases this is unlikely to be true due to the limited number of sites surveyed. Thus the variation among sites may be an underestimate of the actual variation exhibited at this spatial scale. This would likely result in higher power, precision and accuracy than would actually be expected, due to the underestimation of this variance component. The selection of sites within a specific habitat may also introduce a level of bias that is not accounted for within the simulation process, as the “true” trend (i.e. that which would be obtained if exhaustive or near-exhaustive surveys were performed) is unknown. This method of data collection likely leads to conclusions that are biased towards individuals in that habitat, rather than the entire population of the reserve. If the target species only occurs in that habitat, (as could be argued

in a loose sense for blue cod) then this bias is likely to be minimal, but could be much larger if the species occupies multiple habitats (such as spotty). Furthermore, this could be a particular problem if a reserve related change in fish behaviour, or habitat cover results in changes to habitat preference, which likely lead to false estimates of changes in abundance as individuals would move from one habitat to another. Random (transects distributed randomly within the reserve), or more appropriately stratified random sampling (transects distributed at random within habitats, with sample size according to the extent of the habitat) would account for this bias. Logistically, however, this may not be feasible as some locations may not be accessible due to boating and/or diving restrictions (i.e. strong currents) and would require considerably more short dives (likely that given this sampling scheme only one transect would be performed per dive) rather than longer dives at fewer locations to achieve a similar sample size. However, where sampling is carried out at sites of a specific habitat (as is the case for all of the datasets used here) then care must be taken when making assertions regarding the status of the reserve as a whole.

In the past, power has been most often used as an indicator of monitoring design effectiveness (Gerrodette 1987; Bart *et al.* 2004; Sims *et al.* 2006; Maxwell & Jennings 2005; Freilich *et al.* 2005). Although the utility of power analyses in designing an effective monitoring design is undisputed (i.e. many of the requirements of a precise and accurate monitoring design are also requirements of a powerful one), analyses of power (at least from a monitoring perspective) should be superseded by analyses focused on maximizing accuracy and precision. The main arguments against power analysis are rooted in the routine use of point null hypothesis significance testing when assessing monitoring data, but several other reasons specifically related to analyses of power, compared to precision and bias, are also pertinent to the assessment of monitoring design efficacy. Analyses of trends in abundance from a null hypothesis significance testing perspective have the null hypothesis of no change in abundance. In a monitoring context this is almost never true because even the most minor of changes will result in a non-zero trend through time rendering the null hypothesis false. While many have objected to the testing of hypotheses that from the outset are known to be false (Anderson *et al.* 2000; Cole & McBride 2004; Gerrodette 2011), analyses of power still remain the most widely used determinant of monitoring effectiveness. Many have advocated for less reliance on hypothesis testing and more emphasis on the reporting of effects (Nakagawa & Cuthill 2007; Gerrodette 2011), and how precisely they are known (McBride *et al.* 1993; Anderson *et al.* 2000; Wade 2000). In this context prospective analyses of precision

and accuracy are more informative when assessing the relative confidence researchers can place in the resulting estimated trends in abundance than analyses of power alone. A further criticism of null hypothesis testing is the equating of statistical significance with practical or biological significance (McBride *et al.* 1993; Anderson *et al.* 2000). Most power analyses attempt to address this problem by defining their effect sizes (as also performed in this study) as those that are deemed biologically significant (Bart *et al.* 2004; Nakagawa & Cuthill 2007). However, truly biologically significant changes in abundance are often unknown, particularly at the beginning of a monitoring program, and so there is a risk of monitoring programs being established based on false ideals. This also implies that the focus of the monitoring program is to show statistically that a non-zero change has occurred rather than accurately and precisely determining what and by how much it has changed. In addition, a monitoring design with high power does not necessarily imply that it is accurate (Bart *et al.* 2004). For example, monitoring of a subpopulation that displays a pronounced trend has high power, but is heavily biased towards the subpopulation and is not representative of the whole population. As such, bias could potentially be high in monitoring programs based purely on power analyses, which may be misleading when judging the effectiveness of a monitoring program (Bart *et al.* 2004).

Finally identifying targets with regard to precision and bias are the most appropriate ways to design a monitoring program because whereas power analysis focuses on the probability of rejecting an *a priori* false hypothesis, a focus on precision and accuracy shifts the focus towards gathering more data about the true state of the system. It also places greater emphasis on interpreting the data in terms of what it tells you about the magnitude of potentially biologically important changes in abundance, and how certain are we, as researchers, of these changes. This will aid in the identification of more focused and specific monitoring “questions”, ensuring that future monitoring is more relevant and the data collected is more capable of answering questions of ecological importance.

Chapter 4 - Spatial variability of wave energy on an exposed shore and its effect on subtidal macroalgal community structure

4.1 – Introduction

Identifying the physical factors experienced by species has played a key role in the field of ecology, with particular focus on identifying species-specific thresholds and tolerances to these physical factors (Pörtner & Knust 2007; Kearney & Porter 2009). In addition to providing an understanding of the ecological constraints that apply to species in different areas, an understanding of these physical limits has allowed the development of species distribution models that, in conjunction with the development of Geographic Information Systems (GIS), can be used to predict the abundance and distribution of species across large spatial scales (Elith & Leathwick 2009). Species distribution modelling has been used in a wide variety of ecological applications ranging from predicting species' invasive ability (Peterson & Vieglais 2001), distribution pattern changes in response to climate change (Pearson & Dawson 2003; Araújo *et al.* 2005) and in land management and conservation practice (Wilson *et al.* 2005). However, constructing distribution models firstly requires an understanding of the spatial variation of the relevant physical factors for these species and the habitats they occupy. Although not as often published in the ecological literature (often included as part of a species distribution model study, Elith & Leathwick 2009), studies identifying the spatial variation in abiotic factors are vital to our understanding of the ecological significance of these factors. In particular marine areas have typically been less intensively studied than terrestrial areas, and apart from factors that can be inferred from satellite imagery (e.g. sea surface temperature) the factors that may be important are often hidden below the surface (e.g. bottom type, currents) requiring intensive and costly surveys (e.g. remote underwater vehicle deployment, drop cameras or multibeam backscatter surveys for bottom substrate composition) or model predictions of these factors (e.g. ocean circulation modelling for currents and dissolved oxygen content) (Robinson *et al.* 2011). Thus methods identifying the spatial variation in abiotic factors relevant to marine species distributions are an important component of marine ecological and biogeographic studies.

In shallow and intertidal marine environments, wave related forces comprise some of the most important physical forces governing the abundance and distribution of species (England *et al.* 2008; Hill *et al.* 2010; Burrows 2012). The most prominent effect of wave forces is the biomechanical effects it imposes on individuals, with subsequent effects on the rate or the probability of damage, death and in the case of sessile and mobile organisms, dislodgement (Gaylord *et al.* 1994; Utter & Denny 1996; Denny & Gaylord 2002; 2010). Wave forces have been shown to induce an upper limit on the size of macroalgal species

(Gaylord *et al.* 1994; Blanchette 1997), as well as controlling the size and shape of hard coral colonies across a coral reef (Madin 2005; Madin & Connolly 2006), while wave-related indices, such as fetch, have been related to subtidal (Hill *et al.* 2010, Burrows 2012) and intertidal community composition (Thomas 1986; Burrows *et al.* 2008). However, the influence of wave energy extends beyond the mechanical consequences with some species of macroalgae benefitting from increased wave exposure (Leigh *et al.* 1987). Constant movement of algal fronds induced by waves can increase nutrient uptake efficiency of the algae through the constant removal of the nutrient depleted water layer on algal fronds (Leigh *et al.* 1987; Duggins *et al.* 2003) and can also increase photosynthetic efficiency by constant rearrangement of fronds with regard to light exposure (Leigh *et al.* 1987). In addition, wave induced flow can replenish local food availability, with subsequent effects on the feeding and growth of sessile organisms (McQuaid & Lindsay 2000; Sanford & Menge 2001). In the intertidal zone, waves and wave splash possibly have the greatest influence by creating additional areas where marine species can persist (the supralittoral zone). Through constant or more frequent splash and submersion as a result of wave action, desiccation and dehydration stress effects are reduced, allowing organisms to occupy higher positions on the shoreline with increasing wave exposure (Harley & Helmuth 2003). In addition to this, wave exposure in the intertidal zone can also alter community structure and dynamics (Jonsson *et al.* 2006), and facilitate greater food supply allowing for a larger filter feeding and predator biomass (McQuaid & Branch 1985, McQuaid & Lindsay 2000).

Because of the important influences of wave action on marine species, knowledge of the wave forces experienced at different locations is vital in order to predict marine community structure and dynamics to new locations (Hill *et al.* 2010). While there is no replacement for measuring wave-exposure directly, either using dynamometers (Carrington Bell & Denny 1994), or direct wave height using electronic loggers such as wave rider buoys (Wright 1976), these methods are often expensive to maintain (electronic loggers), or logistically unsuitable (dynamometers need to be deployed in great numbers) for obtaining metrics of wave exposure over large enough areas to enable geographic scale predictions (1-10's km). The vast majority of studies examining the effects of wave exposure over large spatial scales therefore often rely on cartographic measures of wave fetch (distances measured along radiating lines from the point of interest to the nearest obstacle that would block waves) (see Thomas 1986; Tolvanen & Suominen 2005; Burrows *et al.* 2008; Hill *et al.* 2010; Leaper *et al.* 2012; Burrows 2012), which gives an indication of the distance over

which wind has blown to generate wind-waves and gives a relative measure of the ‘openness’ of a section of shoreline (Burrows *et al.* 2008). While these metrics, in addition to extensions in the form of wind-weighted (Burrows *et al.* 2008) and bathymetry-weighted fetch (Hill *et al.* 2010), have been successfully applied, they are unlikely to capture the differences in wave exposure on relatively small spatial scales (10-100’s of m). This is because interactions with submerged obstacles, refraction and depth induced wave breaking, are all likely to play increasingly important roles in governing the resultant wave energy at these spatial scales (Gorman *et al.* 2003; Cavaleri *et al.* 2007). Furthermore, identifying the effects of wave action on organisms requires that the resolution of the physical factors affecting them should match as closely as possible the spatial scales on which the organisms operate (even down to scales ~ cm, O'Donnell & Denny 2008), and thus higher resolution representations of wave forces are required to adequately describe many species’ distributions.

An alternative to these approaches consists of constructing models that allow simulations of waves and using these to predict wave exposure. The vast majority of wave modelling approaches involve numerical simulations of waves based on wave physics (Cavaleri *et al.* 2007). SWAN (acronym for Simulating WAVes Nearshore) is a third generation numerical wave model that simulates waves and models how these waves interact with local wind patterns, currents and the seabed as they propagate into coastal shelf areas (Booij *et al.* 1999; Ris *et al.* 1999). It can be applied at any scale relevant to coastal applications, and includes terms that model wind-generation, depth-induced wave breaking, whitecapping (wave-breaking in deeper water when wave height becomes too large compared to the wavelength, Ris *et al.* 1999) and wave-wave interactions that can enhance or dissipate wave energy (Booij *et al.* 1999; Ris *et al.* 1999). SWAN models have previously been applied in coastal engineering scenarios of sediment transport and changes in beach morphology (Castelle *et al.* 2006; Warner *et al.* 2008), as well as coupled with models of water currents to predict storm surges during hurricanes (Xie *et al.* 2008; Sheng *et al.* 2010). Within an ecological context, England *et al.* (2008) developed a SWAN model for a Western Australian embayment and related the bottom orbital velocity generated by waves to marine subtidal macroalgal communities, while Huang *et al.* (2012) related seabed disturbance, generated from SWAN model predictions, to the abundance of eight infaunal species and overall community diversity for a subtidal sandy embayment in south-eastern Australia. However, these are among the few examples of SWAN models being applied in an ecological setting.

The aim of this study was to develop a SWAN wave model to predict wave forces for the Wellington south coast in New Zealand and to identify the variation in wave energy along this stretch of coastline to aid in explaining and predicting differences in intertidal and subtidal community composition among locations in this region. The Wellington south coast is a dynamic and highly wave exposed shoreline, experiencing southerly swell >80% of the time with an average significant wave height of 2.25 m (Carter & Lewis 1995). In addition, seasonal storms can give rise to extended periods where wave heights average 4 m and short periods of time where waves can be 5-8 m in height (Pickrill & Mitchell 1979; Carter & Lewis 1995). The coastal topography and bathymetry is also complex with a mixture of intertidal rocky platforms, sand and gravel beaches and submerged reefs rising from a matrix of sand, boulder and pebble gravels, which are constantly in motion due to wave forces and currents (Bowman *et al.* 1980; Carter 1992; Carter & Lewis 1995).

The specific aims of this chapter are twofold. Firstly I aim to produce maps illustrating the wave energy experienced along a digital representation of Wellington's south coast that will be used to develop predictive models for an array of intertidal species (Chapter 5). Secondly, using the same SWAN model I aim to produce maps of the variation in subtidal bottom orbital speed due to waves, and compare this to biomechanical limits for two species of subtidal canopy forming macroalgae that are present along Wellington's south coast; *Macrocystis pyrifera* and *Ecklonia radiata*. This final aim, which is the primary focus of this chapter, utilises biomechanical information for *M. pyrifera* (Utter & Denny 1996) and *E. radiata* (Thomsen *et al.* 2004). *Ecklonia radiata* is numerically abundant along much of the Wellington South Coast (Choat & Schiel 1982; Pande & Gardner 2009) whereas *M. pyrifera* has a much patchier distribution (Hay 1990). Both species form dense canopies and are therefore engineers of subtidal communities by controlling light penetration to the benthos and providing biogenic habitats for many species of fish and invertebrates (Kennelly 1989; Clark *et al.* 2004; England *et al.* 2008). Elucidating the wave forces in relation to their mechanical thresholds can therefore yield information regarding the probabilities and frequencies of disturbance within these habitats, as well as setting limits for species-specific distribution, size and abundance. This will lead to a better understanding of the factors structuring these communities and can be used to identify the mechanical and biological processes causing differences in community composition among locations. Knowledge of the mechanism and the spatial variation of these processes can be used for management of marine ecosystems, for example to identify areas that are particularly vulnerable to harvesting

of macroalgae (Schiel & Nelson 1990), and in systematic conservation planning to identify areas that encompass as large a range of habitat types as possible in the zoning of marine protected areas or marine reserves (Leslie 2005).

4.2 – Methods

The SWAN model requires several different inputs in order to run. The inputs required include grids representing the bathymetry and bottom roughness (a measure of how much friction/dissipation is experienced by breaking waves and waves traversing shallow areas) of the area of interest, as well as boundary wave conditions that are used to simulate waves entering the computational grid (oceanic swell) and local wind strength and direction. The methods will be split into sections describing; the acquisition of the separate input types required by the model, model boundary conditions, model implementation, model parameters and outputs, processing of model predictions to produce maps, and finally the application of model predictions with regards to the biomechanical limits of *E. radiata* and *M. pyrifera*.

4.2.1 – Model inputs - defining the computational domains

To match previous (Pande & Gardner 2009) and ongoing ecological studies (Chapter 5) the area from Breaker Bay in the east (41°19.8'S, 174° 50.4'E) to Sinclair Head in the west (41° 21.48' S, 174° 42.36' E) was identified as the area where the majority of subtidal and intertidal fieldwork has been performed in the past, and therefore encompasses the area where model results are likely to be most useful with regard to matching wave forces to biological community composition (Figure 4.1). However, to obtain accurate predictions for this area, the wider computational domain had to be large enough to account for edge effects. Edge effects arise due to the fact that the state of a cell in the computational grid is determined by those surrounding it. The states of cells at the edge of the computational grid are therefore partially undefined, and these errors can propagate throughout the computational grid unless adequate boundary conditions are set. Boundary conditions would only be set for the southern boundary, and as such errors can propagate into the computational grid from the undefined east and west boundaries (the northern boundary is predominantly land, and therefore does not require boundary conditions). By definition these undefined boundaries allow wave energy to leave the computational area, but do not simulate waves entering, which in most cases is unrealistic (Zubier *et al.* 2003). The computational grid needs to be large enough so that the east and west boundaries are sufficiently distant from the smaller grid such that these errors do not propagate into the area where accurate

predictions of wave action are required (between Breaker Bay and Sinclair Head). The area adjacent to the boundary where wave information is likely to be affected by these edge effects is encompassed within a 45° sector either side of the predominant wave direction (in this case propagating from south to north along a bearing of 0°) with its apex at the south-east or south-west corners for the east and west boundaries, respectively (illustrated in Figure 4.1) (SWAN team 2006). Wave action in the eastern portion of this area is likely to be affected by the headland to the east of the harbour entrance (Figure 4.1), and as such this headland was also incorporated into the computational domain. For these reasons the computational domain was defined as a 27270 m (east-west) by 13050 m (north-south) grid with corners at $41^\circ 26.480'$ S, $174^\circ 35.640'$ E (bottom-left), $41^\circ 26.862'$ S, $174^\circ 55.212'$ E (bottom-right), $41^\circ 19.434'$ S, $174^\circ 35.900'$ E (top-left) and $41^\circ 19.814'$ S, $174^\circ 55.437'$ E (top-right). This ensured that the headland was incorporated into the computational domain and that boundary effects did not propagate into the area of interest.

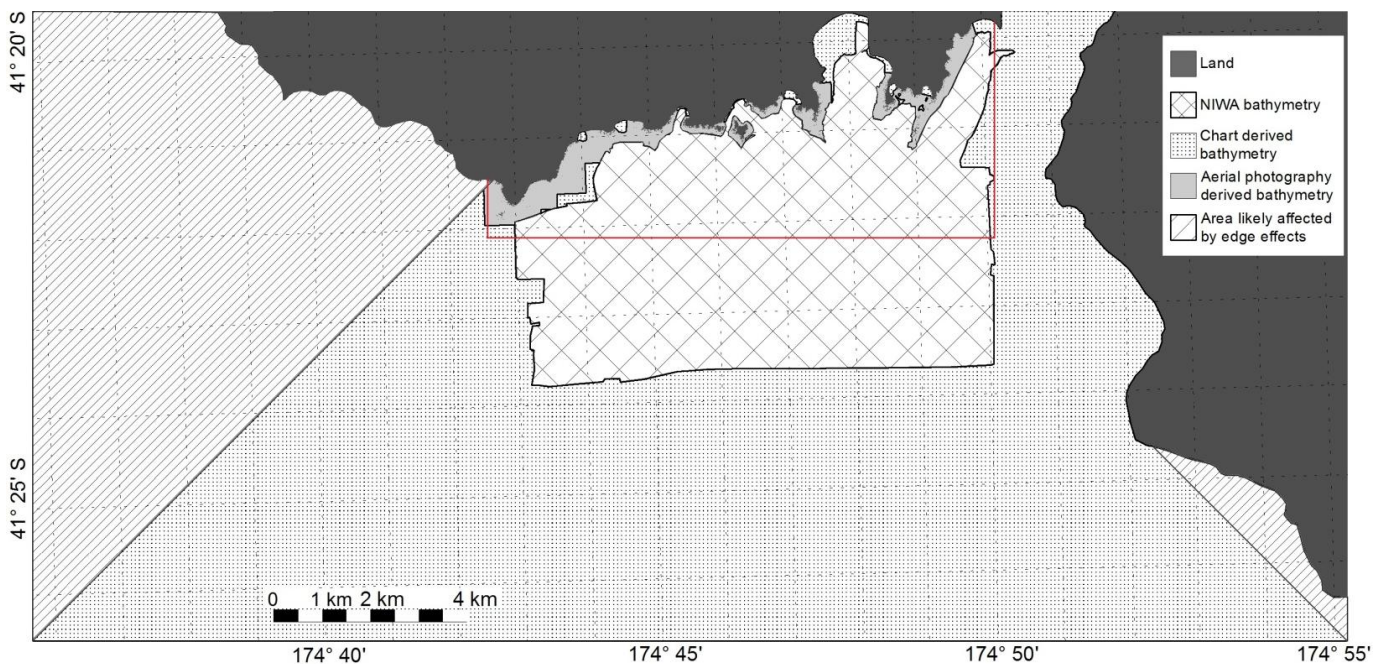


Figure 4.1. Map of Wellington's south coast, showing the sources of the bathymetry data used in defining the SWAN model. The red outline shows the inner grid where model results are reported, while the extent of the map is the same as the computational domain used.

4.2.2 – Model inputs - bathymetry data

Base bathymetry data were obtained from the National Institute of Water and Atmospheric Research (NIWA) in New Zealand. The bathymetry data were collected using multibeam soundings using NIWA's deepwater research vessel *Tangaroa* and was gridded at

2 m resolution. Due to the constraints of ship-based bathymetry acquisition there were considerable gaps in the data (Figure 4.1) due to the vessel's inability to access nearshore areas. To fill in these gaps two methods were utilised. For nearshore bathymetry (coastal areas 0-200 m offshore) aerial imagery was used to predict the bathymetry based on ocean colour, whereas for offshore areas, or surrounding areas where only a coarse representation of bathymetry are required (edges of the computational domain), an interpolated bathymetry layer derived from bathymetry charts was used. The full methods used to acquire, process and combine these sources of information are given as an appendix (Appendix 2A) along with other supporting material. The resultant bathymetry consisted of a 2 m by 2 m resolution gridded map for high resolution nearshore model runs, and a 30 m by 30 m resolution map for initial testing and coarse scale model runs (Figure 4.2).

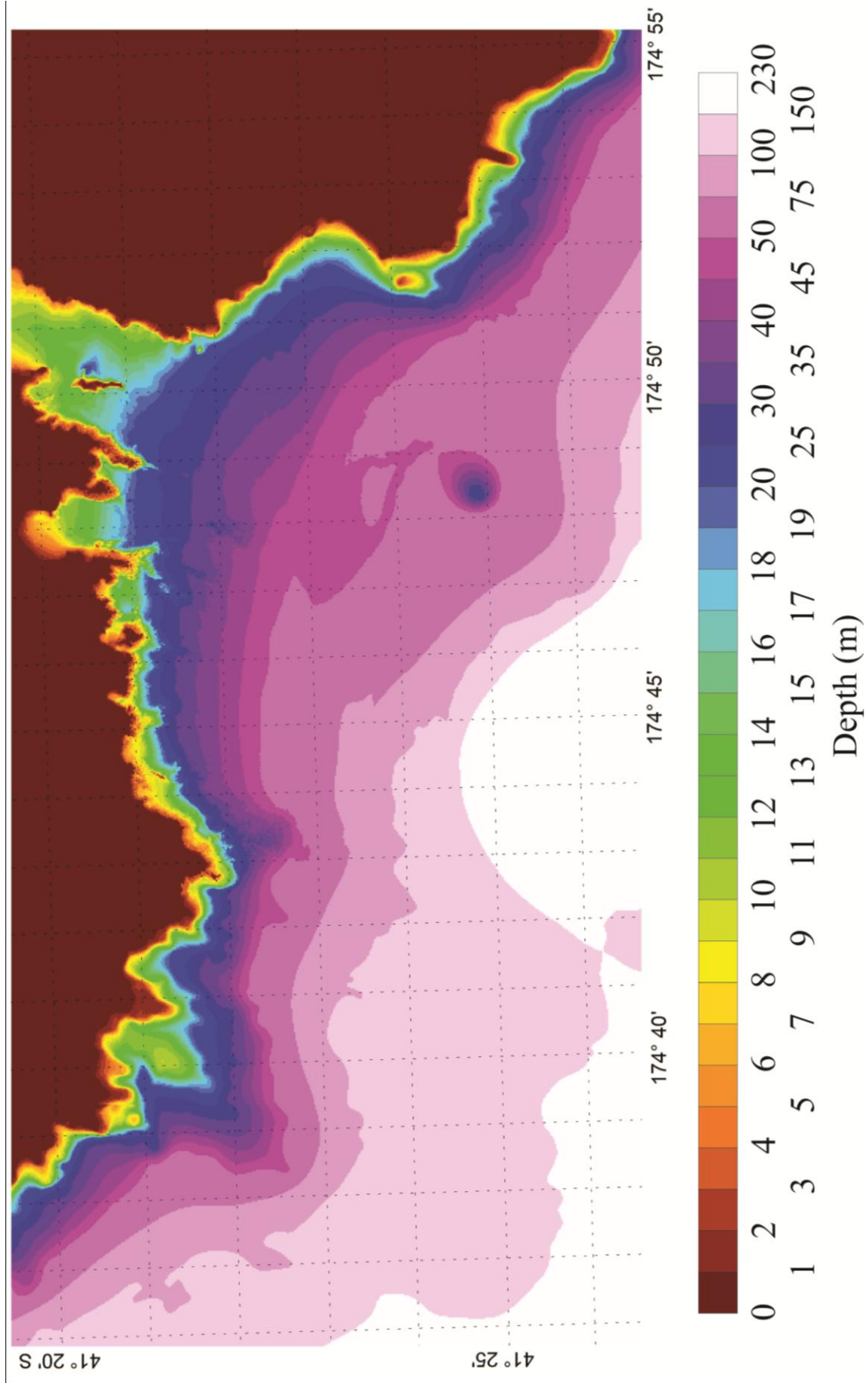


Figure 4.2. Map of the bathymetry defined for the entire computational grid of the SWAN model.

4.2.3 – Model inputs - bottom roughness

The bottom roughness was estimated according to the bottom substrate type present at each point in the computational domain. A multibeam backscatter map collected and produced by NIWA representing the strength of backscatter from the seabed was loaded and visualised in ArcMap (ESRI 2011). The extent of this map was the same as the NIWA bathymetry data (Figure 4.1). Three different types of backscatter were identified: (1) high intensity uniform backscatter was associated with a pebble gravel substrate type, (2) low intensity backscatter was associated with a sand/fine sediment substrate type and (3) areas of overall medium intensity backscatter with high variation in backscatter strength over small spatial scales were classified as submerged bedrock. Note that variation in backscatter strength is likely attributable to variation in aspect of the submerged bedrock, with surfaces perpendicular to the incoming sound-waves displaying the highest backscatter while inclined surfaces that reflect sound away from the direction of the receiver will display low intensity backscatter (Figure 4.3) (Carter 1992). All substrate types were identified by comparison with a shapefile provided by NIWA that had classifications of the different substrate types for Wellington's south coast from the harbour entrance to Owhiro Bay, which was extended using the map of backscatter strength. Because the backscatter map did not encompass the whole computational grid, some assumptions about the surrounding substrate types were made based on the figure presented in Carter & Lewis (1995 - Figure 2 of that paper), aerial photography (Google Earth imagery) and personal observations. A polygon shapefile was created in ArcMap containing outlines of each of these different substrate regions that was subsequently converted to a raster grid of the same proportions as the bathymetry layer (Figure 4.3).

In the SWAN model specification, the bottom roughness is defined by a roughness scale length, which is approximately equivalent to the scale size of variations in the seabed experienced by the waves as they propagate across these areas. Although there is likely to be considerable variation in roughness scale lengths between areas, obtaining estimates of this at the scales required would be logistically infeasible (Cavaleri *et al.* 2007). As such, approximate roughness scale lengths were assigned uniformly to each substrate type based on images of the seabed contained within Carter (1992). Roughness scale lengths of 0.01 m were assigned to areas of sandy substrates (~ cm scale ripples of the seabed), 0.04 m to areas of pebble gravel (approximate size of the variations in the gravel seabed) (Carter 1992) and 0.08 m was assigned to areas of submerged bedrock (based on measurements of the rugosity of

exposed intertidal rocks by laying out a 2 m transect and measuring the departure from a flat surface at 10 cm intervals, and images within Carter [1992] of submerged bedrock). These roughness scale lengths were assigned to the relevant substrate types in ArcMap and then 2 by 2 m and 30 by 30 m gridded representation of these values was exported for the computational area.

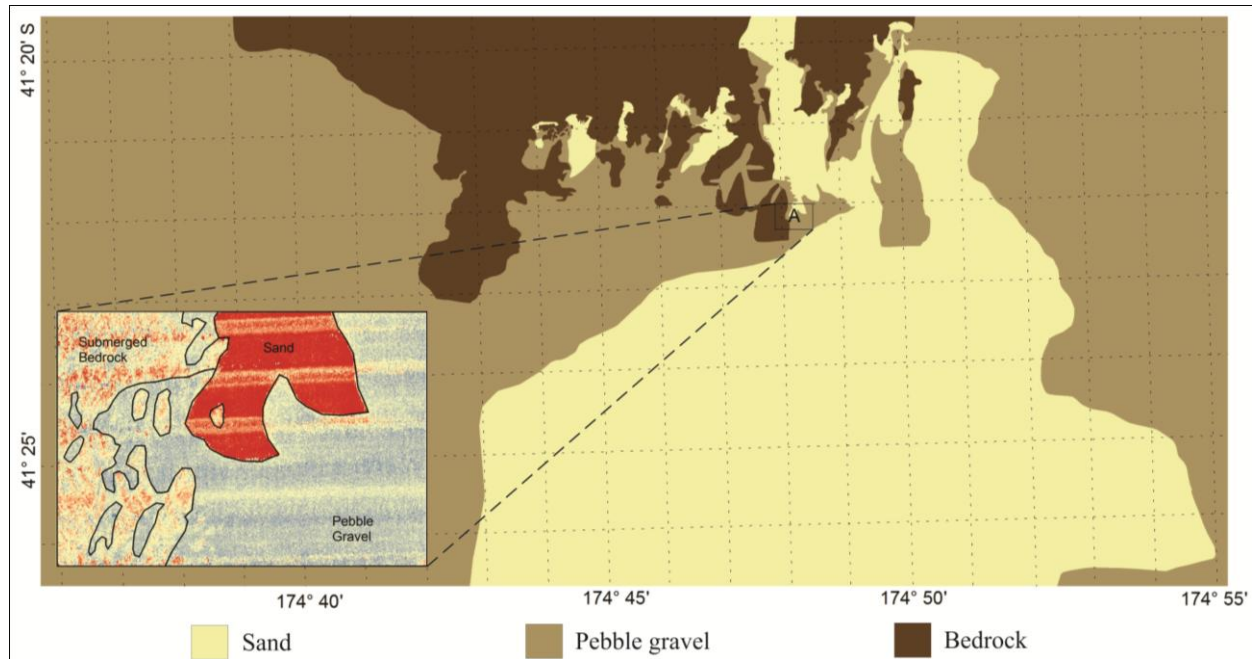


Figure 4.3. Map of the computational domain illustrating the extent and distribution of the different substrate types. Inset A is a cropped portion of the NIWA backscatter map illustrating the differences in reflectance between the three substrate types.

4.2.4 – Model boundary conditions - wind and wave regimes

Wellington's south coast experiences waves as a result of locally wind-generated waves, as well as large swell events as a result of storms in the Southern Ocean (Carter & Heath 1975; Carter & Lewis 1995). These waves are generated far outside the computational grid, but can be accounted for by specifying that wave conditions (significant wave height, period and direction) along one or more of the computational grid boundaries match those of observed wave parameters. Data from NOAA wavewatch III (Tolman 1997) hindcasts were obtained for the nearest virtual buoy location (41° 30' S, 174° 30' E) for the period February 2005 to May 2011. This consisted of hindcast predictions of wave period, direction and significant wave height at three hourly intervals. Rose diagrams of wave height and direction (Figure 4.4) revealed that there was one predominant wave direction with waves coming from bearings of 165-195° accounting for ~ 50% of all records. However, waves originating along bearings of 105-165° accounted for ~15% of the wave records. Subsequently, wave records

were classified into two direction regimes, 165-195° and 115-145° accounting for a large proportion of the hindcast wave predictions (the northerly swell direction shown in Figure 4.4 was found to be associated with periods of moderate to strong northerly winds, and as such would be associated with periods of no, or very little wave action close to shore, in the area of interest). These were subsequently split into categories of significant wave height; 0.5-1 m, 1-1.5 m, 1.5-2 m, 2-3 m, 3-4 m and 4-5 m.

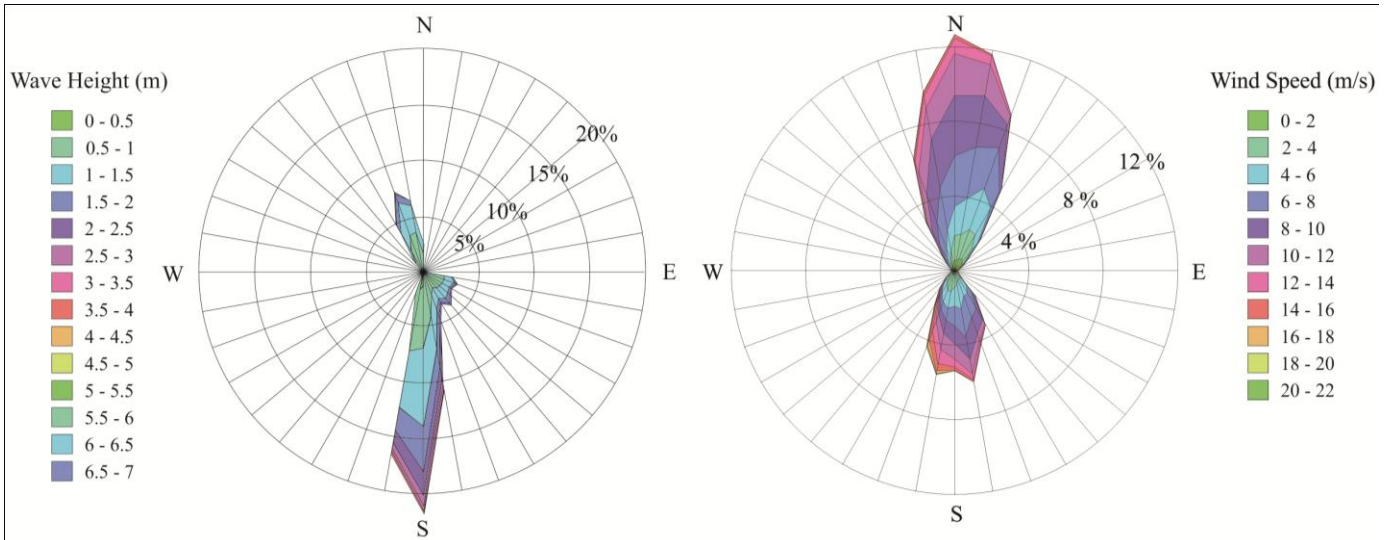


Figure 4.4. Rose diagrams of wave and wind regimes experienced by the Wellington south coast. All directions are specified according to the nautical convention. Data obtained from NOAA wavewatch III.

For each wave height/direction class (2 direction classes, 6 height classes, 12 classes overall) the time periods when these wave conditions prevailed were recorded and matched with the observed wind speed and direction, obtained from the NIWA national climate database (NIWA 2012) for the Wellington Airport station (41° 19.32' S, 174° 48.24' E). Wellington experiences two predominant wind directions, one centred due north, and one centred due south (Figure 4.4). The wave classes were therefore split to represent time periods when incoming waves co-occurred with northerly winds and a second class when waves co-occurred with southerly winds. The wind data closely matched the swell data, with lower significant wave heights associated with either northerly or light southerly winds, whereas large southerly swell events were associated with strong gale-force southerlies (see Figure 4.5 for an illustration of this). Wind speeds within each of the classes were split into six classes 0-2.5 m.s⁻¹, 2.5-5 m.s⁻¹, 5-7.5 m.s⁻¹, 7.5-10 m.s⁻¹, 10-15 m.s⁻¹ and >15 m.s⁻¹. This resulted in 144 separate classes of wave height/direction and wind speed/direction (2 wave direction × 6 height class's × 2 wind directions × 6 wind strengths). For reasons pertaining to

computational time restrictions not all classes could be simulated. Therefore classes that occurred less than 1% of the time (less than 185 records) were excluded, with the exception of the strongest southerly and south-easterly wind and swell classes as these would be necessary to identify maximum wave forces. In addition, south-easterly wave height classes were included for the most frequently occurring wind regime for that wave class. This resulted in 26 sets of model parameters (Table 4.1). The wind speed and direction, along with significant wave height, direction and period were averaged across all records within each group and these values were taken to be representative of that group. The resulting parameters were used to define the boundary conditions at the southern computational grid boundary in the SWAN model simulations, and the resulting wind parameters were defined uniformly across the entire computational grid.

Table 4.1. Description of the wind and wave regimes modelled

Class #	Wave class	Range of values for each class				Averaged parameters used as boundary conditions					Frequency
		Swell		Wind		Wind		Waves			
		Direction (° from N)	Height (m)	Direction (° from N)	Speed (ms ⁻¹)	Speed (ms ⁻¹)	Direction (° from N)	Height (m)	Direction (° from N)	Period (s)	
1	S2	165-195	0.5-1	325-40	0-2.5	1.55	18.22	0.78	181.40	11.01	261
2	S2	165-195	0.5-1	325-40	2.5-5	3.79	11.12	0.78	182.65	10.60	349
3	S2	165-195	0.5-1	325-40	5-7.5	6.32	6.01	0.78	182.71	11.08	468
4	S2	165-195	0.5-1	325-40	7.5-10	8.69	-0.59	0.78	181.87	10.93	416
5	S2	165-195	0.5-1	325-40	10-15	11.26	-3.97	0.79	182.00	11.05	195
6	S2	165-195	0.5-1	145-215	2.5-5	3.80	184.25	0.76	182.19	10.19	300
7	S2	165-195	0.5-1	145-215	5-7.5	6.17	173.65	0.77	180.61	8.13	299
8	S3	165-195	1-1.5	325-40	0-2.5	1.70	19.30	1.21	181.01	10.74	235
9	S3	165-195	1-1.5	325-40	2.5-5	3.75	11.10	1.19	181.66	10.94	333
10	S3	165-195	1-1.5	325-40	5-7.5	6.23	7.22	1.20	182.04	11.14	417
11	S3	165-195	1-1.5	325-40	7.5-10	8.67	1.21	1.21	181.76	11.13	337
12	S3	165-195	1-1.5	325-40	10-15	11.33	-0.82	1.19	182.07	11.34	193
13	S3	165-195	1-1.5	145-215	2.5-5	3.83	179.49	1.22	180.91	10.24	239
14	S3	165-195	1-1.5	145-215	5-7.5	6.24	170.81	1.23	180.20	8.93	288
15	S3	165-195	1-1.5	145-215	7.5-10	8.56	169.23	1.27	179.30	8.55	243
16	S4	165-195	1.5-2	140-210	7.5-10	8.74	172.73	1.72	178.90	9.28	250
17	S4	165-195	1.5-2	140-210	10-15	11.72	183.36	1.76	179.07	8.36	210
18	S5	165-195	2-3	140-210	10-15	12.20	181.88	2.41	178.69	8.57	471
19	S6	165-195	3-4	140-210	10-15	13.15	186.82	3.37	177.27	9.62	121
20	S6	165-195	3-4	140-210	>15	16.66	194.60	3.40	180.04	9.11	75
21	S7	165-195	4-5	175-215	>15	17.00	198.68	4.32	178.07	10.22	32
22	SE2	115-145	0.5-1	150-230	5-7.5	6.00	184.01	0.80	131.42	8.50	75
23	SE2	115-145	0.5-1	330-30	5-7.5	6.36	3.07	0.75	128.02	10.25	153
24	SE2	115-145	0.5-1	330-30	7.5-10	8.64	0.55	0.77	129.25	10.83	126
25	SE3	115-145	1-1.5	135-180	7.5-10	8.65	158.86	1.27	133.34	7.98	64
26	SE5	115-145	2-3	130-210	10-15	11.85	176.08	2.46	129.88	9.21	31

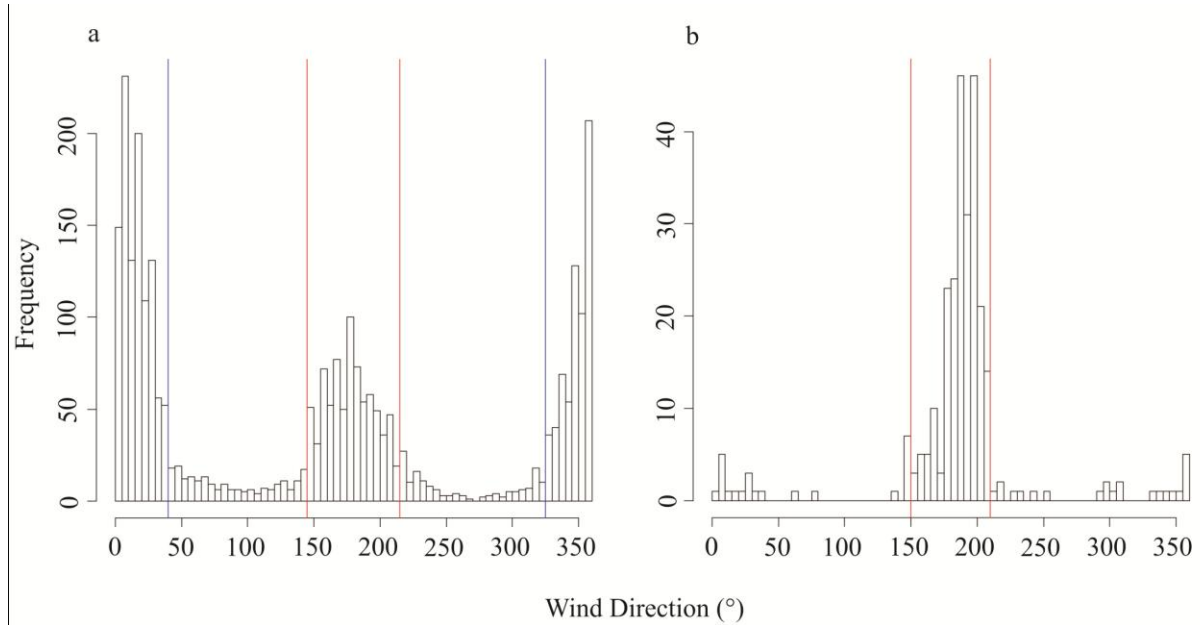


Figure 4.5. Histograms of wind direction for time periods when significant wave heights were hindcast as (a) 0.5-1 m high and (b) 3-4 m high. Red lines indicate the range of wind directions considered being indicative of a southerly wind class, and blue lines indicate the range used for a northerly wind class. Data obtained from the NIWA national climate database (NIWA 2012) for the Wellington Airport station ($41^{\circ} 19.32' \text{ S}$, $174^{\circ} 48.24' \text{ E}$).

4.2.5 – Model implementation – nested grids

Due to the size and resolution of the computational grid, model simulations were run on a nested hierarchical basis to reduce computational time without sacrificing resolution (Cavaleri *et al.* 2007). For each wave class an initial model simulation was performed for the entire computational grid using the 30 m by 30 m resolution bathymetry and bottom roughness data. Within this larger grid, 14 nearshore nested grids were simulated, with each nested grid measuring approximately 1400 m by 1400 m (Table 4.2). The bathymetry and bottom roughness data for these nested grids were cropped from the larger 2 m resolution grids. Subsequent wave model runs were then implemented for each nested grid with the corresponding wind speed and direction, but with wave boundary conditions set by the coarse resolution model predictions for the wave frequency spectra and directions along each of the nested grids four boundaries.

Table 4.2. Locations and extent of the nested grids.

Nest No	Coordinates				Size (m)	
	Bottom left		Top Right		N-S	E-W
	Lat (° ' S)	Long (° ' E)	Lat (° ' S)	Long (° ' E)		
1	41 22.1985	174 42.0390	41 21.4641	174 43.0706	1400	1400
2	41 22.0407	174 43.0163	41 21.3032	174 44.0460	1400	1400
3	41 21.5641	174 43.5720	41 20.8294	174 44.5994	1400	1400
4	41 21.4307	174 44.5691	41 20.6908	174 45.6287	1400	1436
5	41 21.3621	174 45.5924	41 20.6186	174 46.6235	1410	1400
6	41 21.2733	174 46.3944	41 20.5381	174 47.4212	1400	1400
7	41 21.4853	174 47.3018	41 20.7485	174 48.3286	1400	1400
8	41 20.7308	174 47.3293	41 19.9941	174 48.3558	1400	1400
9	41 20.9201	174 47.8048	41 20.1804	174 48.8276	1400	1400
10	41 20.9163	174 47.7989	41 20.1810	174 48.8280	1400	1400
11	41 21.2267	174 47.8343	41 20.4899	174 48.8628	1400	1400
12	41 21.2804	174 48.6997	41 20.5449	174 49.7299	1400	1400
13	41 21.0705	174 49.3216	41 20.3335	174 50.3459	1400	1400
14	41 20.4590	174 49.4197	41 19.7190	174 50.4421	1400	1400

4.2.6 – Model parameters and outputs

The SWAN model and successive nested model runs were performed in generation three mode, enabling the simulation of wave energy loss through depth-induced wave breaking, whitecapping and bottom friction (Booij *et al.* 1999). Triad wave-wave interactions were also activated, which in shallow water transfer wave energy from lower frequencies to higher frequencies (shorter wavelengths), particularly as waves propagate across submerged bars or reefs (Beji & Battjes 1992; Ris *et al.* 1999). These effects are likely to be important as there are several areas in which there are extensive submerged reefs. The optional parameter for bottom friction was set to the formulation presented in Madsen *et al.* (1988). Significant wave height, energy, direction and bottom orbital velocity (root-mean-square of the maxima of the orbital velocity) were output for the nested grids as well as for the coarse model grid.

4.2.7 – Processing model results – subtidal orbital velocity

Subtidal orbital velocity predictions for each of the modelled wave classes were loaded into ArcMap. These values were mapped because drag as a consequence of wave-induced water movement has been shown to be a major determinant of damage and mortality for macroalgal species (Gaylord *et al.* 1994; Denny 1995; Utter & Denny 1996; Thomsen *et al.* 2004). From the model results the maximum and minimum orbital velocity experienced at each location were obtained. In addition an average orbital velocity for each location was

calculated by taking an average of the orbital velocity predictions for each wave class, weighted by the proportion of time that each wave class was prevalent. These were used to produce maps of the magnitude of the maximum, minimum and average subtidal orbital velocities along Wellington's south coast.

4.2.8 – Processing model results – coastline wave energy

To obtain a digital representation of the shoreline each section of coastline was recreated in ArcMap by tracing around all emerged rock visible on aerial photographic images that were also loaded into ArcMap, creating a polyline shapefile representation of the shoreline. The greatest care was taken to capture all emerged rock, but there are likely to be areas (in particular, boulder fields) where there are sections that are not well represented. The line segments (lengths ~2 – 1000's of metres) were then converted to a 2 by 2 m gridded representation of the coastline, by converting the shoreline shapefile to a raster image format. Each cell thus represented a 2 m section of intertidal shoreline. To obtain a representation of the wave energy experienced by each of these coastal cells, the wave energy for the surrounding "wet" cells (i.e., those that are ocean rather than land) were averaged, and the average value assigned to the coastal cell. This was performed in ArcMap using the "raster calculator" function to average the wave energy values of all "wet" cells contained within a separate raster image map (one for each wave class) within radii of 5, 10, 15 and 20 m about each coastal cell. The wave energy was assessed using radii of 5, 10, 15 and 20 m because the bathymetry in the immediate vicinity of each coastal cell is unlikely to be as well defined as further offshore, as the bathymetry prediction failed to account for depths shallower than 2-3 m (see Appendix 2A). As a result of this, predictions of wave energy adjacent to the coastline are likely to be prone to considerable errors, which may be mediated by taking averages at multiple scales to identify which, if any, is an adequate description of the wave energy experienced at each location. This procedure was performed for each wave class, and each averaging radius, to populate the "empty" (i.e., all cells initially have value = 0) coastline raster image with wave energy values for each coastal cell. From the wave class-specific shoreline raster image files the maximum and minimum wave energy values for each cell were calculated, as well as the weighted average of the class-specific energy values using the same weighting scheme as for the production of the subtidal orbital velocity maps. This was performed separately for each averaging radius, thus producing maps of maximum, minimum and average wave energy at 5, 10, 15 and 20 m scales.

4.2.9 – Quantifying the impact of wave forces on subtidal macroalgae

To estimate how wave forces may impact subtidal macroalgal communities the wave-induced forces were compared to biomechanical limits established for the two canopy forming (and thus habitat modifying) macroalgal species, *E. radiata* and *M. pyrifera*. Thomsen *et al.* (2004) showed that *E. radiata* in south-western Australia is damaged or even dislodged at orbital speeds of 2-5 m.s⁻¹. In a biomechanical study, Utter & Denny (1996) determined the breaking strength of *M. pyrifera* stipes in California. Although morphological differences exist between *M. pyrifera* in New Zealand and California (Kain 1982; Nyman *et al.* 1993), their model is implemented here because no studies exist that have covered the biomechanical properties of *M. pyrifera* in New Zealand. As such, this is unlikely to be a definitive description of the response of *M. pyrifera* to wave forces acting along Wellington's south coast, but it does give a relative idea of how these forces may vary between locations and how this may potentially govern their abundance and distribution in this area. A brief description of the biomechanical model for *M. pyrifera* is given here, but for a complete description see Utter & Denny (1996).

The two most important forces acting on macroalgae are acceleration and drag (Gaylord *et al.* 1994; Utter & Denny 1996). The acceleration force arises when the object changes speed and/or direction, whereas the drag force is caused by water flow dragging the object (usually the fronds) in the direction of the water flow creating tension in the stipe (Utter & Denny 1996). In the calculations used here the effects of drag force alone are considered, because these two forces are temporally out of phase (one follows a cosinusoidal pattern with time, whereas the other follows a sinusoidal pattern with time): the drag force is therefore maximal at times of zero accelerational force, and vice versa (Gaylord *et al.* 1994). In addition, the drag force is often the largest hydrodynamic force (Denny *et al.* 1998) and thus considering the maximum drag force in isolation gives an estimate of the maximum force applied. The empirically derived drag force, F_d , on a *M. pyrifera* stipe is given as:

$$F_d = 0.0074 \rho_w A u_r^{1.596}$$

eqn. 4.1

where ρ_w is the density of seawater (here taken to be 1025 kg.m⁻³), A is the maximal projected area of the frond, which can be related to frond length, l , using the equation

$$A = 0.297l^{0.955}$$

eqn. 4.2

and u_r is the velocity of water relative to the fronds. Orbital velocity from wave motion is a function of water depth, and so the bottom orbital velocities are likely to be underestimates of the water velocities experienced by the bulk of the *M. pyrifera* fronds that are typically nearer the ocean's surface. The maximum horizontal water velocity, u_m as a function of height above the seabed, h , is given by:

$$u_m(h) = \frac{\pi H \cosh(kh)}{T \sinh(kd)}$$

eqn. 4.3

where T is the wave period, H is the wave height, d is the water depth and k is the wavenumber given by an approximation to be:

$$k \cong \frac{4\pi^2}{gT^2} \left(\tanh \left(\frac{4\pi^2 d}{gT^2} \right) \right)^{-\frac{1}{2}}$$

eqn. 4.4

where g is the acceleration due to gravity. Using these equations and setting $h=0$, the bottom orbital velocity, u_b is given by (Wiberg & Sherwood, 2008):

$$u_b = \frac{\pi H}{T} \frac{1}{\sinh(kd)}$$

eqn. 4.5

Therefore the bottom orbital velocities (resulting from the wave model) can be used to obtain water velocities at height h above the seabed according to:

$$u_m(h) = u_b \cosh(kh)$$

eqn. 4.6

where k is a function of depth and wave period.

The drag effects resulting from a strong southerly storm corresponding to modelled wave class 21 (significant wave height $H_s = 4.32$ m, wave period $T = 10.22$ s, Table 1) were examined. Using the bathymetry data along with the wave period for this wave class the variation in k across the computational area can be obtained using equation 4.4. The wave forces on four lengths of *M. pyrifera*, 5, 10, 15 and 20 m in the depth interval 3-30 m were investigated. The assumption that under maximum drag force the frond makes a 45° angle with regard to horizontal was made to simplify calculations, and thus its height h above the seabed is given by $l/\sqrt{2}$ or alternatively the water depth, d , if $l/\sqrt{2}$ exceeds d . Subsequently, k , h and the simulated bottom orbital velocities for this wave regime, u_b , were combined using equation 4.6 to calculate the relative water velocity. This combined with A , obtained for each length class using equation 4.2, are employed to calculate the drag force using equation 4.1. The mechanical stress, σ , is the force per unit area:

$$\sigma = \frac{F_d}{a}$$

eqn. 4.7

where a is the cross sectional area of the stipe assumed here to be a constant equal to 4.1×10^{-5} m² (see Utter & Denny 1996). The empirically derived probability of a *M. pyrifera* stipe having a breaking stress less than σ is given by $P(\sigma)$:

$$P(\sigma) = 1 - \exp \left[- \left(\frac{\sigma - 1}{3.16 \times 10^6} \right)^{3.75} \right]$$

eqn. 4.8

Finally using equations 4.7 and 4.8 the probability of breakage was calculated for the area of entire computational grid, based on the predicted orbital velocities for this wave regime and the four modelled length classes of *M. pyrifera*. These are then expressed as maps illustrating the variation in the probability of stipe breakage across Wellington's south coast. Finally, the distribution of large stands of *M. pyrifera* are included on these maps from an aerial image of the Wellington south coast (areas where *M. pyrifera* fronds were visible floating on the surface in Google Earth images obtained on 30/12/2010) to aid in the comparison of breakage probabilities with recent *M. pyrifera* distributions. Because this imagery represents a snapshot in time it could not be used to infer whether these patterns are stable or whether storm events

cause changes in *M. pyrifera* distribution that are consistent with SWAN model predictions. To provide a longer term comparison of *M. pyrifera* distributions in the Wellington region, the distribution obtained from this imagery is qualitatively compared to that given in Figure 4 of Hay (1990). To quantitatively examine the relationship between the observed presence of *M. pyrifera* and the predicted probabilities of stipe failure, 10,000 points were randomly placed within the model area (using ArcMap) in areas of suitable substrate (excluding sandy areas). For each of these points the predicted probabilities of stipe failure for 5, 10, 15 and 20 m plants and the presence/absence of *M. pyrifera* was recorded. A binomial generalised linear model (logistic link function) was fitted to the resulting presence/absence data with probability of stipe failure as a continuous predictor. This was performed independently for each plant length investigated. To account for potential depth limitation or observation bias in the recording of *M. pyrifera* prevalence (i.e. an increase in false negative error rate as plants of a certain size do not reach the surface beyond a certain depth and so would not be registered as present), a second set of 10,000 points was randomly distributed at depths < 10 m and the same analyses applied.

4.3 – Results

4.3.1 – Subtidal orbital velocity

The minimum orbital velocity per cell (assessed across all modelled scenarios) ranged from 0 - 1.406 m.s⁻¹, with 99.4% of the modelled area experiencing bottom orbital velocities less than 0.5 m.s⁻¹ (Figure 4.6). The remaining areas, experiencing speeds greater than 0.5 m.s⁻¹, consisted of shallow near-shore areas of almost emergent reef (Figure 4.6), such as along the submerged pinnacles located at the Sirens, to the west of Owhiro Bay, and the stretch of coastline between the Quarry and Sinclair Head. There is, however, a more sheltered area to the west of Sinclair Head, mostly due to the islands located just offshore of Sinclair Head (Figure 4.6). The stretch of coastline between Breaker Bay and Moa Point is predicted to experience much lower orbital velocities (0-0.3 m.s⁻¹) than areas to the west of Lyall Bay, probably due to the headland to the east of Wellington Harbour entrance protecting this area against the south-easterly swell (Figure 4.6).

The relative distribution of average orbital speeds (Figure 4.7) shows a similar pattern to that of the minimum orbital speeds, with the exception that the section from Breaker Bay to Moa Point experiences similar orbital speeds to the remaining coastline, because the influence of the southerly swell (to which this section is not sheltered) far outweighs the

influence of the south-easterly swell (to which this section is sheltered – Figure 4.6), both in magnitude of orbital speed and in frequency of occurrence (Table 4.1). The average orbital speeds range from 0 – 0.15 m.s⁻¹ in the most sheltered of locations directly behind obstacles (e.g. Island Bay to the north of Taputeranga Island, Moa Point in the lee of the Moa Point peninsula, and north of the Palmer Head reef and Barrett Reef directly east of Palmer Head), to 0.8-1.69 m.s⁻¹ around submerged obstacles (e.g., the pinnacles located at The Sirens rocks, around Moa Point peninsula, Red Rocks to Sinclair Head, and around emergent reefs such as at Palmer Head and Barrett Reef) and in the surf zone along several beaches and bays (Houghton Bay beach and several bays between the Quarry and Red Rocks) (Figure 4.7). Although the maximum average orbital speed across the entire area and the maximum of the minimum orbital speeds are similar (1.406 m.s⁻¹ compared to 1.690 m.s⁻¹, respectively), the average orbital speeds exceed 0.5 m.s⁻¹ across 8% of the modelled areas, compared to just 0.6% when considering the minimum orbital speeds (Figures 4.6 and 4.7).

The maximum orbital speeds exceed 0.5 m.s⁻¹, 1 m.s⁻¹ and 1.5 m.s⁻¹ across 84%, 18% and 1% of the modelled area, respectively, with the locations of the highest orbital speeds being the same as those highlighted for the average orbital speeds (Figure 4.8).

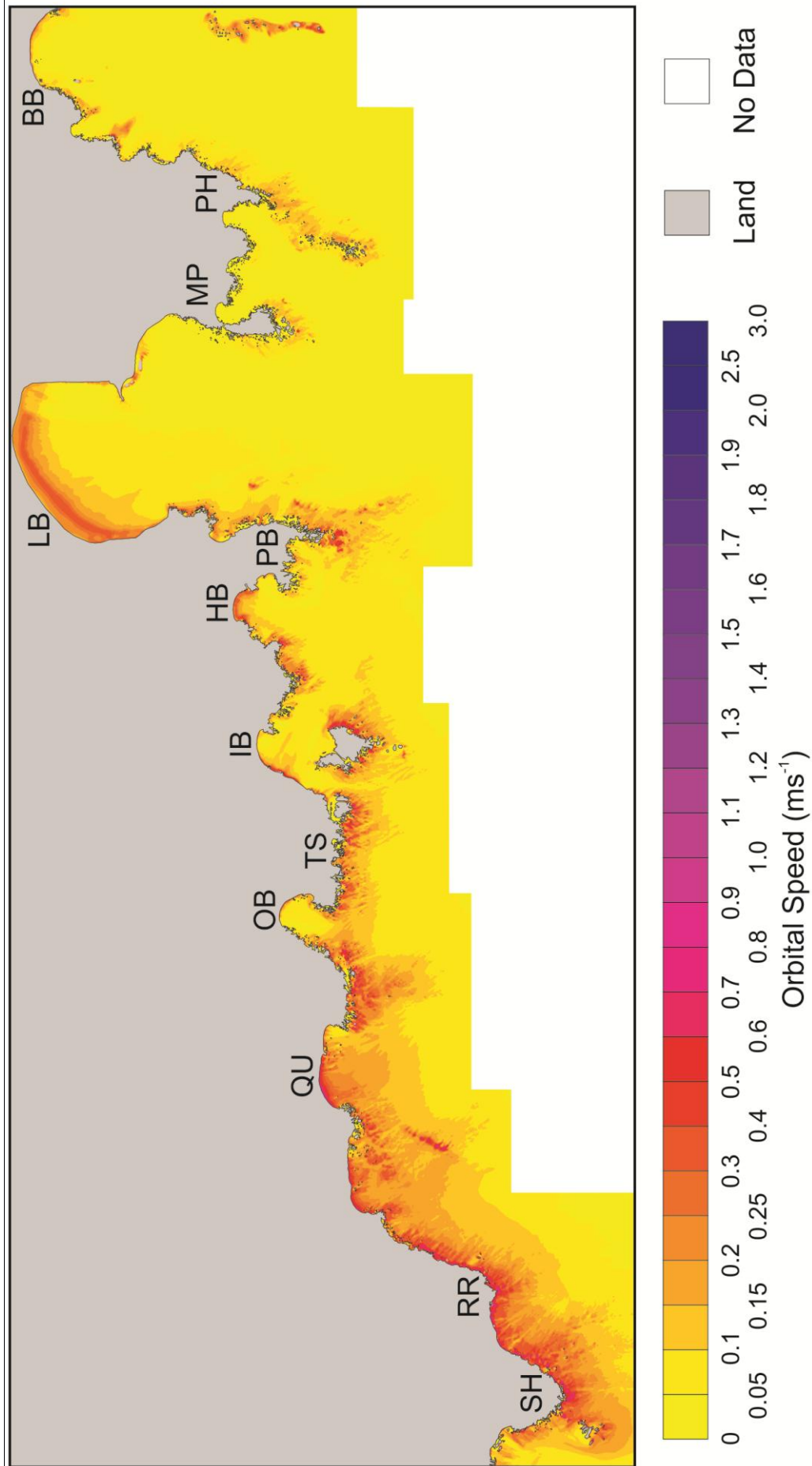


Figure 4.6. Map illustrating the variation in minimum bottom orbital speed across Wellington's south coast from the wave regimes modelled. Abbreviations of location names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, LB – Lyall Bay, PB – Princess Bay, HB – Houghton Bay, IB – Island Bay, TS – The Sirens, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

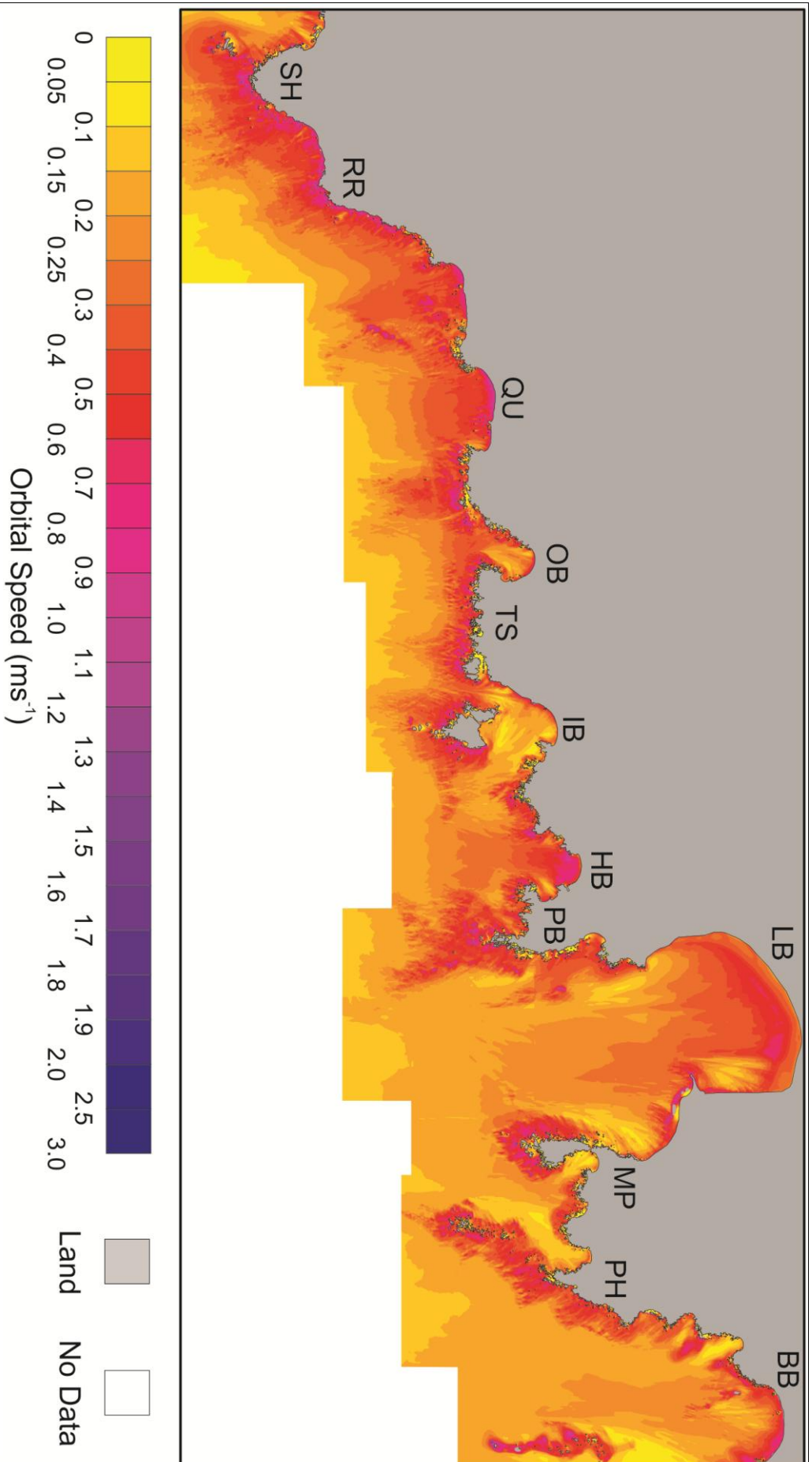


Figure 4.7. Map illustrating the variation in the average bottom orbital speed across Wellington's south coast from the wave regimes modelled. Abbreviations of location names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, LB – Lyall Bay, PB – Princess Bay, HB – Houghton Bay, IB – Island Bay, TS – The Sirens, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

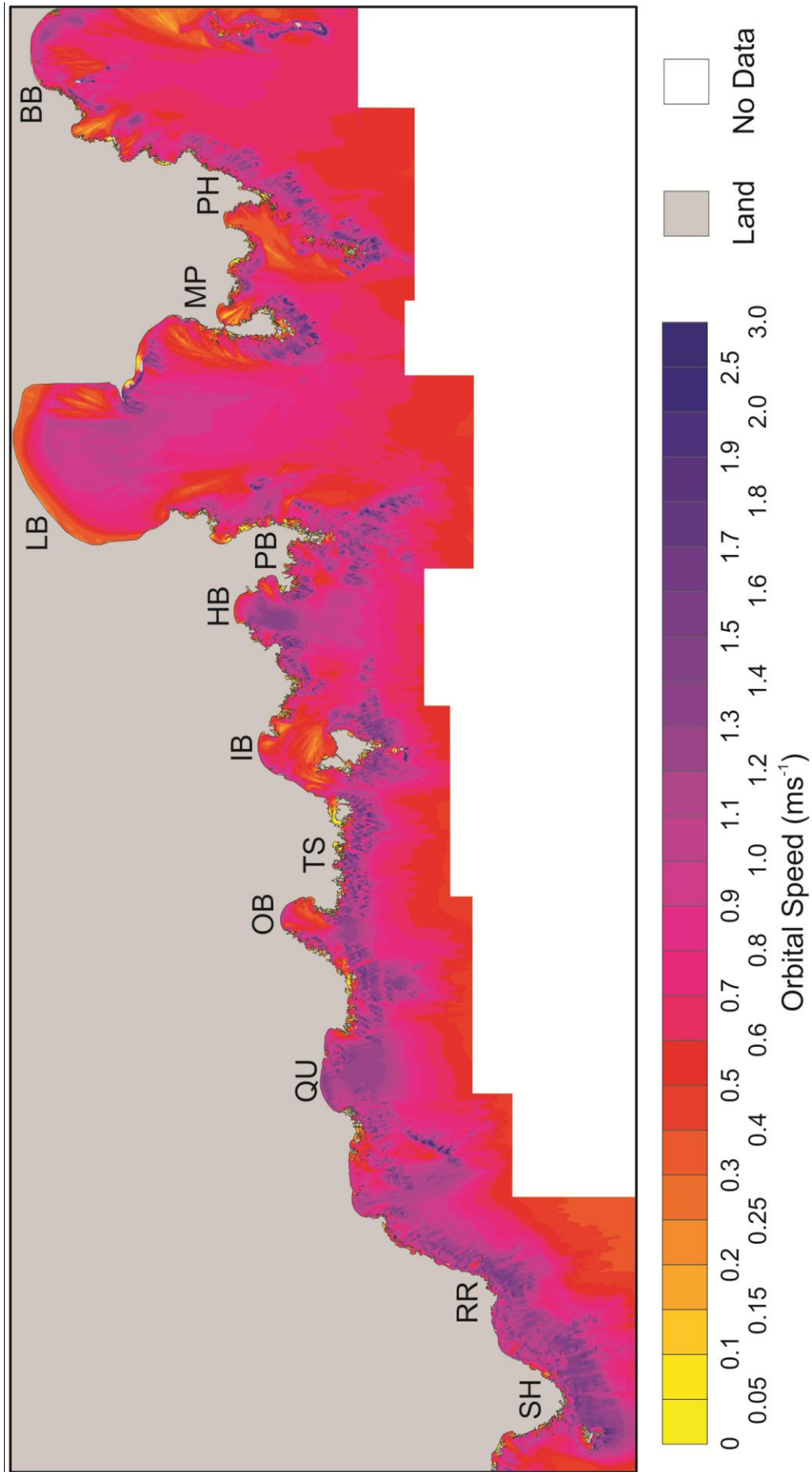


Figure 4.8. Map illustrating the variation in the maximum bottom orbital speed across Wellington's south coast from the wave regimes modelled. Abbreviations of location names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, LB – Lyall Bay, PB – Princess Bay, HB – Houghton Bay, IB – Island Bay, TS – The Sirens, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

4.3.2 – Coastline wave energy

Maximum and average wave energies show very similar distributions with wave energies highest on intertidal projections on fully open sections of coastline (Figure 4.10 – numerous locations projecting from the main shoreline; Figure 4.11 – the intertidal area between Island Bay and Owhiro Bay; Figure 4.13 – the tip of the Moa Point peninsula and Palmer Head reef), as well as around the south facing sides of offshore islands (Figure 4.9 – the islands SW of Sinclair Head; Figure 4.11 – the south side of Taputeranga Island), and lowest energies in leeward locations of major obstacles and for much of the extended shoreline. Minimum wave energies show a similar distribution, but display an overall increasing trend in wave energy moving from east to west.

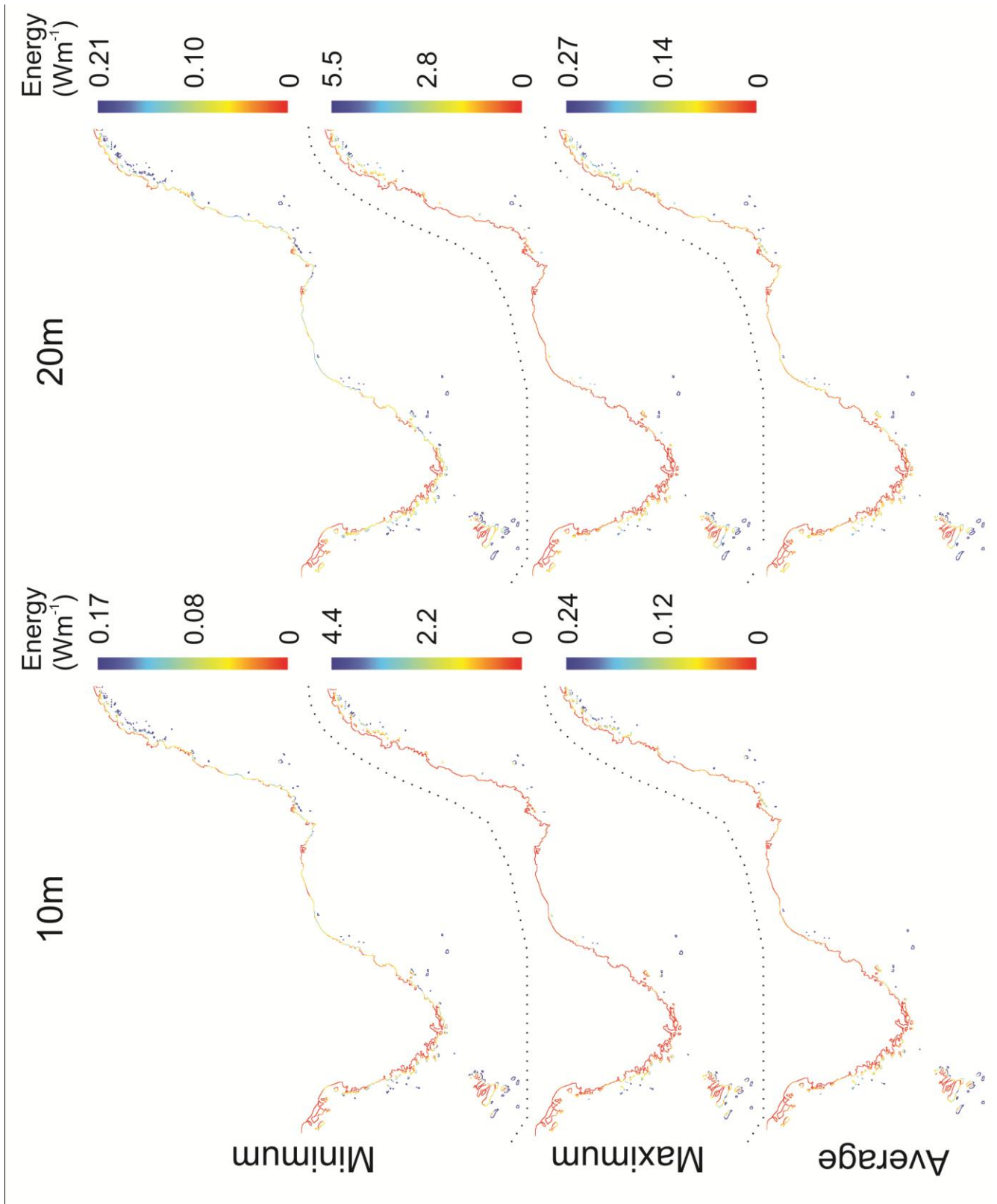


Figure 4.9. Map of wave energy extrapolated to the extended coastline from Sinclair Head to Red Rocks. The minimum, maximum and average wave energies calculated for 10 and 20 m spatial averaging are shown.

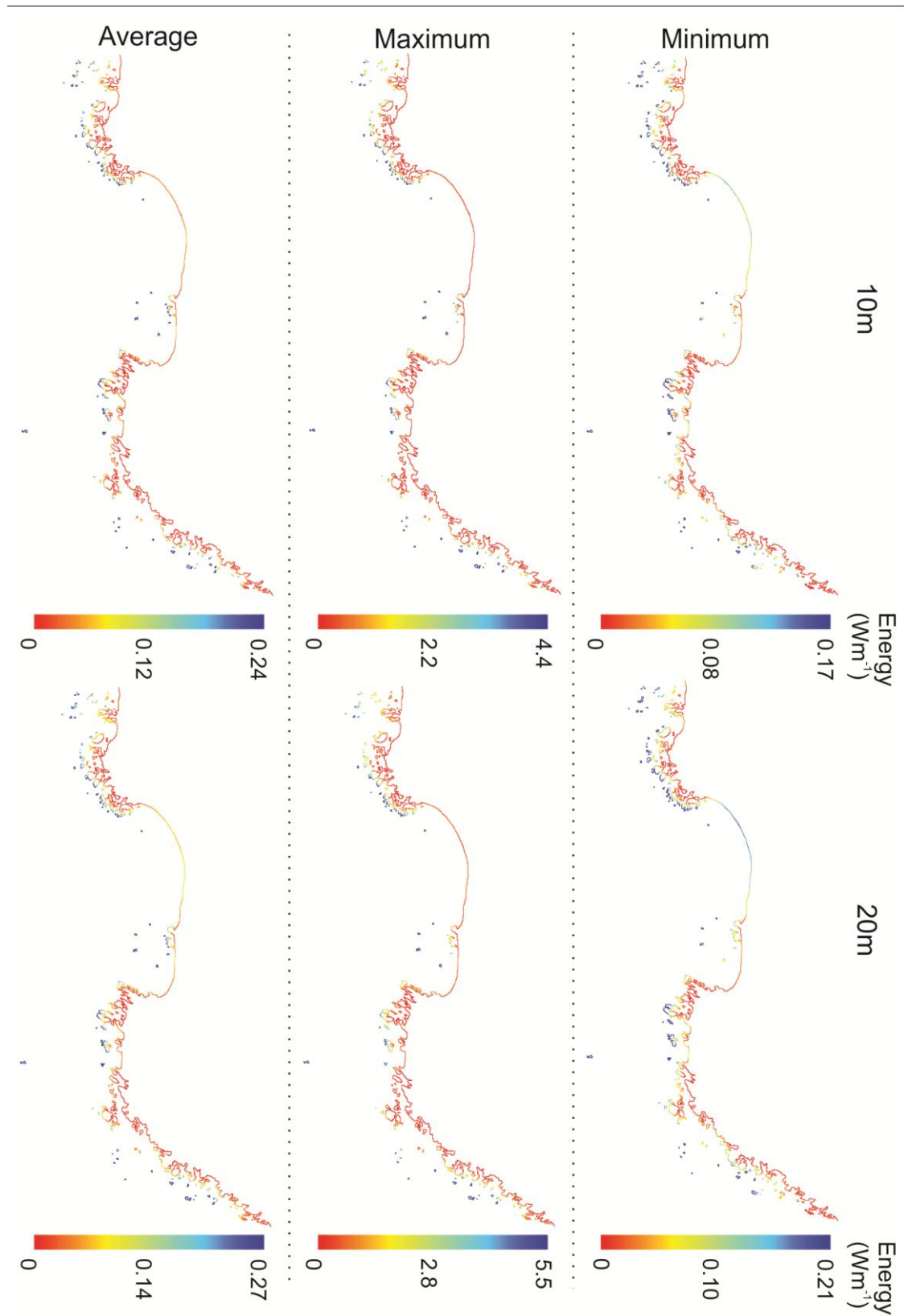


Figure 4.10. Map of wave energy extrapolated to the extended coastline from the Quarry to the western entrance of Owhiro Bay. The minimum, maximum and average wave energies calculated for 10 and 20m spatial averaging are shown.

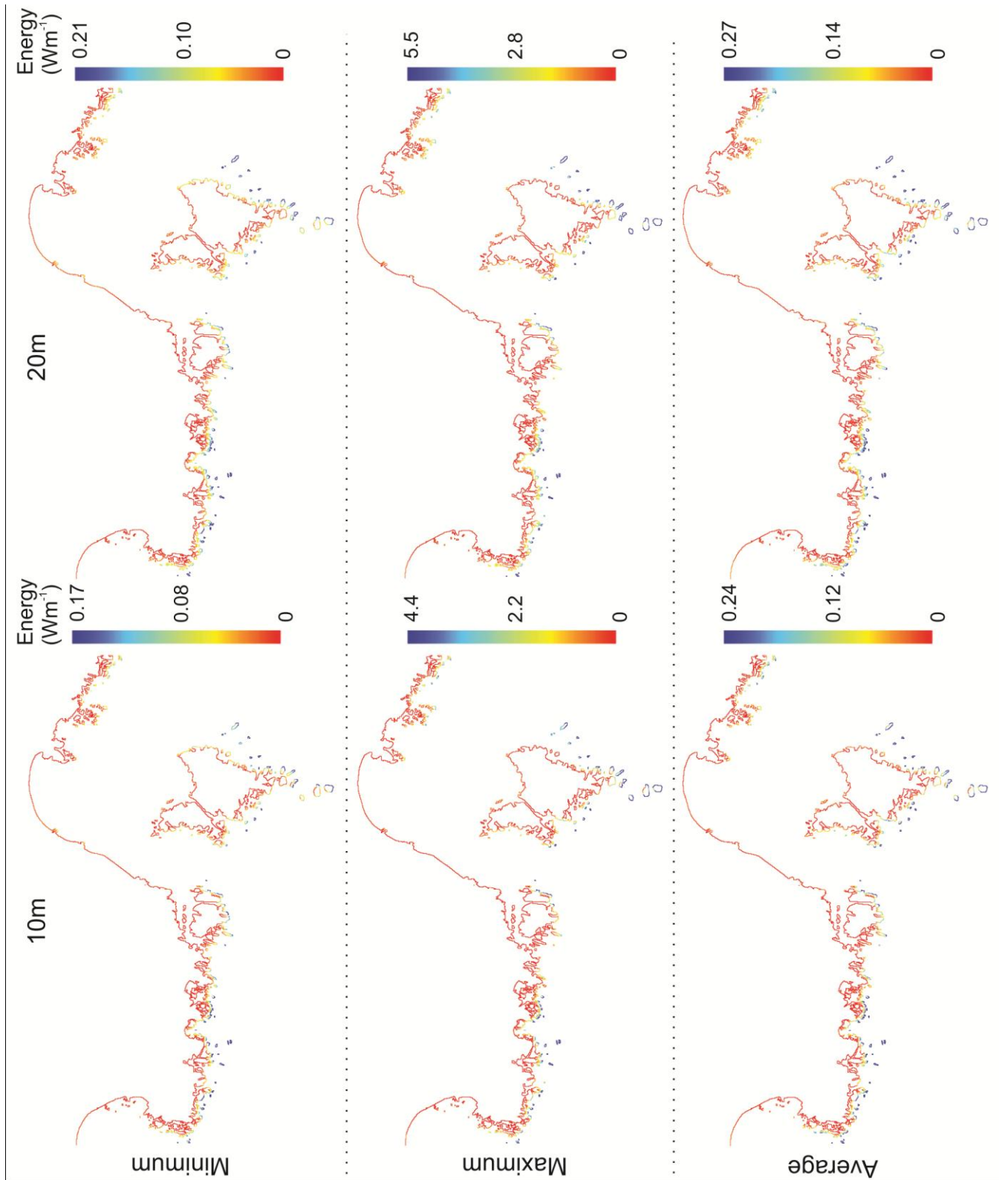


Figure 4.11. Map of wave energy extrapolated to the extended coastline from the eastern entrance of Owhiro Bay to the east side of Island Bay, including Taputeranga Island. The minimum, maximum and average wave energies calculated for 10 and 20 m spatial averaging are shown.

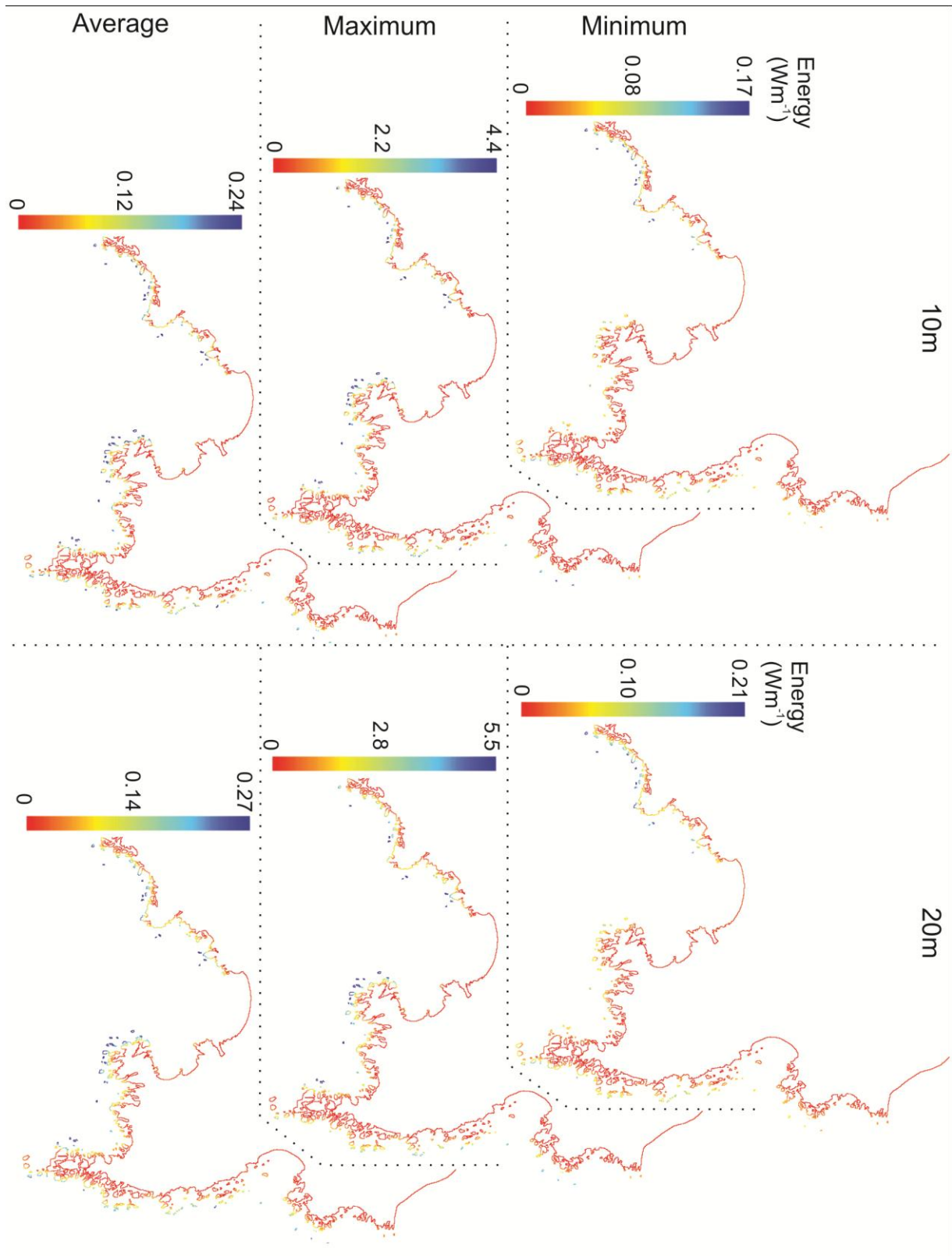


Figure 4.12. Map of wave energy extrapolated to the extended coastline from the eastern side of Island Bay to the western entrance of Lyall Bay, including Houghton Bay and Princess Bay. The minimum, maximum and average wave energies calculated for 10 and 20 m spatial averaging are shown.

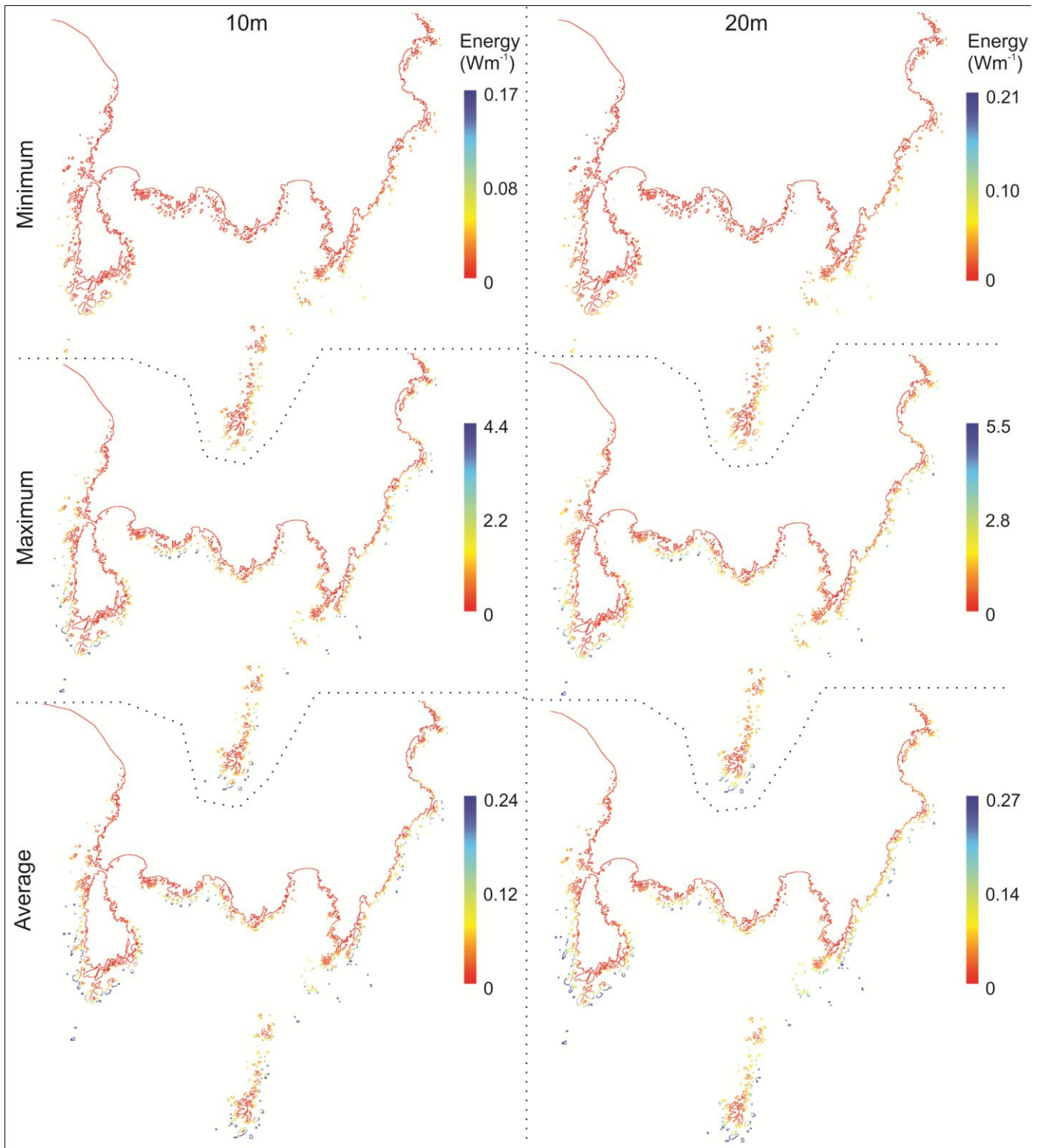


Figure 4.13. Map of wave energy extrapolated to the extended coastline from Moa Point to the entrance of Breaker Bay, including Tarakena Bay and Palmer Head. The minimum, maximum and average wave energies calculated for 10 and 20 m spatial averaging are shown.

4.3.3 – Potential impacts on subtidal macroalgae – *E. radiata*

For *E. radiata* the orbital velocity limit defined by Thomsen *et al.* (2004) of 2 m.s^{-1} was exceeded at some locations for model simulations with swell greater than $\sim 1.2 \text{ m}$ for models with northerly wind regimes (wave classes 8-12) and for all models with significant wave heights greater than 1.7 m (wave classes 16-21, 26). However, the distribution of areas that are predicted to experience these speeds is limited to 0.05% of the modelled area ($\sim 9000 \text{ m}^2$, within a total area of $\sim 1.5 \times 10^7 \text{ m}^2$) at just a few small areas at the tips of Palmer Head reef, Moa Point peninsula, submerged reef north of Princess Bay, south of Taputeranga Island, the pinnacles at The Sirens, the reef southwest of the Quarry and at the Sinclair Head group of islands (the darkest blue colour in Figure 4.8 highlights these areas). For the most part these areas were situated at shallow depths ($\sim 2\text{-}3 \text{ m}$) but surrounded by deeper waters ($\sim 6\text{-}12 \text{ m}$), and coincided with areas that present the first obstacle to incoming oceanic swell.

4.3.4 – Potential impacts on subtidal macroalgae – *M. pyrifera*

The distribution of *M. pyrifera*, identified from aerial photography, closely matches the distribution identified by Hay (1990) for *M. pyrifera* around Wellington (Figure 4 of that paper), with large stands along the coastline in Breaker Bay, behind Palmer Head reef and along the coastline leading into and out of Lyall Bay (Figure 4.14). For 5 m plants the probability of stipe breakage was low across the entire modelled area (maximum of 6.8%, but 99.8% of the modelled area had less than a 1% chance of breakage) and so the resultant maps are omitted. For plants measuring 10 m in length, the probability of stipe failure was less than 1% in all areas where water depths are greater than 10 m (Figure 4.14). At depths less than this the majority of the area was also predicted to have breakage probabilities less than 1%, but there were areas with probabilities between 1 and 5% (for example to the east of Sinclair Head, Red Rocks, and at The Sirens, Figure 4.14), and isolated pockets with probabilities of 5-20% in extremely exposed locations (the tip of the Moa Point peninsula and Palmer Head reef, Figure 4.14), with a maximum predicted stipe failure probability of 68% (south of Taputeranga Island, Figure 4.14). A similar distribution was observed for plants measuring 15 m in length, however, the probabilities in all areas increased, with much of the area shallower than 10 m having probabilities of at least 1%, with many areas having probabilities of 2.5-10%, with higher probabilities in shallower areas (Figure 4.15). The exceptions to this are in sheltered bays, including Island Bay, the western shoreline leading into Lyall Bay, Tarakena Bay (behind the Moa Point peninsula and Palmer Head reef), and the section of nearshore waters between Palmer Head and Breaker Bay (Figure 4.15). However, in waters

deeper than 10 m, the probability of stipe failure remains low, with a few locations displaying probabilities of 1-5% (Figure 4.15). For plants measuring 20 m in length, a similar distribution as for 15m plants was found but probabilities were much higher with the majority of locations in water less than 10 m deep having a 5-20% chance of stipe failure, and the proportion of locations with higher probabilities is substantially larger than for 10 or 15 m plants (Figure 4.16). For all plant lengths, the probability of stipe failure was less than 1% in waters deeper than 20 m (Figures 4.14 - 4.16).

At all locations where there were *M. pyrifera* plants visible on the surface, the probability of stipe failure was low, with the majority of identified locations having a less than 1% chance of stipe failure for all plant lengths investigated (Figures 4.14 - 4.16). The few exceptions included a small patch identified near Princess Bay where the probability of stipe failure peaked at 26% for 20 m plants, 10% for 15 m plants and 2% for 10 m plants, and another patch in Breaker Bay where probability of stipe failure peaked at 44% for 20 m plants, 19% for 15 m plants and 5% for 10 m plants (Figures 4.14 - 4.16). GLMs applied to the presence/absence data extracted from the model predictions displayed a negative correlation with the probability of stipe failure, indicating that *M. pyrifera* tended to be present only when the probability of breaking was low (Table 4.3). This relationship was much more pronounced when examining this relationship in shallower water (compare fitted lines in Figure 4.17 compared to Figure 4.18). Furthermore, the mean probability of stipe failure when *M. pyrifera* is present was ~ 0.27-0.33 that of the mean probability of stipe failure when *M. pyrifera* is absent for points distributed across all depths, but is ~ 0.12-0.14 when points are distributed only between 0 and 10m deep (Table 4.3). The maximum probability of stipe failure was also considerably lower in locations with *M. pyrifera* compared to locations without (Table 4.3). However, there were a few instances of *M. pyrifera* presence in locations with higher probabilities of stipe failure (indicated by larger bars in Figures 4.17 and 4.18), but these represented the minority of the points (e.g. for the < 10 m analyses only 5 points of 185 which landed on patches of *M. pyrifera* had probabilities of stipe failure for a 20 m plant that were greater than 5%).

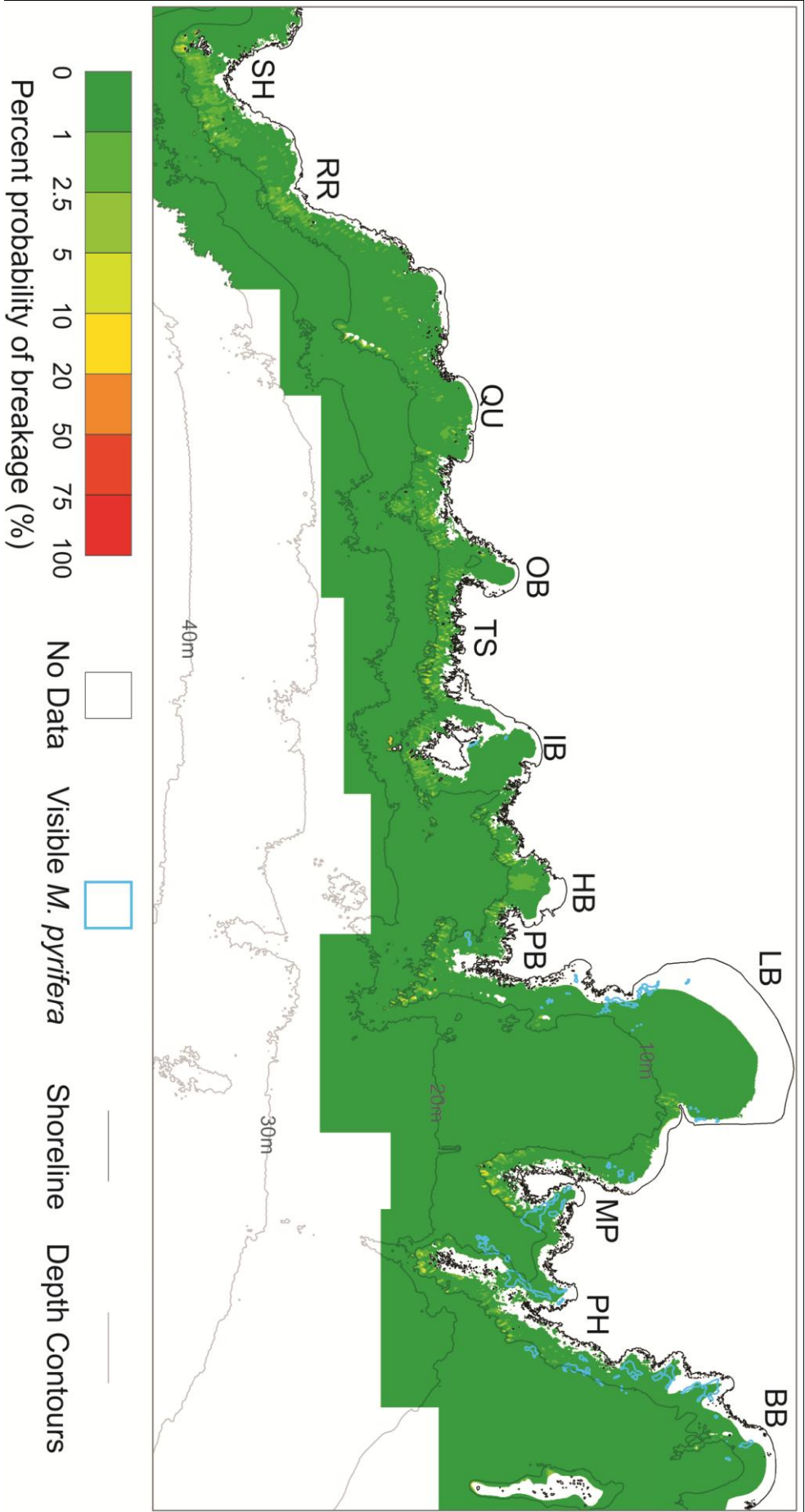


Figure 4.14. Map illustrating the variation in the calculated probability of *M. pyrifera* stipe breakage along Wellington's south coast for plants measuring 10 m in total length. Abbreviations of location names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, LB – Lyall Bay, PB – Princess Bay, HB – Houghton Bay, IB – Island Bay, TS – The Sirens, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

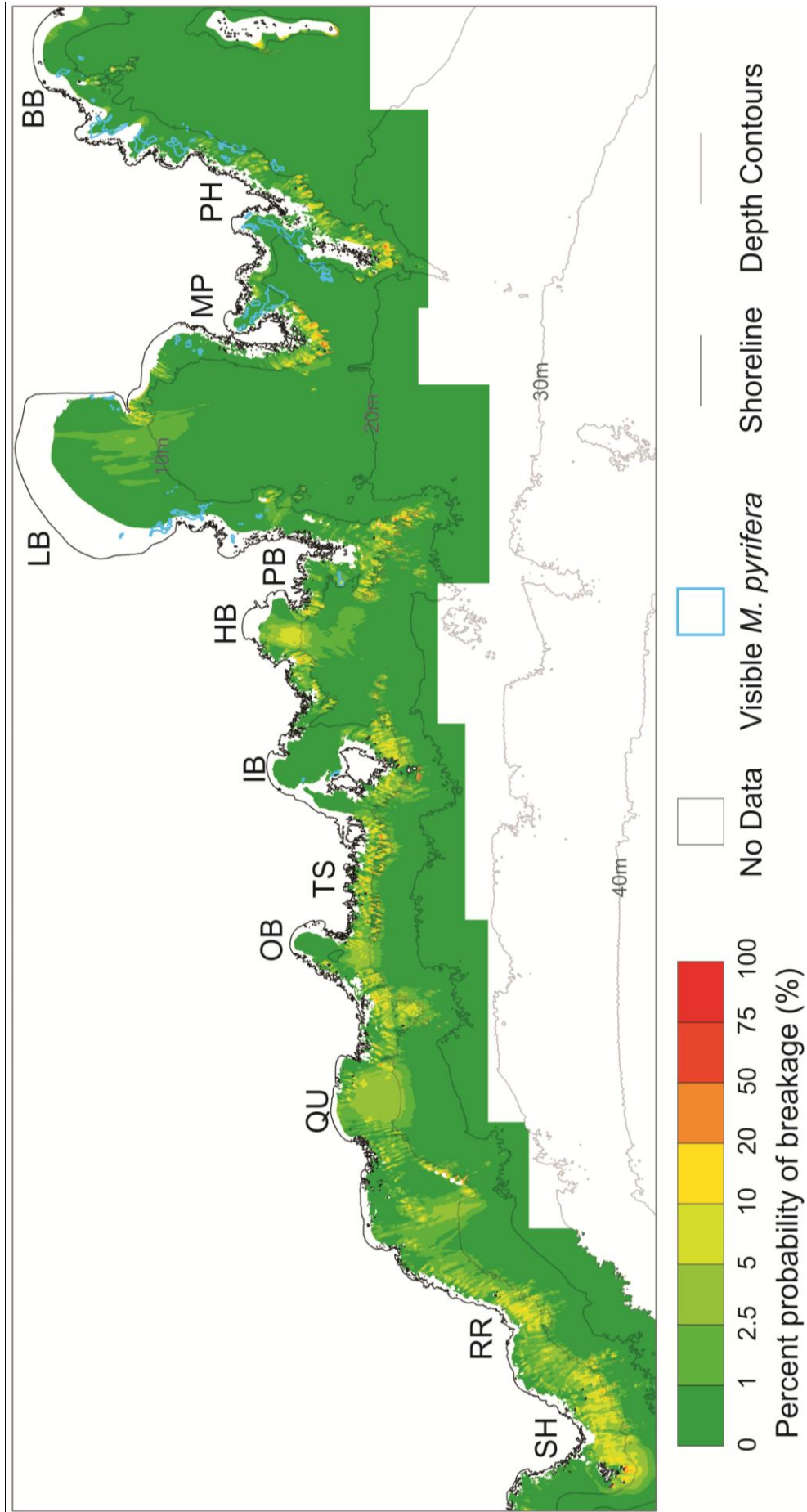


Figure 4.15. Map illustrating the variation in the calculated probability of *M. pyrifera* stipe breakage along Wellington's south coast for plants measuring 15 m in total length. Abbreviations of location names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, LB – Lyall Bay, PB – Princess Bay, HB – Houghton Bay, IB – Island Bay, TS – The Sirens, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

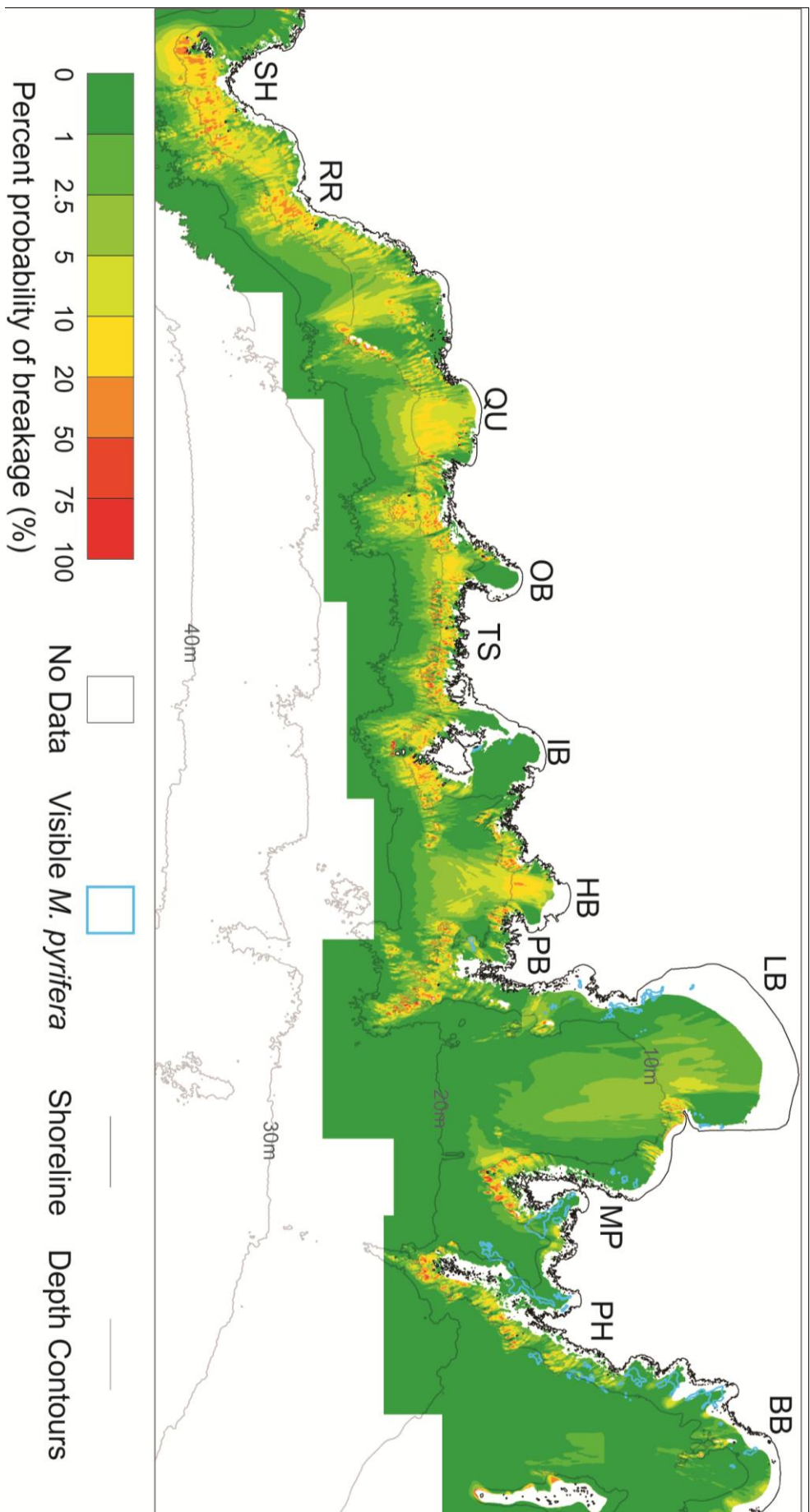


Figure 4.16. Map illustrating the variation in the calculated probability of *M. pyrifera* stipe breakage along Wellington's south coast for plants measuring 20 m in total length. Abbreviations of location names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, LB – Lyall Bay, PB – Princess Bay, HB – Houghton Bay, IB – Island Bay, TS – The Sirens, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

Table 4.3. Summary statistics and results of logistic GLMs relating *M. pyrifera* presence/absence to predicted probability of stipe failure

Depth	Predictor	Mean probability of stipe failure (%)		Max probability of stipe failure (%)		logistic GLM	
		Present	Absent	Present	Absent	intercept (SE)	slope (SE)
All	Prob 5m	0.004	0.012	0.075	1.561	-4.38 (0.13)	-39.8 (15.0)
All	Prob 10m	0.066	0.199	1.38	20.52	-4.36 (0.13)	-2.59 (0.93)
All	Prob 15m	0.3	1	5.76	62.5	-4.24 (0.13)	-0.81 (0.24)
All	Prob 20m	0.82	2.97	15.3	93.6	-4.02 (0.14)	-0.45 (0.11)
< 10 m	Prob 5m	0.004	0.029	0.15	1.86	-2.63 (0.09)	-107.7 (12.3)
< 10 m	Prob 10m	0.06	0.49	2.14	20.15	-2.58 (0.09)	-7.16 (0.81)
< 10 m	Prob 15m	0.29	2.21	8.84	61.76	-2.53 (0.09)	-1.60 (0.18)
< 10 m	Prob 20m	0.78	5.81	22.83	93.23	-2.52 (0.09)	-0.59 (0.06)

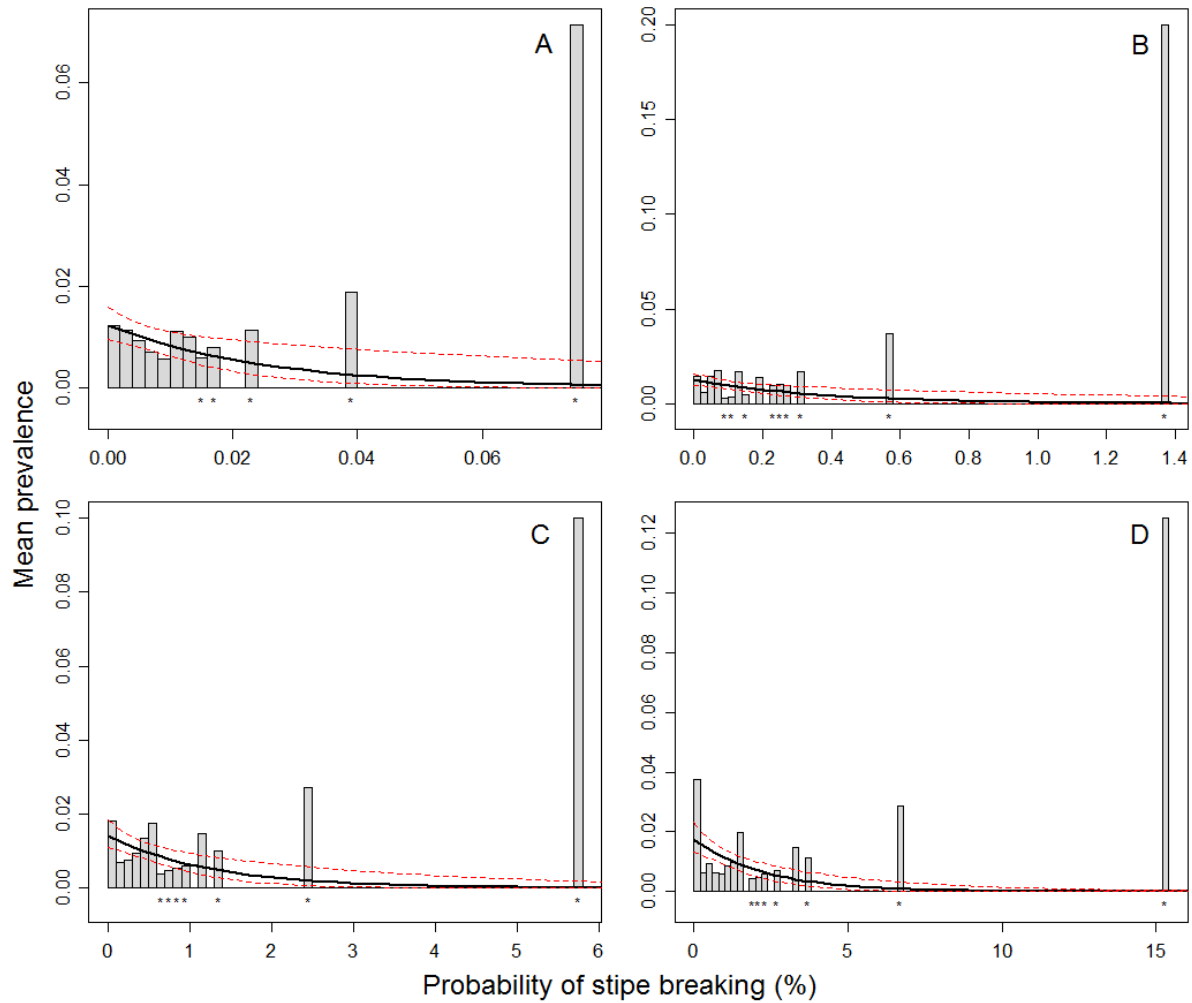


Figure 4.17. Mean prevalence plotted against predicted probability of stipe breakage for plants of size 5 m (A), 10 m (B), 15 m (C) and 20 m (D) using data gathered from all depths. Lines represent the fitted logistic regression line and its 95% confidence interval. Grey bars indicate the mean observed prevalence of *M. pyrifera* in intervals along the x-axis measuring 0.002 (A), 0.02 (B), 0.1 (C) and 0.2 (D) respectively. Bars with a * below them indicate an interval for which only a single *M. pyrifera* presence was recorded, some of which are unusually large due to the lower overall number of points in that interval.

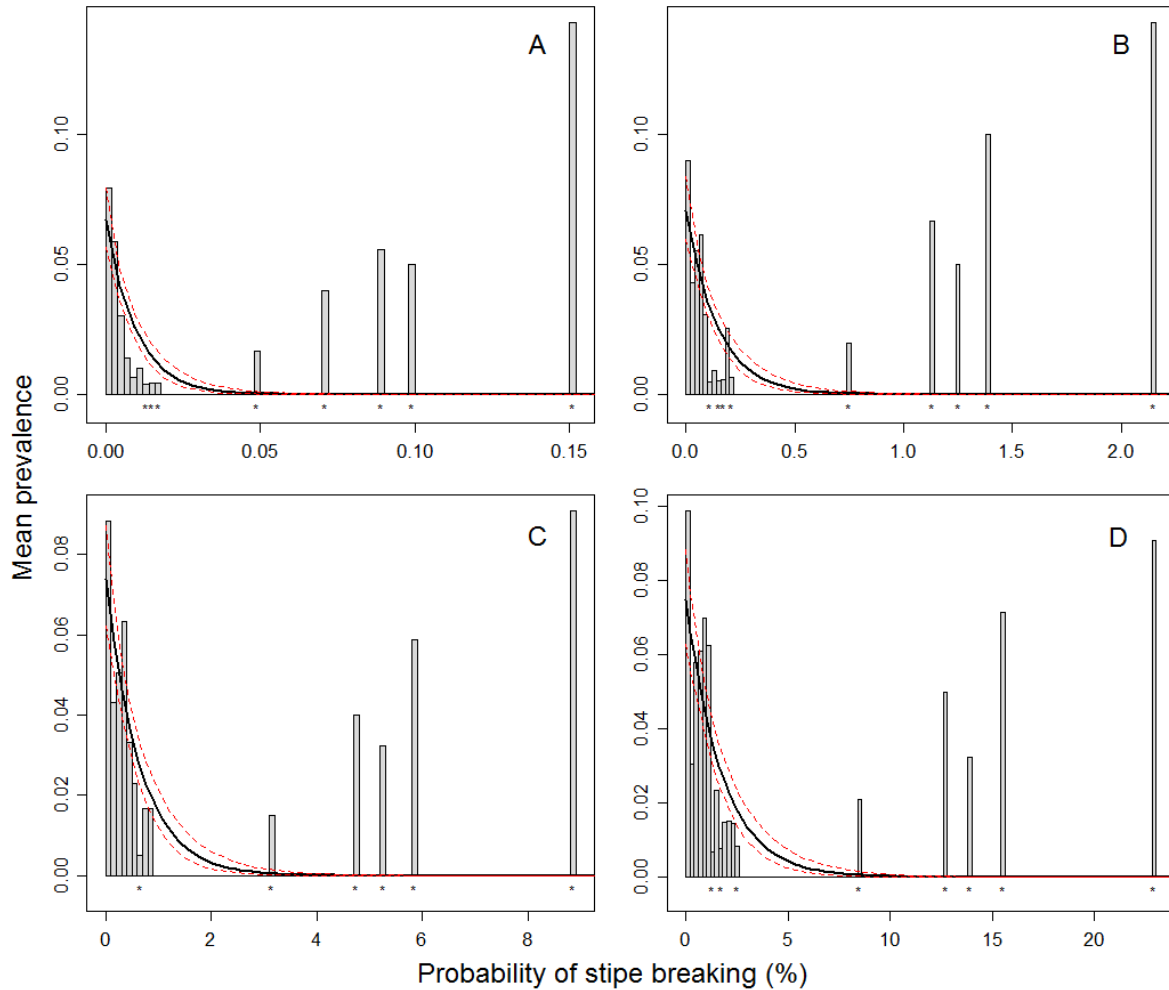


Figure 4.18. Mean prevalence plotted against predicted probability of stipe breakage for plants of size 5 m (A), 10 m (B), 15 m (C) and 20 m (D) using data gathered from locations with depths less than 10 m. Lines represent the fitted logistic regression line and its 95% confidence interval. Grey bars indicate the mean observed prevalence of *M. pyrifera* in intervals along the x-axis measuring 0.002 (A), 0.02 (B), 0.1 (C) and 0.2 (D) respectively. Bars with a * below them indicate an interval for which only a single *M. pyrifera* presence was recorded, some of which are unusually large due to the lower overall number of points in that interval.

4.4 – Discussion

This study highlights the role played by wave energy in structuring shallow subtidal ecological communities. Even though wave forces are considerable during storm events (the force imposed by water velocities of 2 m.s^{-1} is roughly equivalent to the force imposed by air velocities of $\sim 210 \text{ km.h}^{-1}$) (Denny & Gaylord 2002) they are unlikely to cause damage to healthy *E. radiata* plants, while only low mortality rates would be expected for *M. pyrifera* plants.

4.4.1 – Coastline wave energy

The coastline wave energy output from the SWAN model illustrates patterns that are consistent with expectations of wave forces along Wellington's south coast, with the most prominent projections of intertidal rock coinciding with the highest wave energies, and locations leeward of islands or other obstacles being the most sheltered. In addition, submerged reefs provide some degree of shelter, examples of which include the coastline north of the reef projecting eastward from Taputeranga Island (in Island Bay), extending to the area of shelter beyond Island Bay itself that is sheltered by the blocking effect of Taputeranga Island. Other examples include Princess Bay (reef visible in Figure 4.8) and Tarakena Bay that are largely sheltered by the reef extending southward of Palmer Head. Submerged reefs are likely to decrease wave energy through two processes, energy dissipation through bottom friction and depth-induced breaking (Karambas & Koutitas 1992; Padilla-Hernández & Monbaliu 2001; Monismith 2007). Energy dissipation through bottom friction is a result of the interaction of the waves with the seabed, which becomes a dominant component of wave dynamics in shallow waters (Padilla-Hernández & Monbaliu 2001). This effect can significantly reduce wave energies in areas with high surface relief (coral reefs being an example of high bottom friction due to the complexity of growth forms – Monismith 2007), as these areas have much higher resistance (friction) to wave propagation. Friction also causes the steepening of waves as they propagate into shallower waters, which eventually leads to wave breaking. Wave breaking usually occurs when the wave height exceeds 78% of the water's depth (Utter & Denny 1996). Waves measuring 3 m in height are likely to break in water depths of ~ 3.8 m, whereas 5 m waves will break at depths of ~ 6.4 m. Thus for 3 m waves in the study area, wave breaking can occur ~ 0-40 m offshore for rocky subtidal/intertidal areas, but up to 160 m in sandy bays, whereas 5 m waves may break ~ 30-100 m offshore, and up to 250 m offshore, in rocky subtidal/intertidal areas and sandy bays, respectively (measurements obtained haphazardly from 0 to 3.8 m contour and 0 to 6.4 m contour for rocky areas, and Houghton Bay as an example of an exposed bay). As the wave rears up prior to breaking, the wave's energy is first converted into gravitational potential energy and once the wave breaks, energy is dissipated through sound, heat and the creation of turbulence and vortices and is further dissipated as the broken wave propagates (Karambas & Koutitas 1992). In areas where there is a reef present, waves are likely to break further from the shoreline and therefore much of the wave's energy is dissipated prior to it reaching the shore. Although bathymetry-weighted fetch may be able to capture some of this variation by

down-weighting fetch measurements in areas with extensive submerged reefs (as in Hill *et al.* 2010), these measures are unlikely to capture the full complexity of energy dissipation through breaking and bottom friction that is possible using a numerical wave model, such as SWAN.

4.4.2 – Subtidal orbital velocity and consequences for macroalgae

The Wellington south coast is characterised by macroalgal assemblages (Choat & Schiel 1982; Pande & Gardner 2009) that are particularly speciose (approximately one-third of New Zealand's algal species are found in the Cook Strait region), containing species representative of both North and South island macroalgal assemblages (Nelson 2008). Also this area has frequently been considered to be on the boundary of two biogeographic provinces (Shears *et al.* 2008) with species existing at the edge of their natural ranges, potentially making species more susceptible to environmental stresses (Sagarin *et al.* 2006). Therefore developing an understanding of the spatial variation in wave forces can be used to explain how waves may act to structure macroalgal assemblages through the creation of different disturbance regimes in different areas and at different depths (Goldberg & Kendrick 2004; England *et al.* 2008). This, in combination with the mixing of species from different biogeographic areas, may act to promote the richness and diversity of macroalgae along the Wellington south coast by selecting for or against certain species in certain areas dependent on their biomechanical limits.

Comparatively, the maximum speeds predicted by the SWAN model ($2\text{--}3\text{ m.s}^{-1}$) were similar to maximum instantaneous wave speeds ($1.5\text{--}2\text{ m.s}^{-1}$) measured *in-situ* for locations open to waves in the northwest USA (Eckman *et al.* 2003), and to maximum values ($\sim 3\text{ m.s}^{-1}$) predicted by SWAN models for exposed locations in Western Australia (England *et al.* 2008). Orbital speeds were also predicted to be greater in shallow water ($< 10\text{ m}$) than at depth (Figures 4.6 - 4.8). At depths less than 5 m along Wellington's south coast the macroalgae *Carpophyllum maschalocarpum*, *Landsburgia quercifolia* and *Lessonia variegata* are more abundant than *E. radiata*, which is most abundant at 7-15 m depth (Choat & Schiel 1982; Schiel 1990). Although alternative explanations cannot be excluded (depth, light intensity, herbivory, competitive ability etc) for this macroalgal depth zonation (Schiel 1990), studies of the biomechanical thresholds of these species of macroalgae may shed light on how these species persist in such wave-swept environments. Species of *Lessonia* are present on exposed rocky shores in Australasia and South America (Martin & Zuccarello 2012) and

Lessonia nigrescens, which is found along the South-American Pacific coast, has adaptations regarding the structure of stipe tissue (closely packed cells, with thick cell walls that are aligned along the major stress axes of the tissue) that allow it to thrive in the most wave-swept locations (Koehl 1999). It remains to be seen whether *Lessonia variegata*, which is endemic to New Zealand (Martin & Zuccarello 2012), has similar adaptations, but if so, these may provide a mechanism by which this species can persist at these wave-exposed locations.

The results for *E. radiata* suggest that healthy plants are unlikely to be damaged in southerly storms (significant wave height > 4 m) because only at a few locations at depths of ~ 2 - 3 m were bottom orbital speeds predicted to exceed 2 m.s^{-1} , identified by Thomsen *et al.* (2004) as the lower threshold for stipe damage for *E. radiata*. However, wave forces are unlikely to act in isolation. Age, damage due to herbivory, and scouring and fracturing effects due to continual wave forces are all likely to have weakening effects on the mechanical properties of individual plants (Denny *et al.* 1989; Duggins *et al.* 2001; Thomsen *et al.* 2004; Mach *et al.* 2007). These effects acting in unison will increase the probability of damage or dislodgement at lower orbital speeds than would be predicted for a healthy, undamaged individual. In addition, Thomsen *et al.* (2004) noted that the vast majority of *E. radiata* tested for mechanical properties became dislodged at the reef rock level when the rock to which the *E. radiata* holdfast was attached became dislodged. The rock type along Wellington's south coast is sedimentary greywacke, consisting of layers of grey sandstone interspersed with harder layers of mudstone, or argillite (Kennedy & Beban 2005). The predominant feature of this rock type at this locality is its high fracture density (~ 5 to > 20 m^{-2}) enabling the easy removal by hand of sizeable chunks of rock in some places (Kennedy & Beban 2005, and personal observations). Given the inherent weakness of the rock type and the predicted orbital speeds there could be a far greater capacity for dislodgement of *E. radiata* plants through failure of the substrate than by stipe or holdfast failure.

The drag forces imposed on individual plants increases with size due to an increase in projected surface area (Gaylord *et al.* 1994). Therefore waves may impose an upper limit on the size of *E. radiata* plants by selectively pruning or removing individuals above a certain size particularly in the more exposed areas. This could potentially alter the density of the canopy, with subsequent effects on the degree of shading (Clark *et al.* 2004), which is likely to be important for understorey species' composition (Toohey *et al.* 2004) also allowing other

habitats to form (Kennely 1987; Toohey *et al.* 2007) with subsequent impacts on community dynamics.

The results for *M. pyrifera* indicate that stipe failure is likely for larger plants in the event of southerly storms along much of the Wellington south coast. However, based on the probability of stipe failure, plants measuring 5-15 m in length should be able to persist in many regions, even in areas where water depth is less than 10 m and orbital speeds are considerably higher. Many of the regions where *M. pyrifera* was visible from aerial photography and those reported in Hay (1990) were in locations where the probability of dislodgement was low, and the fitted logistic regression relationships indicate a negative correlation between prevalence of *M. pyrifera* and wave exposure, suggesting that *M. pyrifera* distribution is limited by wave exposure along the south coast. Because of the comparative nature of this study, alternative explanations for these patterns, such as due to temperature, availability of suitable substrate and nutrients (Hay 1990) cannot be eliminated. Rocky reefs are however found across the entire south coast (see Figure 4.3 for an illustration of the extent of subtidal bedrock) at a range of depths, and therefore availability of suitable substrate is unlikely to explain these patterns. In addition, although the Wellington coastline and harbour are near to the northern limit for *M. pyrifera* (suggested to be at Castlepoint on the east coast of the north island and Kapiti Island on the west coast, such that Wellington is ~ 60 km south of its northern limit, Brown *et al.* 1997) small-scale temperature differences are unlikely to be a factor influencing the spatial distribution of *M. pyrifera* on the open coastline, (as has been suggested by Hay 1990 for the spatial distribution of *M. pyrifera* in Wellington Harbour) because summer temperatures on the Wellington south coast are ~ 1.5-2 °C cooler than harbour temperatures and are within the temperature limits of *M. pyrifera* (Hay 1990). It has previously been reported that *M. pyrifera* may be unable to persist in locations that have nitrate concentrations lower than $1\mu\text{mol.l}^{-1}$ for sustained periods of time (Hay 1990). Consequently nitrate concentrations along the Wellington south coast, which are on average ~1-2 $\mu\text{mol.l}^{-1}$, (Bradford *et al.* 1986; Hay 1990) may contribute to limiting *M. pyrifera* growth at certain times, but is unlikely to explain the observed spatial variation of *M. pyrifera* due to both the existence of an otherwise rich macroalgal community at many locations where *M. pyrifera* is absent and the well mixed nature of the water column (Hay 1990). Spatial variability in grazing pressure by kina (*Evechinus chloroticus*) may also be responsible for these spatial patterns: however, it has been reported that kina abundances are higher at the eastern end of the area investigated (Pande & Gardner 2009), coincident with

the location of the majority of *M. pyrifera* stands and therefore grazing seems an unlikely explanation. Therefore it is likely that patterns of *M. pyrifera* distribution can be attributed to the spatial variation of wave forces in this area. In addition, during storms, high mortality rates have been recorded from kelp forests in southern California (Seymour *et al.* 1989). However, comparisons between the recorded mortality rate of storm-induced wave forces and those predicted by this biomechanical model revealed that the model vastly underestimated mortality rates (Utter & Denny 1996). Utter & Denny (1996) predict that for an El-Niño Southern Oscillation-induced storm the mortality rate of a Californian kelp forest would be 0.1-26.2%, whereas the true mortality rates were 13-94%. Thus, the predicted probabilities presented here in my modelling may also be large underestimates of mortality rates under the modelled conditions. The combinatorial effects of age, damage by herbivory and continuous wave forces (creating fractures and causing sub-lethal damage) are all likely to increase the probability of stipe failure, but the single largest contributor to mortality has been attributed to stipe entanglement (Seymour *et al.* 1989). This has the effect of doubling or even tripling the drag forces on a single stipe, leading to a much higher probability of stipe failure and even causing the dislodgement of kelp holdfasts from the substrate (Seymour *et al.* 1989; Utter & Denny 1996). Another significant factor is likely to be plants that are caught in breaking waves. The water speeds when waves break are an order of magnitude higher than the bottom orbital speeds produced by the SWAN model ($\sim 25 \text{ m.s}^{-1}$, Denny & Gaylord 2002). If *M. pyrifera* plants were to be caught in breaking waves then the wave-induced forces would be much higher than calculated, with subsequent effects on the probability of stipe failure (Utter & Denny 1996). Given these limitations and the likely differences in morphology between the plants used to develop the biomechanical model and those found along Wellington's south coast (see Kain 1982 and Nyman *et al.* 1993 for discussion of morphological differences between New Zealand and Californian *M. pyrifera*), the predictions of stipe failure should be interpreted as giving a conservative, rather than absolute measure of the differences in disturbance probability among locations.

4.4.3 – Model limitations

Much of Wellington's south coast shoreline is predicted to be very sheltered. This is likely a limitation of the model as well as the complexity of the shoreline. The exact topography of emergent substrate (intertidal platforms, boulders etc) is unknown for nearly the entire coastline. Because of this wave propagation over emergent obstacles was not

modelled, and each obstacle was essentially considered a void whereby wave energy could propagate around, but not through or over. As a result the predicted relative wave energies for much of the shoreline behind these obstacles is likely to be lower than in reality, as waves overtopping obstacles are likely to contribute to the overall wave energy at each location, particularly when storm and high tide conditions coincide. In addition, differences in water level due to the tides were not modelled. This was mostly due to time constraints as each model run takes between one and three hours to complete for each coarse scale model run, and similar times for each nested grid. In addition, the exact timing of the surveys measuring bathymetry was unknown, and so there is some uncertainty over whether the bathymetry represents high, mid or low tide depth measurements. Wave forces at the shoreline are likely to be highest at high tide mainly due to the water being ~ 1.3 m (Wellington tidal range) deeper than at low tide. This will cause waves to break closer to the shoreline, with less energy dissipation and therefore the wave energies reported by the model may change significantly with water level. However, the relative distributions of wave energies are likely to be similar, but may be exaggerated more in the areas of high exposure compared to low exposure due to these effects. There are likely to be locations where tidal height has a much greater influence on wave exposure, such as those that are obstructed at low tide but relatively unobstructed at high tide (relatively because the obstacle remains but is submerged, thus presenting less of an obstacle to waves). At these locations the model is unlikely to provide adequate measures of wave exposure. However, these are unavoidable drawbacks of the model as it would be logistically infeasible to obtain the topography of obstacles for such a large area so that wave interactions could be modelled adequately. Future studies could model wave energies assuming simple profiles for emergent substrate (e.g. table-like in profile, related to projected width, or randomly generated within certain bounds) and assess how these compare among themselves and to the scenario modelled here to assess the relative error introduced by excluding the effects of waves overtopping obstacles and tidally driven differences in water level.

A further limitation of the model is that the defined digital shoreline is unlikely to capture the true shoreline in all of its detail. The shoreline itself is also variable as it changes with the tide. Therefore, unlike in terrestrial ecology and biogeography where the landscape is consistent (at least over \sim tidal timescales) and tools such as satellite altimetry (Hilton *et al.* 2003) and other remote sensing applications allow for the mapping of landscapes in great detail, mapping of shorelines is limited by the available aerial photography. Areas not well

represented are likely to be boulder fields where the size of shore segments (size of boulders) is less than the image resolution, preventing the adequate representation of these areas. This includes much of the shoreline from the Quarry to Sinclair Head which consists of a series of boulder fields with intermittent sandy bays. However, for these applications the level of detail achieved is at least as good as, if not better than, many other representations of digital shorelines.

The bathymetry data used to develop the wave model consisted of a combination of ship-based multibeam measures of water depth, water depth estimated from processing aerial photography and matching imagery to the relevant multibeam depth information, and in some locations using depth contours from nautical charts to estimate bathymetry (see Appendix 2A). The nautical charts were only used to provide information regarding the surrounding bathymetry for coarse scale model runs and mostly in water depths greater than 20-30 m where errors in bathymetry are unlikely to have considerable effects on wave predictions. However, there may be considerable errors in the nearshore bathymetry due to the use of aerial imagery. Multispectral aerial imagery has been used to predict ocean depths ($< 15\text{-}20$ m) in other studies (Stumpf *et al.* 2003), but due to the costs of obtaining imagery (~ 1000 NZD), and the uncertainty over whether it could be applied in this setting (most, if not all, applications are in the tropics and due to the fact that Wellington's south coast experiences swell much of the time, many of the areas of interest may be obscured by white caps and wave-driven froth) this technique was not used here. The potential error introduced using the method developed here was $\sim \pm 2\text{-}3$ m (see Appendix 2A), and thus there may be considerable errors in the final bathymetry. In particular for water depths less than 2-3 m the method performs poorly, due to the relative paucity of points in the multibeam dataset with depths less than 3 m. Systems such as Lidar (Irish *et al.* 2000) provide accurate measures of nearshore shallow bathymetry, but given the costs these methods are also likely to be beyond many researchers.

In addition, the formulations of physical processes used here represent one possible set among many of the alternative parameterisations available within SWAN (Booij *et al.* 1999; Ris *et al.* 1999). Examination of alternative parameterisations of bottom friction and wind-wave interactions revealed that mis-identifying the correct formulation could introduce errors up to 5-10% of the mean orbital velocity and wave energy (see Appendix 2C for a more rigorous treatment of this), but would most likely influence the magnitude of the

predicted values rather than the relative distribution. This is an area, which given validation data, could be explored in more detail, but is unlikely to affect the overall conclusions of this study (Appendix 2C).

Despite the limitations of the methods adopted here, the data collation approach employed here provides an adequate representation of the bathymetry and only further reductions in the cost of alternative methods (Lidar, multispectral or hyperspectral imagery) will yield more accurate representations.

4.4.4 – Conclusion

This study details the development of a high resolution model of wave forces to aid in the description of subtidal (this chapter) and intertidal (Chapter 5) species communities along an approximately 11 km stretch of coastline which experiences persistently high wave exposure. This represents one of the few examples (but see England *et al.* 2008; Huang *et al.* 2012 for others) where wave modelling has been used in an ecological context. Although the data requirements of wave modelling are likely to be beyond many ecologists, in terms of the joint availability of accurate bathymetry, weather and wave information (as suggested by Burrows *et al.* 2008), when this information is available, the development of SWAN models can provide information that would otherwise be missing from studies of intertidal and subtidal species and communities. Despite model limitations these results will likely be useful in determining the drivers of community dynamics, both temporally with regard to episodic storms/disturbance regimes and also spatially in describing differences in both subtidal and intertidal species composition among locations.

Chapter 5 - A novel wave-modelling approach for predicting fine spatial scale differences in intertidal community composition: application to a wave-exposed temperate shore

5.1 – Introduction

In light of the predicted ecological changes associated with climate change (Walther *et al.* 2002; Hampe & Petit 2005; Harley *et al.* 2006; Hawkins *et al.* 2008), ocean acidification (Findlay *et al.* 2010; Kroeker *et al.* 2010), an increased number of invasive species (Dukes & Mooney 1999; Gurevitch & Padilla 2004; Didham *et al.* 2005), as well as effects associated with pollution and degradation of the environment (Piola & Johnston 2007), it is important to establish baselines of species' distributions and abundances (Hardman-Mountford *et al.* 2005). It is usually unknown where and how future perturbations may occur and because of the absence of widespread sampling effort it is unlikely there will be baseline data for these impacted areas. The collection of spatially explicit biological data is often restricted by monetary costs (Nicholls 1989) and the expertise required to perform this work at the scales required to achieve even relatively small spatial coverage. Given the costs of monitoring there is a pressing need to make greater use of the data that are collected, either by uncovering scientific relationships pertaining to the monitored species within a hypothesis testing framework (Nichols & Williams 2006), or uncovering quantitative relationships between species abundances and the environment (Rodríguez *et al.* 2007). The latter can be utilised to expand the applicability of monitoring data over much larger areas through the development of species distribution models.

Species distribution models have been utilised extensively to achieve broad spatial coverage describing the abundance and distributions of species in marine, freshwater and terrestrial domains (reviewed by Elith & Leathwick 2009). In simple terms a species distribution model is any model that uses observations of species abundance or presence-absence at specific locations and relates this to environmental data collected at these locations through a correlative or predictive model framework (Guisan & Thuiller 2005; Kearney & Porter 2009). These species-environment relationships can take the form of continuous relationships that may be linear (Guisan *et al.* 2002), non-linear (Guisan *et al.* 2006; Elith & Leathwick 2009) or can be based on specific thresholds that are empirically derived based on field data (De'ath & Fabricius 2000) or relate to species life history traits (Kearney & Porter 2009). Over large areas it is inexpensive to obtain environmental data, relative to the cost of collecting biological data, (Nicholls 1989) using weather stations, climatic projections, measures obtained from geographic information system (GIS) representations of landscapes, and aerial photography. Such environmental data, along with the empirically derived species-environment relationships, can be used to determine species distributions across entire

landscapes, achieving much greater spatial coverage than the surveyed sites. These predictive models have been successfully utilised in conservation and management practice (Wilson *et al.* 2005) as well as forecasting the future distribution of species based on current environmental thresholds (Araujo *et al.* 2005; Guisan & Thuiller 2005).

Although the use of species distribution models of marine species or species assemblages has increased over the last decade (Elith & Leathwick 2009), both in temperate (Leathwick *et al.* 2006; 2008a) and tropical areas (De'ath 2007; Pittman *et al.* 2009), the number of marine species distribution models is still far less than in terrestrial ecology (Robinson *et al.* 2011). Specifically, there is an almost complete absence of predictive distribution models describing rocky intertidal species (although see Zacharias *et al.* 1999), despite the extensive study of the physical and biological factors affecting intertidal species (Menge & Branch 2001). The production of zonation charts for specific areas of coastline under different qualitative descriptions of environmental conditions have been widely utilised since Stephenson and Stephenson (1949; 1972) first described general rocky intertidal zonation patterns. These can be thought of as an early qualitative approach to predictive modelling of intertidal species distributions, but there have been fewer attempts to define quantitative boundaries (beyond tidal height) or relationships that can be used to describe the distribution of intertidal species in relation to environmental factors. One of the most widely studied factors affecting intertidal species is wave action with studies including its effects on zonation patterns (Lewis 1961; Harley & Helmuth 2003), intertidal productivity (Leigh *et al.* 1987), algal morphology and mechanical strength (Gaylord *et al.* 1994; Kitzes & Denny 2005) and its ability to promote or mediate biological interactions, structuring entire communities (Menge 1976; Jonsson *et al.* 2006). However, using this knowledge to predict the distribution of intertidal species has largely been hampered by the inability to predict wave forces over large spatial scales, whilst maintaining fine spatial resolution in predicted wave forces. Although metrics of wave exposure, such as fetch, have been utilised extensively as a proxy for wave exposure over large spatial scales (Thomas 1986; Burrows *et al.* 2008) they are unable to distinguish between wave exposure regimes on a finer scale (~10's-100's of meters). Furthermore, they do not account for effects such as refraction and depth-induced wave breaking that can amplify or reduce wave forces as they propagate towards the shore (Hill *et al.* 2010). Without incorporating these factors predictive models are unlikely to provide accurate predictions of intertidal community structure.

Amongst physical factors the intertidal zone is also strongly controlled by exposure to large changes in temperature, salinity and UV radiation levels with regard to changing exposure to the air and the sun throughout the tidal cycle (Denny *et al.* 2006; Miller *et al.* 2009; Russell & Phillips 2009). For example, intertidal limpet body temperatures can, in the space of a few hours, go from $\sim 10^{\circ}\text{C}$ to $\sim 40^{\circ}\text{C}$ (Denny & Harley 2006). The topography of intertidal surfaces is therefore likely to play a key role in determining what species are present given varying physiological responses to temperature, salinity and radiation stress (Mercurio *et al.* 1985; McGuinness & Underwood 1986; Underwood 2004; Martins *et al.* 2010). In particular, the aspect and inclination of intertidal surfaces are likely to create specific microhabitats, particularly with regard to the light intensity incident upon them and the degree of water pooling on these surfaces. These factors are also likely to interact with wave exposure because wave-induced splash and/or surge will act to cool and rehydrate individuals, thus reducing the degree of heat, salinity and desiccation stress individuals experience on these surfaces (Miller *et al.* 2009) and are therefore likely to influence intertidal community composition.

The south coast of Wellington in New Zealand (Figure 5.1) is a particularly wave exposed section of coastline, frequently experiencing waves ~ 2 m in height, with yearly storms causing waves 5-8 m in height, and the largest storms causing waves ~ 15 m in height occurring once or twice a century (Carter & Lewis 1995). This section of coast, along with much of the shoreline of Cook Strait separating New Zealand's North and South Islands (Figure 5.1), lacks the typical zonation patterns exhibited by most temperate rocky shores (Morton & Miller 1968; Gardner 2000). The mid intertidal band of mussels is virtually absent along Cook Strait shores, and the upper intertidal is also only sparsely occupied by barnacles, with bare rock being particularly prominent (Gardner 2000; Helson & Gardner 2004; Phillips & Hutchinson 2008; Demello & Phillips 2011). Pande & Gardner (2009) have also suggested that a natural environmental gradient exists along the Wellington south coast from the harbour entrance in the east to the entrance of the Cook Strait in the west (Figure 5.1), with subtidal species abundance being greater in the east compared to the west. In addition, water column characteristics (particulate organic matter, percent organic matter, Chl-a) also vary along this shoreline in a manner consistent with their being a gradient with higher concentrations at eastern sites compared to western sites (Helson & Gardner 2007). Although many studies have examined various aspects of the intertidal community along the Wellington south coast, most have focussed on the almost complete absence of mussels and

comparative studies with the harbour (Gardner 2000; Helson & Gardner 2004; 2007; Helson *et al.* 2007; Phillips & Hutchinson 2008; Demello & Phillips 2011), rather than examine the factors that determine the abundance and distribution of multiple species within this region.

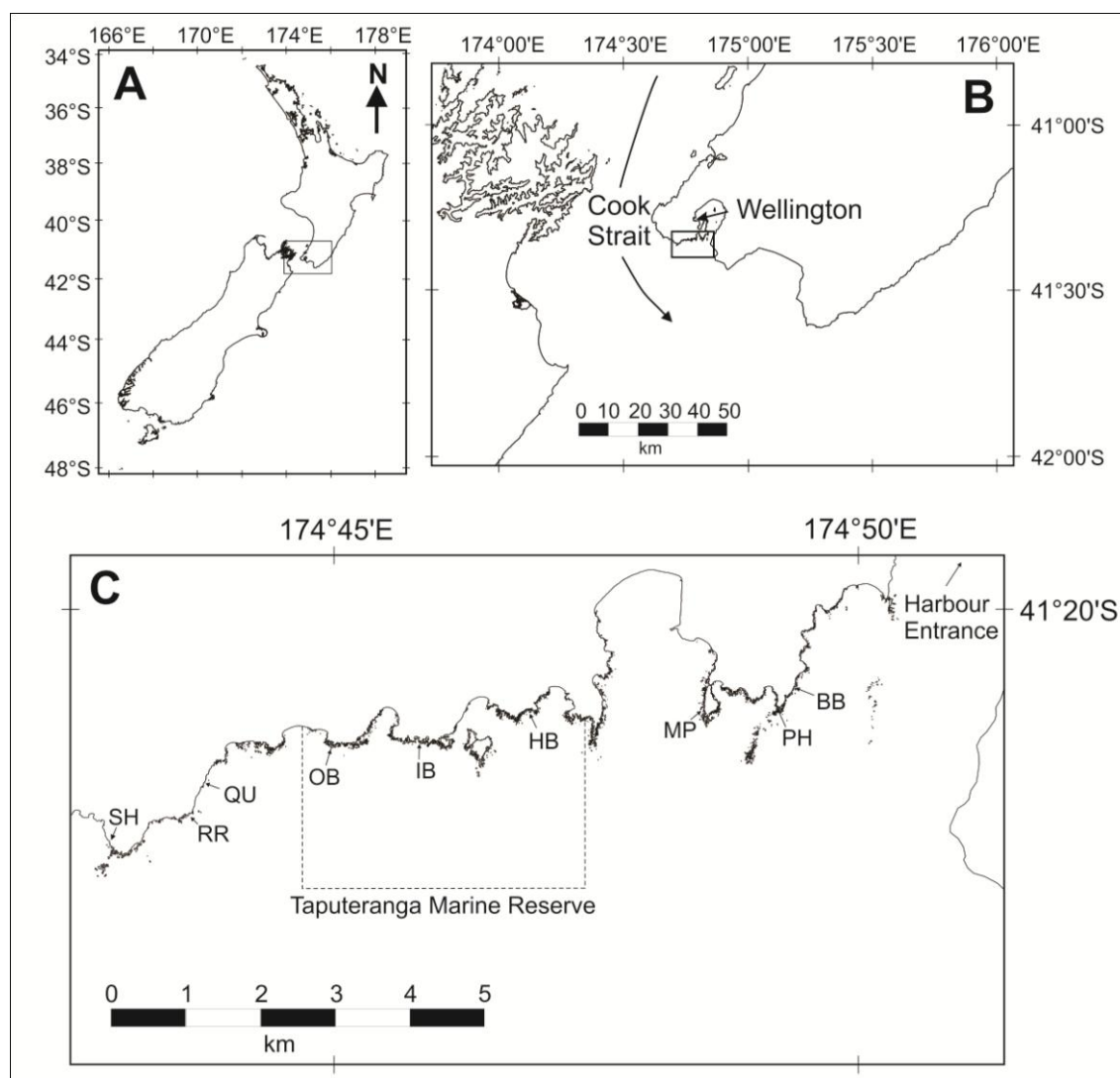


Figure 5.1. Maps showing New Zealand (A) with insets showing the study location with respect to the Cook Strait separating the North and South Islands (B) and the locations of individual study sites within this region (C). Abbreviations of site names are BB – Breaker Bay, PH – Palmer Head, MP – Moa Point, HB – Houghton Bay, IB – Island Bay, OB – Owhiro Bay, QU – Quarry, RR – Red Rocks, SH – Sinclair Head.

The aim of this study is to develop predictive models for the distribution and abundance of the dominant intertidal rocky shore species present along Wellington's south coast. Combining biotic survey monitoring data with abiotic factors of the survey locations, the relationships between species and the physical factors governing their distribution, within this region, will be determined. Given that this area is unusual compared to other temperate rocky shores (almost complete lack of mussels, high availability of bare rock), this will

further our understanding of the possible mechanisms operating to structure intertidal communities in this area and also may be able to identify or eliminate potential reasons why this stretch of coastline is dissimilar to those found elsewhere in temperate regions. This information is not only useful in identifying and describing the ecology of these species in this area but can also be used to make predictions about the intertidal community composition in un-surveyed locations. This is further aided by the development of a SWAN wave model for this region (Chapter 4), which provides predictions regarding wave energy for the entire coastline at relatively high spatial resolution so that the species distribution model predictions can be applied across much of the shoreline. SWAN wave models have been applied in coastal engineering scenarios of sediment transport (Warner *et al.* 2008), as well as for predicting damage due to storm surges during hurricanes (Sheng *et al.* 2010), but have rarely been applied in a marine ecological context (however see England *et al.* 2008; Huang *et al.* 2012). The wave model results in combination with the data driven predictive models provide the opportunity to develop a predictive representation of intertidal communities for this stretch of coastline. Developing predictive baselines can expand the utility of baseline data, which is usually limited in its spatial coverage, by providing a means for future researchers to identify, with a certain level of confidence, the species or abundances that were present at certain locations, even if the location was previously un-surveyed. Knowledge of the spatial variation of these communities can also be used in systematic conservation planning with regard to the placement of marine protected areas (Leathwick *et al.* 2008a) to identify areas that encapsulate the greatest range and/or coverage of different community types.

5.2 – Methods

5.2.1 – Study area

Wellington's south coast is a highly dynamic wave exposed shoreline (Carter & Lewis 1995) and because of a 140° phase difference in the timing of the tides between the east and the west coast of New Zealand, also experiences considerable tidal flow predominantly from the north-west to the south-east through Cook Strait (Bowman *et al.* 1980). Consequently Wellington's south coast experiences a much reduced tidal range (~1.5 m at springs, Morton & Miller 1968) than either the east or the west coast of the North or South Islands. The vertical zonation patterns of intertidal organisms are therefore strongly compressed (Morton & Miller 1968). The coastline itself is predominantly eroded greywacke, which is a sedimentary rock consisting of a mix of medium- to coarse-grained sandstone with layers of fine-grained argillite, or mudstone (Kennedy & Beban 2005). The coastline is

topographically complex consisting of a mix of bedrock outcroppings, boulder fields, subtidal-intertidal pinnacles and sandy beaches (Morton & Miller 1968). The study area encompassed the entire coastline from Breaker Bay in the east (41° 20.556' S, 174° 49.379' E) to Sinclair Head in the west (41° 21.690' S, 174° 42.859' E) (Figure 5.1).

5.2.2 – *Intertidal sampling*

Permanent monitoring plots were established at each of nine sites along the shore (Figure 5.1). Of the nine sites, five were established on sections of gently sloping shoreline of various aspects and wave exposures with the sites themselves largely consisting of broken up bedrock formations and large boulders with a mix of bedrock and small to medium sized cobble between major formations (Breaker Bay [41° 20.556' S, 174° 49.379' E], Moa Point [41° 20.706' S, 174° 48.534' E], the Quarry [41° 21.243' S, 174° 43.734' E], Red Rocks [41° 21.468' S, 174° 43.578' E], Sinclair Head [41° 21.690' S, 174° 42.858' E]). A further three sites were established on more topographically complex sections of shoreline with the sites consisting of a main continuous intertidal platform on the shoreward side and a multitude of intertidal platforms further offshore rising at their highest ~2-3 m above low tide and immediately surrounded by water ~ 3-5 m deep on the seaward side, and in some cases on all surrounding sides (Houghton Bay [41° 20.712' S, 174° 46.842' E], Island Bay [41° 20.94' S, 174° 45.810' E], Owhiro Bay [41° 20.976' S, 174° 44.970' E]). One such site (Owhiro Bay) was established entirely on one of these disconnected intertidal platforms. The final site was established at a location consisting predominantly of many abrupt, sharply rising projections of bedrock dotted throughout the site surrounded by a shallow-graded and shallow-depth (surveyed locations surrounded by water < 2 m deep at high tide) pebble-gravel beach (Palmer Head, [41° 20.694' S, 174° 49.224' E]).

5.2.3 – *Collection of biological data*

At each of the nine sites 5 permanent 50 × 50 cm quadrats were established at each of three tidal levels. At each site the tidal range was split into three approximately equal sized bands. The high intertidal extended from the height of the highest barnacle to the upper mid shore, mid intertidal was centred on the midpoint between the highest barnacle and the chart datum, and the low intertidal band extended from upper low shore to the chart datum. These bands coincided with the predominant intertidal zonation patterns found on this coastline, with the high intertidal being sparsely occupied by barnacles (*Chamaesipho* spp.), mid intertidal consisting mostly of bare rock, several species of limpet (*Cellana* spp. and

Siphonaria spp.) and towards its lower limit a band of encrusting algal species (coralline algae, various brown crusts and the cushion-forming green alga *Codium convolutum*), and the low intertidal consisting of a patchwork of turfing red and brown macroalgal species amongst small and larger canopy forming brown algae.

Each quadrat was placed on exposed bedrock or large boulders, avoiding areas with large cracks or undulations in the surface, and areas with tide pools but was haphazardly placed within these constraints. Each quadrat was marked by two bolts drilled and set into the rock using expanding masonry plugs at the top corners of the quadrat. The extent of the monitoring plot was determined by laying a 50 × 50 cm stainless steel quadrat, gridded into a hundred sub grids 5 × 5 cm, over the designated area and lining up the corners with the two corner bolts. Photographs were taken of each quadrat once per season (every 12 weeks) for two years from August 2009 to August 2011. To improve the accuracy of each digital image, 4 photographs were taken of each quadrat, with each image capturing one quarter of the area sampled (images were ~ 4MB taken using an 11 MP camera). All efforts were taken to ensure that photographs were taken parallel to the surface to avoid introducing error due to differences in perspective. Percent cover of sessile and algal species was recorded using Coral Point Count with Excel extensions (CPCe, Kohler & Gill 2006) by employing 400 points per quadrat. In the high and mid intertidal zones there was little to no overlying algal canopy and so this method was mostly not confounded by layers of alternate organisms. However, in the low intertidal there were often many layers and where possible the species underlying the topmost layer were also recorded, but this was not possible in all cases. Mobile invertebrate abundance was recorded by counting all visible individuals within the confines of the quadrat. Due to the high abundance of *Austrolittorina* spp. (on most occasions *Austrolittorina antipodum* and *Austrolittorina cincta* could be distinguished, however successfully identifying small individuals in cracks was not always possible, therefore these species were grouped and henceforth are referred to as *Austrolittorina* spp.) in high intertidal quadrats, their abundance was estimated by counting the number of individuals in each of ten randomly chosen 5 × 5 cm sub-squares of the quadrat and extrapolating their abundance by multiplying their summed abundance by ten. Mobile invertebrate abundance was recorded in the low intertidal quadrats, but because the algal canopy likely obscured most counts, these were not considered for further analysis due to the likely inaccuracy in recorded abundances. In addition, the presence-absence of all algal species within the quadrat was recorded to account for species that may have been missed using the % cover estimation method or not

adequately recorded using the point-intercept recording method. This method of sampling the intertidal community allowed for optimal use of time in the field to collect a large amount of long-term data. Identification to species level was not always possible from photographs, or in the field. In these cases individuals were grouped to genus level or into morphological groupings where appropriate. Due to weather constraints some plots could not be sampled in some seasons, however, the majority of plots were sampled in the subsequent survey. The exception was for plots at the Quarry site, which was established during the second survey (spring 2009) and only successfully returned to twice after this (summer 2010, winter 2010). Despite this, data from this site, and other plots that were less frequently monitored, are included as the method of analysis does not focus on any particular season or survey, but pools data from all surveys to make predictions about year round community structure: such data may be informative in accurately predicting this.

5.2.4 – Identifying characteristic species

A multivariate analysis was used to identify the species that were characteristic of the differences exhibited amongst quadrats. The biological dataset was split into three categories; sessile invertebrates, mobile invertebrates and macroalgae due to the difference in data types (e.g., % cover for sessile invertebrates and macroalgae and counts for mobile invertebrates). The BIOENV procedure in PRIMER-E v.6 (Clarke & Gorley 2006) was used to identify a reduced set of species that were representative of the whole community. BIOENV performs a search through all possible combinations of species sets and assesses the degree of correlation between the full dataset and datasets with a reduced number of species by calculating the Spearman rank correlation coefficient (ρ) between the resemblance matrix of the full dataset and the reduced dataset. This gives a measure of the agreement between the full and reduced datasets and allows the identification of the species that are most indicative of overall differences in community structure amongst quadrats. The BIOENV analysis was applied to the following datasets; high intertidal mobile invertebrates, sessile invertebrates and macroalgae, mid intertidal mobile invertebrates, sessile invertebrates and macroalgae and low intertidal macroalgae to identify the species that were most characteristic of the entire community. This was performed separately for each season, as some species may be a particularly important component of the community in some seasons, but may be less important (seasonal) or entirely absent (ephemeral) in others. This ensures that the predictive models are performed on species that are present year round, but also includes species that

are seasonal and thus may only be present at certain times, and the model results therefore identify their spatial distribution at these times

For each BIOENV analysis the smallest group of species that achieved a correlation coefficient of $\rho \geq 0.95$ was selected for further analysis. All BIOENV analyses used Bray Curtis similarity resemblance matrices based on transformed data, using a log transform for mobile invertebrates to reduce the importance of particularly abundant species (Austrolittorinids ~ 1000 's) and a square root transform for sessile invertebrates and macroalgal percent cover to reduce the importance of quantitatively dominant species (Clarke & Gorley 2006). In addition, the prevalence of each species for each survey was calculated to check that all commonly occurring species were also considered for further analysis.

5.2.5 – Predictor variables

Predictor variables were quantified based on *in situ* field measurements and a SWAN wave model developed to model and predict wave action experienced at each location (see Chapter 4). The methods used to measure/derive these values are shown in Table 5.1.

Table 5.1. Predictor variables used in the regression and classification analyses.

Factor	Code	Description/Method	Continuous/ Discrete
Inclination	Inc	Measured as the slope defined by placing a 0.5 m rule from the top to the bottom of the plot and measuring the angle to the closest 5° using an anglemeter	Continuous
Aspect	Asp	<p>Measured as the angle (to the closest 5°) between the horizontal plane component of the surface normal vector and magnetic north. These were then transformed according to the following equation</p> $A = \frac{1 - \cos(\varphi)}{2}$ <p>where A is the transformed aspect and φ is the measured aspect. This transformation was applied such that North facing aspects (e.g., $\varphi=0$ and $\varphi=360$) have $A=0$, whilst South facing aspects ($\varphi=180$) have $A=1$. East and West are treated equally with $A=0.5$. All flat surfaces (Inclination = 0), were assigned an aspect of 0.</p>	Continuous
Substrate Type	Subs	Substrate type as one of greywacke bedrock (HG), greywacke boulder (HGB), sandstone-dominated greywacke (SG).	Discrete
Average Wave Energy	Wave ave	As the influence of wave action may extend across distances to a certain extent (i.e., splash), for each wave class (see Chapter 4 for descriptions of the separate wave classes) the magnitude of wave energy is averaged across cells (2 m by 2 m) within radii of 5, 10, 15 and 20 m about each digitised coastal location. The average, maximum and minimum wave energy were determined as the weighted average (weighted by proportion of time this wave class prevails), maximum and minimum values across all wave classes experienced at each location. This was performed separately for each spatial scale averaging, leading to 4 possible factors for each of Wave ave, Wave min, and Wave max.	Continuous
Maximum Wave Energy	Wave max		Continuous
Minimum Wave Energy	Wave min		Continuous
Distance from harbour	Dist	Distance from 41° 20' S, 174° 51' E measured in ArcMap, as a proxy for changes in water column composition.	Continuous

A predictive modelling approach was adopted to determine the factors and relationships governing the abundance and distribution of each species. As the wave exposure values for different spatial scales represent alternative representations of the same data, each spatial scale was tested separately by running identical modelling procedures for each spatial scale and comparing the resulting models based on predictive performance. Furthermore, within each spatial scale Wave min and Wave max were highly correlated with Wave ave ($\rho=0.78-0.95$), but not as highly correlated with each other ($\rho=0.62-0.72$). Thus for each spatial scale, two alternative models were fitted, one with all factors excluding Wave ave (modelling Wave min and Wave max) and the other with all factors except Wave min and Wave max (modelling Wave ave). Thus a total of 8 possible predictor sets were examined (four spatial scales 5, 10, 15 and 20 m, and two expressions of wave action; overall average,

or maximum and minimum values) and the resulting models were compared based on predictive performance to identify the best set of predictors.

In recent years there has been considerable progress with predictive modelling aided by the advance in machine learning methods such as classification and regression trees (CART) (De'ath & Fabricius 2000), and its extensions in classification analyses in the form of random forests (RF) (Prasad *et al.* 2006; Cutler *et al.* 2007) and in regression analyses in the form of boosted regression trees (BRT) (Leathwick *et al.* 2006; Leathwick *et al.* 2008b; Elith *et al.* 2008). Analyses using RF were performed to model macroalgal distributions, whilst BRT was used to model sessile-invertebrate % cover and mobile-invertebrate abundances.

5.2.6 – Tree based analysis methods

Tree-based analysis methods are rooted in the simple concept of decision trees. A decision tree consists of a sequence of binary partitions in the range of single or multiple predictor variables based on the identification of regions in predictor space that have the most homogenous response (Figure 5.2) (De'ath & Fabricius 2000; Hastie *et al.* 2001; Elith *et al.* 2008). When multiple explanatory variables are present each successive split can be implemented in the range of any of the explanatory variables, but being subject to splits higher in the tree (Elith *et al.* 2008). As a result, interactions between factors are modelled automatically and in a way that is simple to interpret. As the tree 'grows' each split is based on a diminishing proportion of the whole dataset and so there is a risk of over-fitting (i.e., explaining noise rather than signal). Over-fitting due to overly large tree size can decrease the model's predictive capability as it increases the number of nuisance or non-informative descriptors. To counteract this, ν -fold cross validation can be used (where ν is the number of folds) to "prune" the decision trees (De'ath & Fabricius 2000). This process involves splitting the whole dataset into ν subsets (ν is usually 10) and then building trees of all sizes based on data within $\nu-1$ of the ν subsets. Each tree is then used to make predictions on the response values in the remaining subset and the deviance (i.e., sum of squared differences for a Gaussian distributed response, Ridgeway 2007) between predicted and observed values is calculated. A tree size that minimises the predicted deviance offers the highest predictive capability whilst minimising over-fitting (De'ath & Fabricius 2000; Elith *et al.* 2008).

5.2.7 – *Boosted regression tree analysis of invertebrate abundance/% cover*

Boosted regression trees build on the decision tree framework but add several components to improve predictive capabilities (Elith *et al.* 2008). Boosting is a method that increases model accuracy by building and subsequently averaging many simple models in an iterative stagewise process (Figure 5.2). An initial decision tree is built that best reduces some loss function, such as deviance, that is usually a measure of predictive capability. The next tree is built on the residuals from the initial tree using the same loss criterion to identify the tree that best decreases the predictive deviance. The fitted values are then re-estimated due to the addition of the second tree and the residuals calculated. This process of building and adding trees continues in a stagewise fashion, until the final BRT model is a combination of all trees (usually ~ 1000 's) with each tree's contribution weighted by a factor known as the learning rate. BRT models involve a level of stochasticity in that each tree is built using a random subset of the data determined by a "bag fraction" which is the proportion of the data that is randomly selected to fit each new tree (Figure 5.2). This introduces some variation to the fitting and resulting predictions between model runs, but provides benefits in the form of reduced over-fitting and improvements in model accuracy (Elith *et al.* 2008).

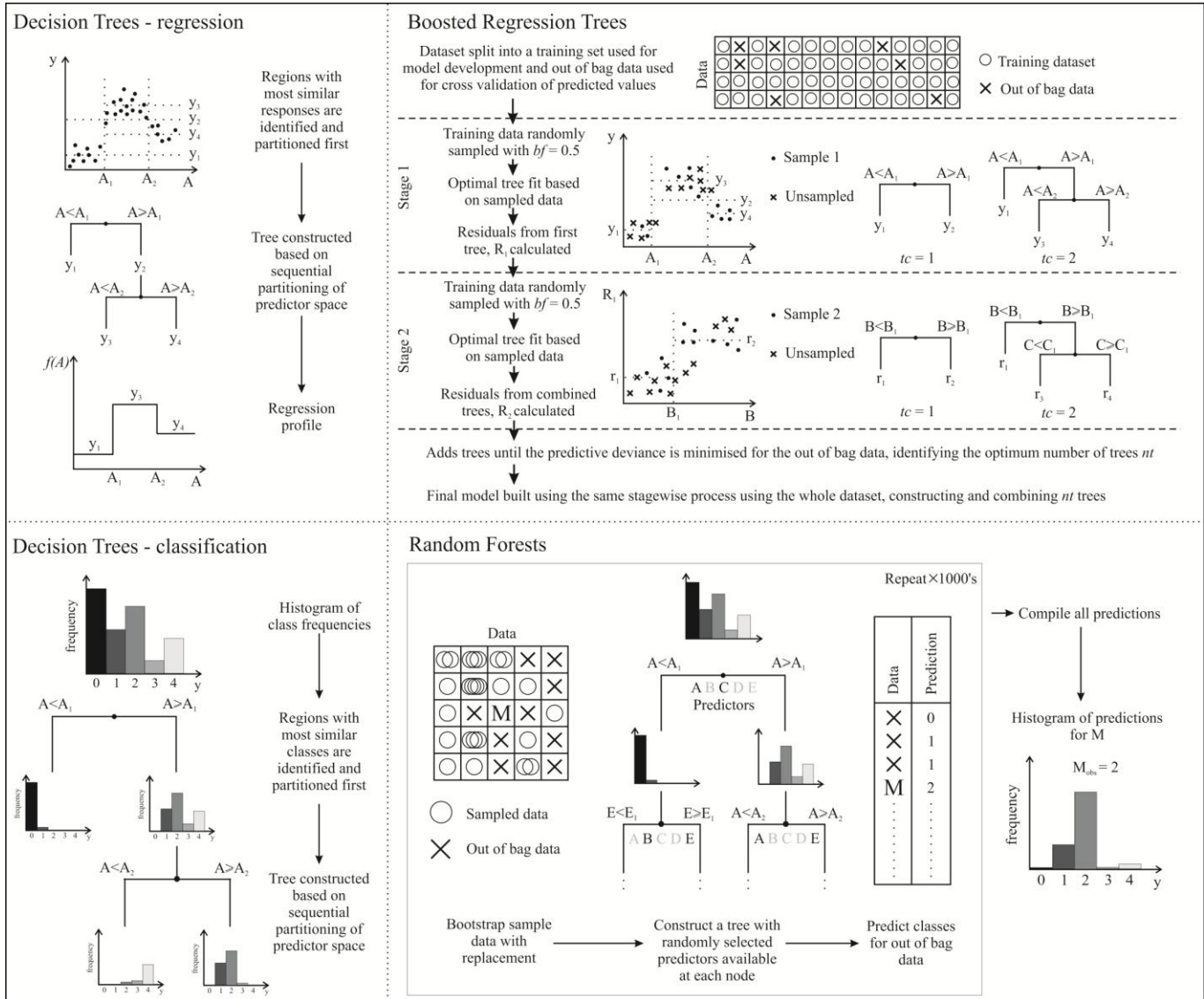


Figure 5.2. Illustrations of the processes involved in decision tree analyses for regression (upper panels) and classification (lower panels).

The whole procedure requires the estimation of four modelling parameters to achieve optimal predictive performance; tree complexity, learning rate, number of trees, and bag fraction. Tree complexity (tc) is equal to the number of nodes in each tree, with one referring to a tree consisting of a single binary split. Higher tree complexities can be used to model higher order interactions between parameters ($tc = 2$, fits a maximum of two-parameter interactions) and thus can be used to model multiple factor interactions. The learning rate (lr) controls the contribution of each tree to the overall model. A low lr is often most appropriate, particularly when introducing stochasticity into the modelling process (through bag fractions), to avoid overly large variation in predicted values between repeat modelling runs (Elith *et al.* 2008). This arises because each tree is estimated based on a fraction of the data

(*bf*), and as such there is variation from run to run over which trees are fitted and in what order the variation in the data is explained. However, by introducing a lower learning rate each tree's contribution is reduced, leading to influential trees having less weight in the final model and greater consistency between model runs. However this also leads to a greater number of trees (*nt*) being required to achieve the lowest predictive deviance. The parameters *nt*, *lr* and *tc* are thus all connected, with higher *tc* usually requiring lower *lr* and higher *nt* to achieve minimum predictive deviance. As with simple decision trees, over-fitting can be a problem, but in this case arises when too many trees are added. In a similar fashion to pruning decision trees, for a given *lr*, *tc* and *bf*, the optimum *nt* can be determined by *v*-fold cross validation of the models predictive performance. The routine implemented by Elith *et al.* (2008) (*gbm.step*) involves adding trees until the predictive deviance (calculated for the out of bag data using *v*-fold cross validation) is minimised, identifying the optimum *nt* for model development. A final BRT model using the whole dataset is then constructed with the optimum parameters (illustrated in Figure 5.2).

For each predictor set every combination of *lr* (0.01, 0.0075, 0.005, 0.0025, 0.001), *tc* (1, 2, 3, 4) and *bf* (0.65, 0.7, 0.75) was investigated, with *nt* estimated by 10-fold cross validation with respect to predictive deviance for each unique parameter set using the *gbm.step* routine developed by Elith *et al.* (2008), based on the previous *gbm* routines written by Ridgeway (2007, 2010). The response to the predictor Distance was set to be monotonic, and both monotonically increasing and decreasing relationships were investigated. This was so that distance modelled a change in water column characteristics between water exiting Wellington Harbour and water originating in the north-west of Cook Strait. Due to the variability in the modelling process (introduced through the stochastic element of the modelling procedure), each parameter set was repeated 20 times (Leathwick *et al.* 2006), and the estimates of minimum predictive deviance, and its standard error were recorded across all 20 repeats. The parameter and predictor set with the lowest predictive deviance and its standard error (averaged across 20 repeats) was chosen and results are reported for these parameter sets. For the final model, the relative importance of each predictor (a measure of how often a predictor is chosen for splitting) is reported as well as cross-validated residual deviance (1 SE) and the cross-validated proportion of the total deviance explained D^2 . Partial dependency plots for the four most important factors (determined by relative importance) were plotted using the *gbm.plot* routine developed by Elith *et al.* (2008) for species where

BRT models achieve a $D^2 \geq 0.2$. These partial dependency plots illustrate the response across the predictor range, integrating across the response of all other predictor values.

Mobile and sessile invertebrate abundances/percent cover estimates for species identified using the BIOENV routine were averaged across surveys for each quadrat. The mobile invertebrate abundance data were modelled based on a poisson distribution because it was count based (Dennis *et al.* 2010; O'Hara & Kotze 2010), whereas the percent cover data were transformed according to a logistic transform (Warton & Hui 2011) and modelled with gaussian distributed errors. As the logistic transform is not defined for proportions equal to zero, percent cover values for species with zero percent cover in some quadrats were transformed according to a modified logistic transformation with an added correction in the numerator and the denominator;

$$s = \ln \left(\frac{p + \varepsilon}{1 - p + \varepsilon} \right)$$

eqn. 5.1

where p is the percentage cover, s is the logistic transformed value and ε is the minimum non-zero percent cover recorded (Maxwell & Jennings 2005; Warton & Hui 2011). All analyses were performed in R version 2.12.2 (R Development Core Team 2011).

5.2.8 – Random forests analysis of macroalgal presence-absence data

Classification analysis using RF is another technique within the machine learning, decision tree family (Breiman 2001) and has increased accuracy and higher successful classification rates than ordinary classification trees (Cutler *et al.* 2007). This is achieved by constructing many classification trees, each built on a bootstrap random sample (with replacement) of the whole data set (Figure 5.2). For each tree the predictor variables for the out-of-bag (OOB) data (data not selected in the bootstrap sample, usually $\sim 1/3$ of the whole dataset) are then passed down the classification tree to obtain a prediction for that observation (Figure 5.2). To improve classification accuracy the results of many classifiers can be combined provided the classifiers have low pairwise correlations (Breiman 2001; Cutler *et al.* 2007). To reduce correlations between subsequent trees, at each node in the tree's construction only a random subset of predictors is available for partitioning, and the best split is chosen from amongst these predictors (Figure 5.2). This ensures there is diversity in the construction of the trees, thereby reducing correlation amongst trees and increasing

classification accuracy (Prasad *et al.* 2006). Approximately one third of the observations are left out in the construction of each tree, and therefore predictions for each observation are made in approximately one third of all trees. The predictions for each observation across all trees are tallied up, and the class receiving the most votes is chosen as the predicted value for that observation. These are independent predictions, as OOB data is not used in tree construction and thus the model's predictive capacity can be calculated as the total OOB misclassification rate, sensitivity (% presences correctly classified) and specificity (% of absences correctly specified) (Cutler *et al.* 2007). Predictor importance is calculated based on loss in predictive performance. The values of the specific predictor in question are permuted amongst the OOB data. If the predictor has little or no influence over the response class then permuting the values for this predictor should have no influence on overall misclassification rate. However, if the predictor is important then there will be an increase in the misclassification rate as predictors are uncoupled from their true classes. The modified misclassification rate is estimated by passing the permuted predictor variables down each tree in the forest. The difference between the original and the modified misclassification rates, divided by the standard error, gives a measure of the individual variable's importance (Cutler *et al.* 2007).

The macroalgal species chosen by the BIOENV analysis were split into two groups, one consisting of species that, although they may display seasonality in abundance, are present year round, and another group of species that is entirely ephemeral and absent in some seasons. Ephemeral species were those that were typically only observed during the spring and summer months (ephemeral reds such as *Helminthocladia* sp., and ephemeral browns such as *Colpomenia sinuosa*, *Leathesia difformis*), but, *Porphyra* spp., *Ulva* spp. and *Undaria pinatifida* were also considered in this class as they display strong seasonality. To analyse macroalgal distributions the percentage cover data were reclassified as a binary measure of presence-absence within each quadrat. Within each quadrat, species, other than those considered here to be ephemeral, were classified as present if they were present in two or more of the eight surveys (two surveys were used rather than one such that presence would only be recorded for each quadrat if this species was able to persist at that location). As this may be misrepresentative of the ephemeral species (that may be absent in seven of the eight surveys, but completely dominant in the remaining survey) they were classified as present if their maximum percent cover (across surveys) exceeded 1% in any of the eight surveys.

RF classification analyses were performed on the macroalgal presence-absence classes using the randomForest package in R (Liaw & Wiener 2002). Distance was omitted from these models because, unlike the BRT routine that allows some control over factor responses (monotonic increasing/decreasing), the random forest routine has no such control over predictor response. Consequently it is likely that the Distance factor would model site-specific differences that may be associated with other variables (e.g., wave exposure) to the detriment of wider applicability of the model. The remaining predictors of the eight predictor sets were then modelled by implementing the randomForest function with the number of trees set at 10,000 and the number of predictors available at each node set to the square root of the total number of predictors available (Cutler *et al.* 2007). This was performed for each predictor set and the predictor set with the lowest OOB error rate was chosen. Predictors that had a negative impact on predictive performance were excluded from models and the model rerun with the remaining predictors. The OOB error rate, sensitivity and specificity of the model with the lowest OOB error rate are presented, as well as estimates of variable importance. A further parameter, Cohen's- κ was calculated according to the equation

$$\kappa = \frac{n(a + d) - (a + c)(a + b) - (b + d)(c + d)}{n^2 - (a + c)(a + b) - (b + d)(c + d)}$$

eqn. 5.2

where n is the number of observations, a is the number of presences correctly predicted, b is the number of absences incorrectly predicted as presences, c is the number of presences incorrectly predicted as absences, and d is the number of absences correctly predicted. Cohen's- κ gives a measure of the agreement between the model predictions and the recorded data after accounting for agreements that could have arisen by chance (Manel *et al.* 2001) and ranges between 0, indicating agreement is entirely by chance, and 1, indicating absolute agreement between predictions and observations. It is therefore a more robust measure than the total OOB error rate, which can be affected by high/low prevalence values (Manel *et al.* 2001). Finally, partial dependency plots for the four most influential factors are plotted for models with κ -values greater than 0.5 (remaining partial dependency plots are included in Appendix 3).

5.2.9 – Example predictive maps

As an illustration of how the model results can be applied to the surrounding coastline, maps are presented of the predicted abundance/percent cover and presence-absence

of algal species for the area around Island Bay (in a rectangle ~ 1.5 km E-W and ~1.2 km N-S, from bottom-left: 41° 21.24' S, 174° 45.72' E, to top-right: 41° 20.61' S, 174° 46.77' E). The coastline values of wave energy (Wave min, Wave max etc) (see Chapter 4 for maps of wave energy) as well as aspect (calculated as the aspect for each line segment in ArcMap) and distance were exported from ArcMap (where they were stored in a .shp file) for each coastal point (2 by 2 m grid cells) in this area. Because inclination and substrate type could not be determined for each location the model predictions are presented assuming an inclination of 45° and HG substrate type. The individual data for wave energy, aspect and distance obtained from ArcMap were then combined with inclination and substrate type to create a dataset of predictor values. The predict functions in gbm (for BRT models) and randomForests was then used to make predictions for the abundance/percent cover and presence-absence of algal species, respectively, for each location based on the values in the prediction dataset. This was only performed for species where models achieved either a D^2 greater than 0.2 or Cohen's- κ greater than 0.5 for BRT and randomForest models respectively. The model predictions were loaded and visualised in ArcMap to produce the final maps.

5.3 – Results

5.3.1 – BIOENV analyses of characteristic species

The majority of individuals were classified to species or genus level. Exceptions include *Siphonaria* sp. (pulmonate limpet) and *Patelloida corticata* (true limpet) that are easily confused, and only distinguished by examining their underside, which could not be performed in the field because of the risk of mortality when removing them. These are grouped into the species group entitled Siphonaria. Similarly *Helminthocladia* sp. and *Catenellopsis oligarthra* were pooled into Ephemeral-reds as they co-occurred regularly both in space and through time; *Colpomenia* spp. and *Leathesia difformis* were grouped into a group entitled Colpomenia due to difficulties distinguishing between these species. The species chosen by the BIOENV analysis as being most indicative of the overall community varied amongst surveys (Table 5.2). The majority of species that were included in the most parsimonious group of species (smallest number of species to achieve a correlation coefficient of 0.95) was mostly consistent amongst surveys (Table 5.2). Of the high intertidal species, 11 of the 12 species identified as indicative of the wider community were selected in seven or eight of the eight survey specific datasets. In the mid intertidal, 11 of the 19 species were chosen in 7-8 of the surveys, two species were chosen in the majority of cases (*Codium*

convolutum and *Hildenbrandia* spp.), whilst two macroalgal species were identified on two-three occasions due to seasonal effects (*Porphyra* sp. and Ephemeral reds), as were two mobile-invertebrate species (*Notoacmea* sp. and *Sypharochiton pelliserpentis*) and the remaining two mobile invertebrate species were chosen as indicative of the wider community in one survey (Table 5.2). In the low intertidal zone, seven core species were identified (in all seasons) and a further eight species were identified by the BIOENV routine in one or more of the surveys (Table 5.2). Based on these findings all species that were identified as characteristic of the wider community on more than two occasions (including across tidal heights) were incorporated into the predictive analyses. In addition, *Halopteris* sp., *Caulacanthus ustulatus*, *Xiphophora gladiata* and *Cystophora* spp. were incorporated due to their high prevalence (greater than 20%) and *Undaria pinnatifida* was incorporated as it is an invasive species and assessing its current distributional characteristics may be important for future monitoring. Therefore the groups modelled consisted of five mobile invertebrate species from the high intertidal zone (correlation coefficient, ρ , for this group of species with the rest of the community; $\rho_{ave} = 0.96$, $\rho_{min} = 0.96$, $\rho_{max} = 0.97$ across surveys), eight mid intertidal mobile invertebrate species ($\rho_{ave} = 0.98$, $\rho_{min} = 0.93$, $\rho_{max} = 0.99$), two sessile invertebrate species at high and mid intertidal heights (high: $\rho_{ave} = 0.99$, $\rho_{min} = 0.98$, $\rho_{max} = 0.99$, mid: $\rho_{ave} = 0.98$, $\rho_{min} = 0.96$, $\rho_{max} = 0.98$), and four high zone ($\rho_{ave} = 0.97$, $\rho_{min} = 0.96$, $\rho_{max} = 0.99$), seven mid zone ($\rho_{ave} = 0.98$, $\rho_{min} = 0.98$, $\rho_{max} = 0.99$) and sixteen low zone ($\rho_{ave} = 0.98$, $\rho_{min} = 0.96$, $\rho_{max} = 0.99$) macroalgal species groups, of which *Porphyra* sp., ephemeral-reds, *Ulva* sp., *Undaria pinnatifida* and *Colpomenia* were considered to be ephemeral species.

Table 5.2. BIOENV analysis results identifying species most responsible for differences in community structure amongst sampling units. Species prevalence amongst sampling units is also given.

Species/Species group name	Description	Tidal Height						Constituent species
		High		Mid		Low		
		no. seasons	Prevalence	no. seasons	Prevalence	no. seasons	Prevalence	
Mobile Invertebrates								
<i>Notoacmea</i>	Limpet	7	0.82	2	0.47			<i>Notoacmea</i> sp.
<i>Cellana denticulata</i>	Limpet	8	0.77	8	0.97			
<i>Cellana ornata</i>	Limpet	8	0.82	8	0.93			
Siphonaria	Limpet	8	0.78	7	0.97			<i>Siphonaria australis</i> , <i>Patelloida corticata</i>
<i>Austrolittorina</i>	Sea snail	8	0.96	8	0.45			<i>A. australis</i> , <i>A. cincta</i>
<i>Sypharochiton pelliserpentis</i>	Chiton	1	0.20	3	0.49			
<i>Cellana radians</i>	Limpet			8	0.83			
<i>Risellopsis varia</i>	Sea snail			7	0.54			
<i>Diloma aethiops</i>	Sea snail			1	0.14			
<i>Onchidella nigricans</i>	Sea slug			1	0.15			
Sessile Invertebrates								
<i>Chamaesipho brunnea</i>	Barnacle	8	0.94	8	0.7			
<i>Chamaesipho columna</i>	Barnacle	8	0.59	8	0.66			
Macroalgae								
<i>Porphyra</i>	Foliose red	8	0.60	2	0.22			<i>Porphyra</i> spp.
<i>Gelidium pusillum</i>	Turfing red	8	0.47					
<i>Apophlaea sinclairii</i>	Encrusting red	7	0.26					
<i>Hapalospongidion saxigenum</i>	Encrusting brown			8	0.31			
Ephemeral Reds	Turfing red			3	0.3			<i>Helminthocladia</i> sp., <i>Catenellopsis oligarthra</i>
Crustose coralline algae (CCA)	Encrusting coralline	8	0.33	8	0.94	8	0.99	Non-geniculate corallines
<i>Hildenbrandia</i> spp.	Encrusting red			5	0.49	1	0.5	<i>H. kerguelensis</i> , <i>Hildenbrandia</i> sp.
<i>Diplura</i> sp.	Encrusting brown			8	0.41	8	0.47	<i>Diplura</i> sp.
<i>Codium convolutum</i>	Cushion forming green			5	0.2	5	0.24	
Coralline turf	Turfing coralline					8	0.81	Geniculate corallines
<i>Champia novae-zelandiae</i>	Turfing red					8	0.47	
<i>Caulacanthus ustulatus</i>	Turfing red					2	0.25	
<i>Ulva</i> sp.	Foliose green					3	0.35	<i>U. lactuca</i> , <i>Ulva</i> sp.
<i>Ralfsia expansa</i>	Encrusting brown					2	0.10	
<i>Zonaria</i> sp.	Turfing/Small brown					8	0.72	<i>Z. turneriana</i> , <i>Zonaria</i> sp.
<i>Halopteris</i> sp.	Turfing/Small brown						0.32	<i>H. funicularis</i> , <i>H. virgata</i>
<i>Xiphophora gladiata</i>	Small brown					2	0.28	
<i>Glossophora kunthii</i>	Small brown					1	0.14	
<i>Cystophora</i> spp.	Large brown						0.22	<i>C. retroflexa</i> , <i>C. scalaris</i> , <i>C. torulosa</i>
<i>Undaria pinnatifida</i>	Large brown						0.09	
<i>Carpophyllum maschalocarpum</i>	Large brown					8	0.73	
<i>Durvillaea antarctica</i>	Large brown					8	0.25	
<i>Colpomenia</i>	Ephemeral brown					6	0.52	<i>C. sinuosa</i> , <i>C. durvillaei</i> , <i>Leathesia difformis</i>

5.3.2 – Results of boosted regression tree analyses

Models of species' abundances within the high intertidal quadrats performed better than in the mid intertidal with an average D^2 of 0.3 (range 0.04-0.62) for high intertidal quadrats compared to 0.19 (range 0.07-0.5) for mid intertidal quadrats (Table 5.3).

Table 5.3. Boosted regression tree model results for sessile and mobile invertebrates giving statistics related to model performance, predictor importance, and the modelling parameters for the model with the lowest cross-validated residual deviance. In each case the optimal number of trees was determined by 10-fold cross validation. Model performance statistics represent the mean value across 20 repeat runs with the same model parameters, whilst the reported number of trees (*nt*) is the median number identified across these 20 repeats. (+/-) refers to the Distance predictor with + indicating a monotonically increasing function and - indicating a monotonically decreasing function.

Species	Height	Model Performance			Predictor Relative Importance							Model Parameters				Wave scale size
		Null deviance	Cross validated residual deviance (SE)	D ²	Inc	Asp	Subs	Wave ave	Wave min	Wave max	Dist (+/-)	lr	bf	tc	nt	
Sessile Invertebrates																
<i>Chamaesipho brunnea</i>	H	4.2	1.6 (0.3)	0.62	9	9	13	27			42 (+)	0.0075	0.75	1	3025	15 m
	M	3.5	3.1 (0.4)	0.12	3	3	42	42			10 (+)	0.001	0.75	4	1675	10 m
<i>Chamaesipho columna</i>	H	7.1	3.8 (0.7)	0.46	16	8	6		12	12	46 (-)	0.0025	0.65	3	7875	20 m
	M	3.9	2.8 (0.5)	0.27	1	7	1	19			72 (-)	0.001	0.75	1	2600	20 m
Mobile Invertebrates																
<i>Notoacmea</i> sp.	H	6.0	4.0 (0.8)	0.34	12	11	1	58			18 (+)	0.001	0.7	4	3275	20 m
	M	5.3	4.7 (1.1)	0.12	9	4	19	55			13 (-)	0.0025	0.7	3	1275	10 m
<i>Cellana denticulata</i>	H	5.7	5.5 (1.6)	0.04	14	16	10	49			11 (+)	0.0075	0.75	4	1350	5 m
	M	4.1	2.9 (0.6)	0.30	21	5	2		38	10	24 (+)	0.0025	0.65	4	3275	10 m
<i>Cellana ornata</i>	H	10	9.5 (1.2)	0.05	21	11	10	46			12 (+)	0.005	0.75	2	2000	5 m
	M	10.9	9.7 (1.4)	0.12	23	15	9	33			20 (-)	0.0075	0.75	3	1700	5 m
<i>Austrolittorina</i>	H	494	287 (55)	0.42	19	16	1		38	14	12 (-)	0.0075	0.7	4	3650	15 m
	M	45.3	42.3 (16.5)	0.07	13	12	11	45			19 (-)	0.0075	0.65	4	1250	10 m
Siphonaria	H	4.9	3.9 (0.6)	0.20	22	15	3		35	8	17 (+)	0.01	0.65	2	1250	15 m
	M	10.3	5.2 (1.1)	0.50	42	9	23		4	14	8 (-)	0.005	0.75	1	2400	5 m
<i>Sypharochiton pelliserpentis</i>	M	2.3	1.9 (0.5)	0.16	2	17	31		20	7	23 (-)	0.001	0.7	1	1550	20 m
<i>Cellana radians</i>	M	2.8	2.3 (0.4)	0.20	10	14	19	26			31 (-)	0.0025	0.65	3	2025	10 m
<i>Risellopsis varia</i>	M	2.9	2.8 (0.8)	0.06	18	20	5	30			27 (-)	0.0075	0.7	4	950	10 m

The two *Chamaesipho* (barnacle) species had relatively high D² values for the high shore quadrats, but lower D² values at mid tidal heights. These two species had contrasting responses with regard to Distance (Figure 5.3), but both showed a positive response with

regard to wave exposure (Figure 5.3). In addition, *C. columna* showed a preference for flat to slightly inclined surfaces (<40°) (Figure 5.3).

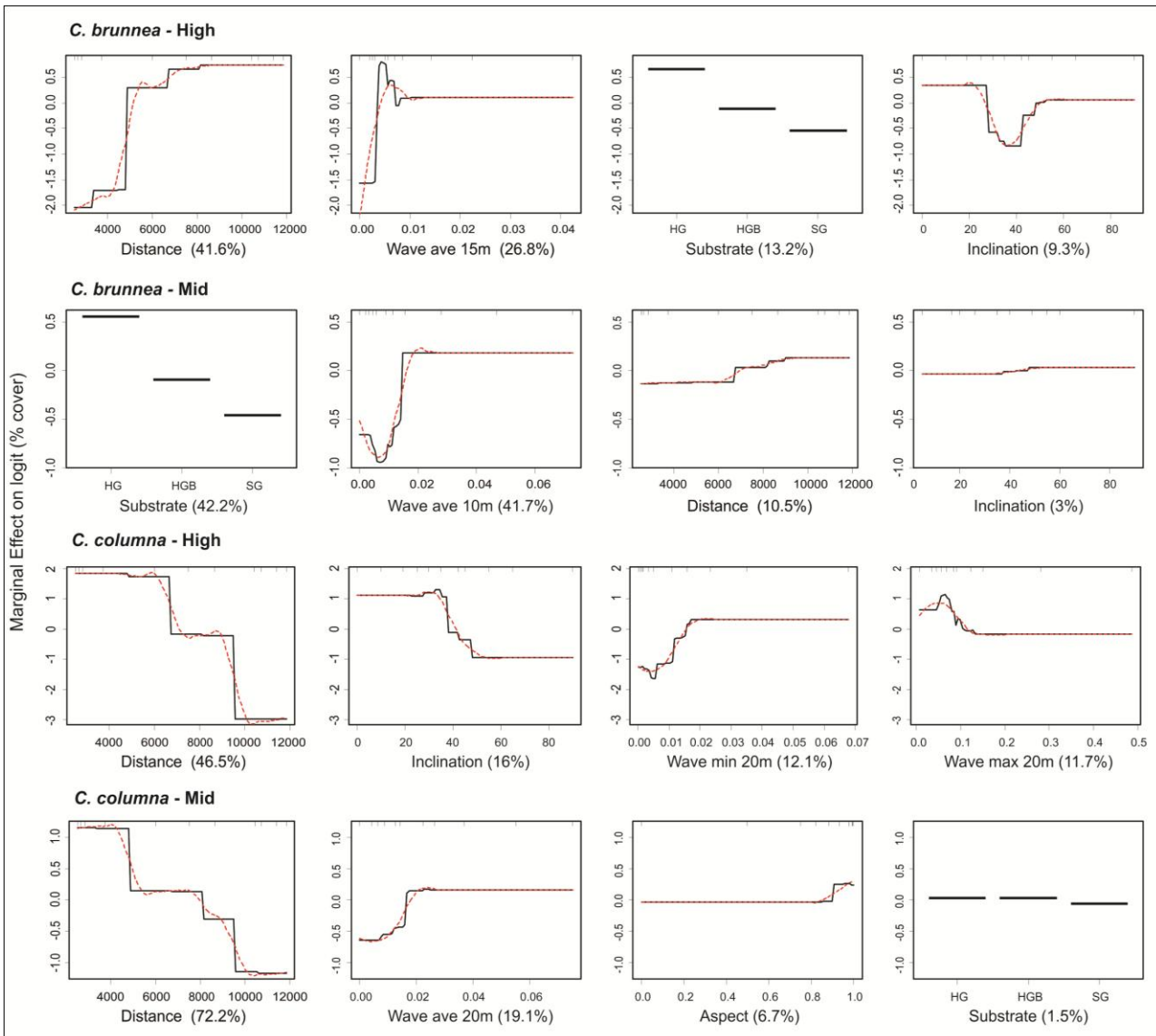


Figure 5.3. Partial dependency plots of BRT models for sessile invertebrate species. Black lines illustrate the fitted function of the marginal effect of each predictor on the logistic transformed % cover, whilst dotted red lines indicate a smoothed fit to the fitted function. Values in parentheses next to x axis labels indicate predictor relative importance.

The abundances of mobile invertebrates were in general less well predicted by these models than the abundance of sessile invertebrates (Table 5.3). Wave forces were the best predictors for species occupying the high tidal zone, with all displaying increases in abundance with increasing wave exposure (Figure 5.4). Siphonaria, however, showed a decrease in abundance for the highest wave exposures and was most abundant at moderate wave exposures (Figure 5.4). Models for the larger limpets, *C. denticulata* and *C. ornata*, at high tidal heights had very low D^2 values indicating poor predictive performance (Table 5.3).

At mid intertidal heights, *C. denticulata* was more abundant in more exposed locations, tending to prefer flat to moderately inclined surfaces, with increasing abundance moving away from the harbour mouth (Figure 5.4). This is in contrast to *C. radians*, which displayed opposite patterns in abundance in response to distance and wave exposure (Figure 5.4). Siphonaria at mid intertidal heights did not display the same preference for medium to high wave exposure as individuals at high tidal heights, but were more abundant on flat to moderately inclined surfaces, and at locations with SG substrate type (Figure 5.4). Models for the remaining species had low predictive power ($D^2 \leq 0.16$). However, *Notoacmea* sp. abundance displayed similar responses to wave action and inclination as at high tidal heights (Appendix 3, Figure A3.1).

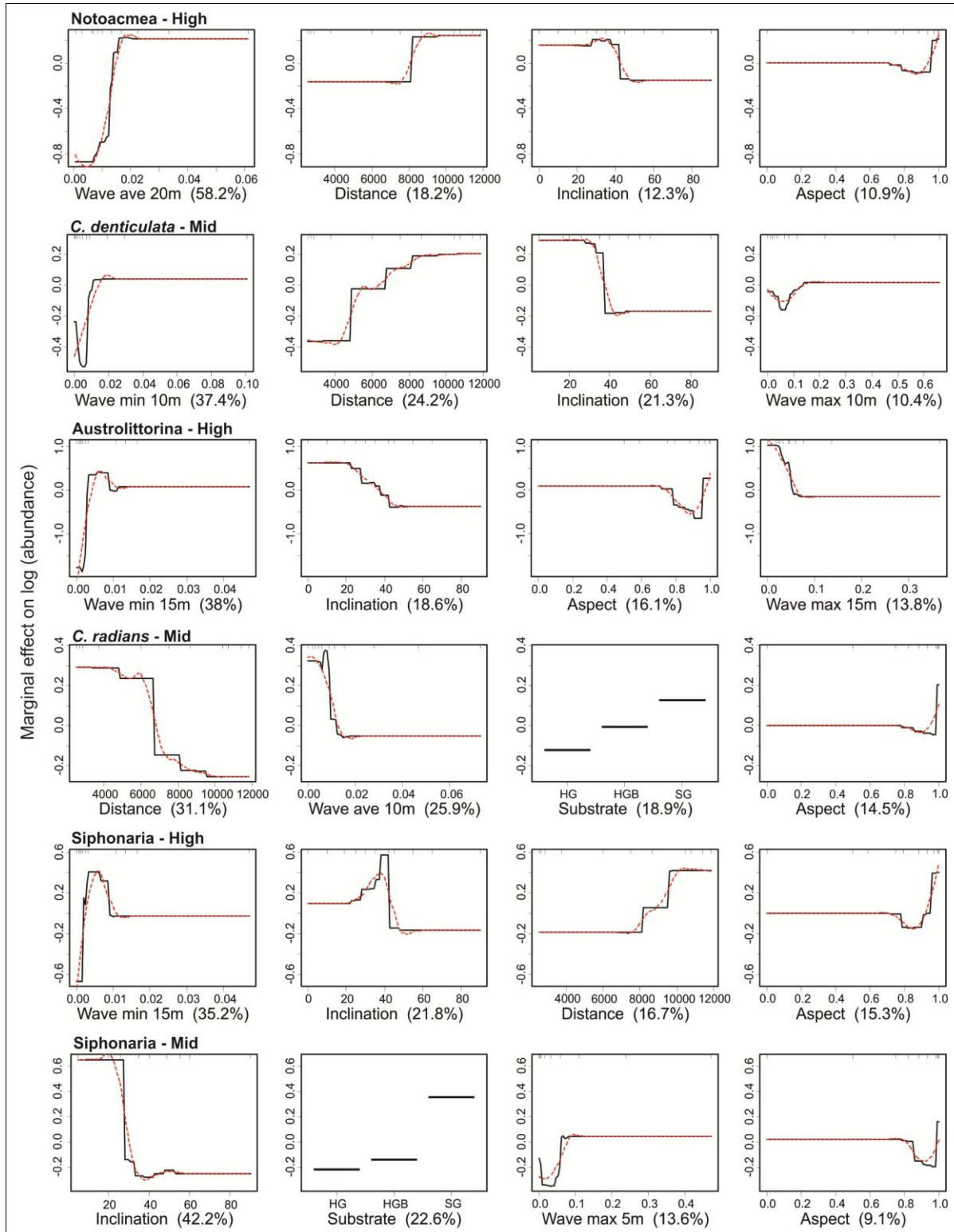


Figure 5.4. Partial dependency plots of BRT models for mobile invertebrate species where models achieved a $D^2 \geq 0.2$. Black lines illustrate the fitted function of the marginal effect of each predictor on the log transformed abundance, whilst dotted red lines indicate a smoothed fit to the fitted function. Values in parentheses next to x-axis labels indicate predictor relative importance.

5.3.3 – Results of random forests analyses

Models for CCA at mid and low tidal heights were not performed as it was present in all but one surveyed location at mid tidal heights and in all low surveyed locations. The classification analyses achieved a high classification accuracy, with all 25 models achieving OOB error rates less than 40%, and nearly half of all models (12) achieving error rates less than 20% (Table 5.4). Mean OOB error rates were 19.9% (median: 21.7%) and sensitivity (proportion of presences correctly predicted) and specificity (proportion of absences correctly predicted) were similarly high, with a mean rate of 74.2% (median: 76.2%) and 73.1% (median: 82.8%). Cohen's- κ corresponded closely to OOB error rates, with low OOB error rates corresponding to high κ values for all but two groups, *Porphyra* spp. – high and *C. maschalocarpum* (Table 5.4). These had low OOB error rates, but also low κ values. There was considerable variation in model performance amongst tidal heights with models for species at high and mid tidal heights performing poorly compared with models for low intertidal species (Table 5.4).

At high tidal heights only one species achieved a relatively low OOB error rate (*Porphyra* spp., OOB error 11.1%), however, examination of Cohen's- κ revealed that agreement between predictions and observations was due entirely to chance ($\kappa=0$) with all absences misclassified as presences (Table 5.4). Models for the remaining species had κ -values of 0.34-0.42 indicating some agreement between observations and predictions, more than would be expected by chance. Models for *Gelidium pusillum* predicted that it was more likely to be found in wave-exposed locations, on moderately inclined surfaces that were east/west to southerly facing whereas *Apophlaea sinclairii* was more likely to be found on flat surfaces at medium to high wave exposures, displaying a preference for the sandstone dominated (SG) substrate type (Appendix 3, Figure A3.3). Models describing CCA predicted a preference for the SG substrate type, with some indication that it was more likely to be found at higher wave exposures on flat to moderately inclined surfaces (Appendix 3, Figure A3.3).

Table 5.4. Model results for algal presence-absence, including OOB error (% observations misclassified), sensitivity (% presences correctly classified), specificity (% absences correctly classified), and Cohen's- κ (proportion of agreements corrected for chance agreement) for the model with the lowest OOB error. Values in parentheses indicate the fraction of presences/absences correctly classified for sensitivity/specificity respectively. Predictor importance is the average % increase in OOB error when that factor is omitted.

Species	Height	OOB error (%)	Sensitivity (%)	Specificity (%)	Cohen's- κ	Predictor Importance						Wave Scale Size
						Inclination	Aspect	Substrate	Wave min	Wave max	Wave ave	
<i>Porphyra</i> sp.	H	11.1	100.0 (40/40)	0.0 (0/5)	0.00	3.5	-0.8	5.4	7.8	9.5		15 m
	M	35.6	66.7 (14/21)	62.5 (15/24)	0.29	1.7	-0.9	9.3			6.4	20 m
<i>Gelidium pusillum</i>	H	26.7	83.9 (26/31)	50.0 (7/14)	0.35	3.5	6.2	1.0			11.1	20 m
<i>Apophlaea sinclairii</i>	H	28.9	50.0 (8/16)	82.8 (24/29)	0.34	6.8	5.5	7.7	2.2	12.7		15 m
<i>Hapalospongidion saxigenum</i>	M	22.2	62.5 (10/16)	86.2 (25/29)	0.50	0.8	2.4	1.3	9.0	13.5		20 m
Ephemeral Reds	M	28.9	55.5 (10/18)	81.5 (22/27)	0.38			13.8	5.9	9.6		20 m
CCA	H	28.9	76.2 (16/21)	66.6 (16/24)	0.42	5.1	-2.8	15.1	6.2	6.2		20 m
<i>Hildenbrandia</i> sp.	M	28.9	84.4 (27/32)	38.5 (5/13)	0.25	2.4	-2.4	0.9	7.2	5.0		20 m
	L	26.1	90.3 (28/31)	40.0 (6/15)	0.34		3.1	3.4	10.9			20 m
<i>Diplura</i> sp.	M	31.1	68.2 (15/22)	69.6 (16/23)	0.38	2.5	2.8	14.4	5.8	-0.6		10 m
	L	10.9	90.9 (20/22)	87.5 (21/24)	0.78	4.6	4.4	13.6	19.7	10.1		20 m
<i>Codium convolutum</i>	M	26.7	46.2 (6/13)	84.4 (27/32)	0.32	1.4	10.8	7.1			11.0	10 m
	L	10.9	63.7 (7/11)	97.1 (34/35)	0.67	15.3	5.6	9.6	8.8	1.8		10 m
Coralline Turf	L	2.2	100 (43/43)	66.7 (2/3)	0.79	6.3	4.7	-0.1			2.7	10 m
<i>Champia novae-zelandiae</i>	L	17.4	79.2 (19/24)	86.4 (19/22)	0.65	-0.5	6.3	15.6	13.4	9.6		20 m
<i>Caulacanthus ustulatus</i>	L	15.2	60.0 (9/15)	96.8 (30/31)	0.62	-0.1	1.2	0.5			19.7	20 m
<i>Ulva</i> sp.	L	21.7	68.4 (13/19)	85.2 (23/27)	0.54	7.0	8.4	1.6	17.4	0.8		15 m
<i>Zonaria</i> sp.	L	2.2	100 (40/40)	83.3 (5/6)	0.90	1.8	10.5	2.2	16.4	4.7		20 m
<i>Halopteris</i> sp.	L	30.4	61.1 (11/18)	75 (21/28)	0.36	10.0	0.2	0.7	5.1	-1.7		10 m
<i>Xiphophora gladiata</i>	L	28.3	33.3 (5/15)	90.3 (28/31)	0.27	6.7	5.0	7.5	6.1	9.6		15 m
<i>Cystophora</i> spp.	L	13.0	76.5 (13/17)	93.1 (27/29)	0.71		4.2	11.0	19.7	13.0		20 m
<i>Undaria pinnatifida</i>	L	13.0	78.5 (11/14)	90.6 (29/32)	0.69	9.2		18.3	16.7			15 m
<i>Carpophyllum maschalocarpum</i>	L	17.4	92.1 (35/38)	37.5 (3/8)	0.33		0.6	4.3	14.1	5.9		20 m
<i>Colpomenia</i>	L	13.0	93.1 (27/29)	76.5 (13/17)	0.71	1.8	1.2	5.1	18.8	8.9		10 m
<i>Durvillaea antarctica</i>	L	8.7	75.0 (12/16)	100.0 (30/30)	0.80	-1.5	-0.7	-0.3	18.7	17.5		20 m

Models for macroalgal groups at mid tidal heights had mean OOB error rates of 28.9% (median: 28.9%), with similarly low κ -values (0.25-0.5). The model for *H. saxigenum*, however, had a κ -value of 0.5 (Table 5.4), with the model predicting that this species was present predominantly at the most exposed locations (Figure 5.5), with maximum and minimum wave exposure indices having the highest predictor importance (Table 5.4). The response displayed by *Porphyra* sp. at mid tidal heights was again unclear but showed an increased likelihood of occurrence on HG substrates at moderate inclinations and high wave exposures (Appendix 3, Figure A3.4). Ephemeral red algae were more likely to be found on the SG substrate type at mid to high wave exposures (Appendix 3, Figure A3.4). Of the encrusting algal types *Hildenbrandia* sp. was more likely to be found at high wave exposures, but not at the most exposed locations (decline at highest wave exposures revealed by Wave max) and on inclined surfaces, whereas *Diplura* sp. was most likely to be found on the SG substrate type in sheltered, south-facing locations with moderate to wall like inclinations (Appendix 3, Figure A3.4). *C. convolutum* displayed a preference for south-facing, wave-sheltered locations (Appendix 3, Figure A3.4).

Models for species at low tidal heights achieved low OOB error rates, averaging 15.36% (median 13.0%), with high sensitivity (mean: 77.47%, median: 78.5%) and specificity (mean: 80.4%, median: 86.4%) as well as similarly high κ -values (mean: 0.61, range 0.27 – 0.9). For the encrusting species, models indicate that *Diplura* sp. and *C. convolutum* predominantly occupy wave-sheltered locations, favouring the SG substrate type, with *C. convolutum* also showing a strong preference for more inclined surfaces (Figure 5.5). Models for *Hildenbrandia* sp. indicate a preference for non-North facing boulder substrates but showed contrasting responses with regard to wave exposure, tending to be present at low to mid wave exposures, when compared to mid tidal height models (Appendix 3, Figure A3.5). The predictor response for coralline turf indicates a preference for flat to moderately inclined surfaces of any aspect except those facing due south (Figure 5.5).

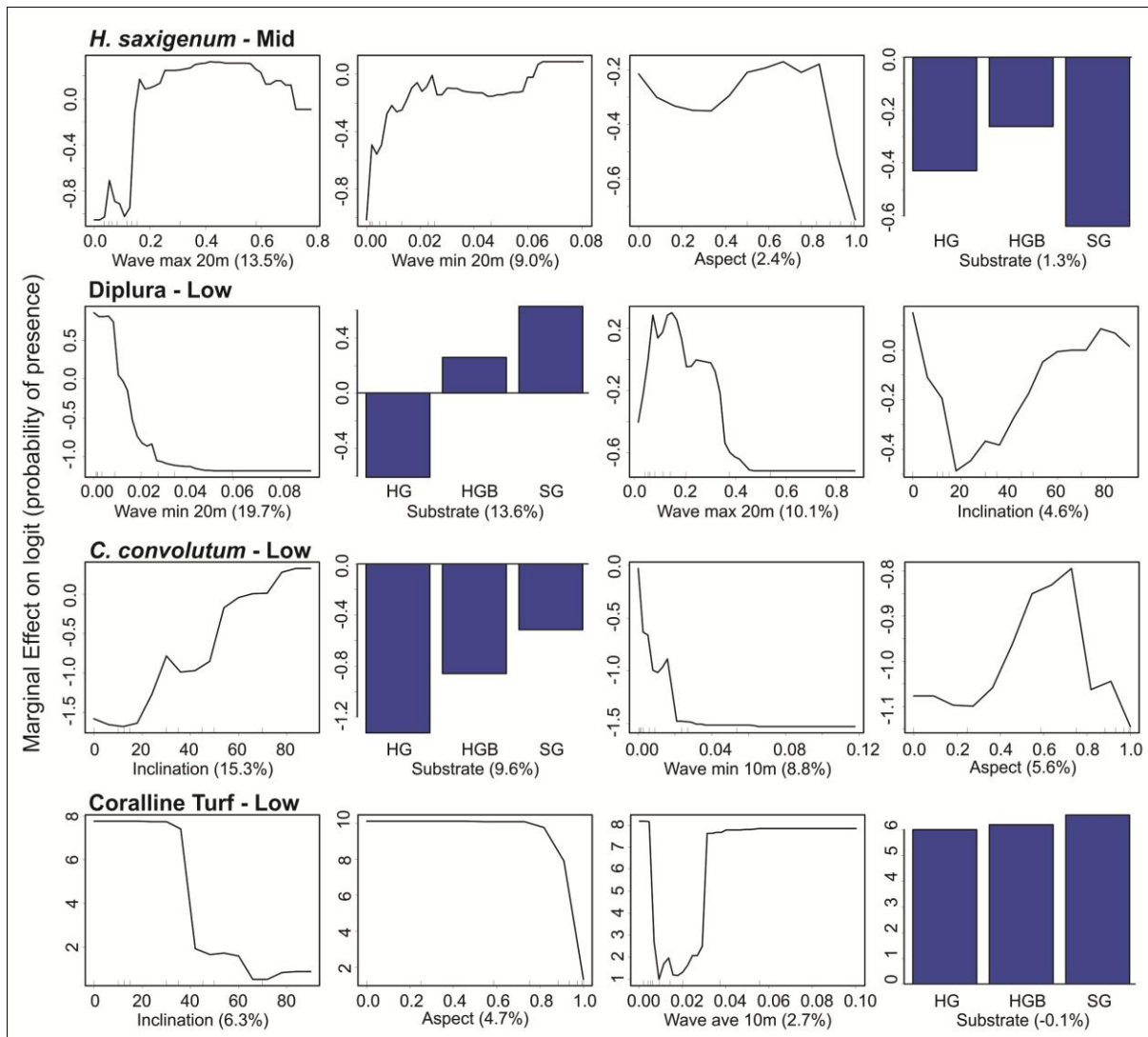


Figure 5.5. Partial dependency plots for encrusting algal species presence-absence based on relationships obtained from random forests analyses. Plotted functions illustrate the logistic transformed probability of each species being present as a function of each predictor for the top four predictors ranked by predictor importance. Values in parentheses next to x axis labels indicate predictor importance.

Models of the understory/turfing algal species reveal that *Zonaria* sp. was present at all locations except those that face due-south and experience very high wave action (Figure 5.6), with *Halopteris* sp. displaying similar responses with regard to wave action and aspect, but tending to be found predominantly on flat to moderately inclined surfaces ($< 30^\circ$) (Appendix 3, Figure A3.5). Models for *C. novae-zelandiae* indicated a preference for the SG substrate type but displayed a similar response to wave exposure as *Zonaria* sp. (Figure 5.6). Models for *C. ustulatus* predict that it is most likely to be found in wave-exposed locations, with other factors having little effect (Figure 5.6). The ephemeral species, *Ulva* sp. and *Colpomenia* were revealed to occur predominantly in wave-sheltered locations, displaying a

preference for the SG substrate type (Figure 5.6). Both were also predicted to be more likely to occur on flat surfaces, with *Ulva* sp. less likely to occur on south-facing surfaces (Figure 5.6).

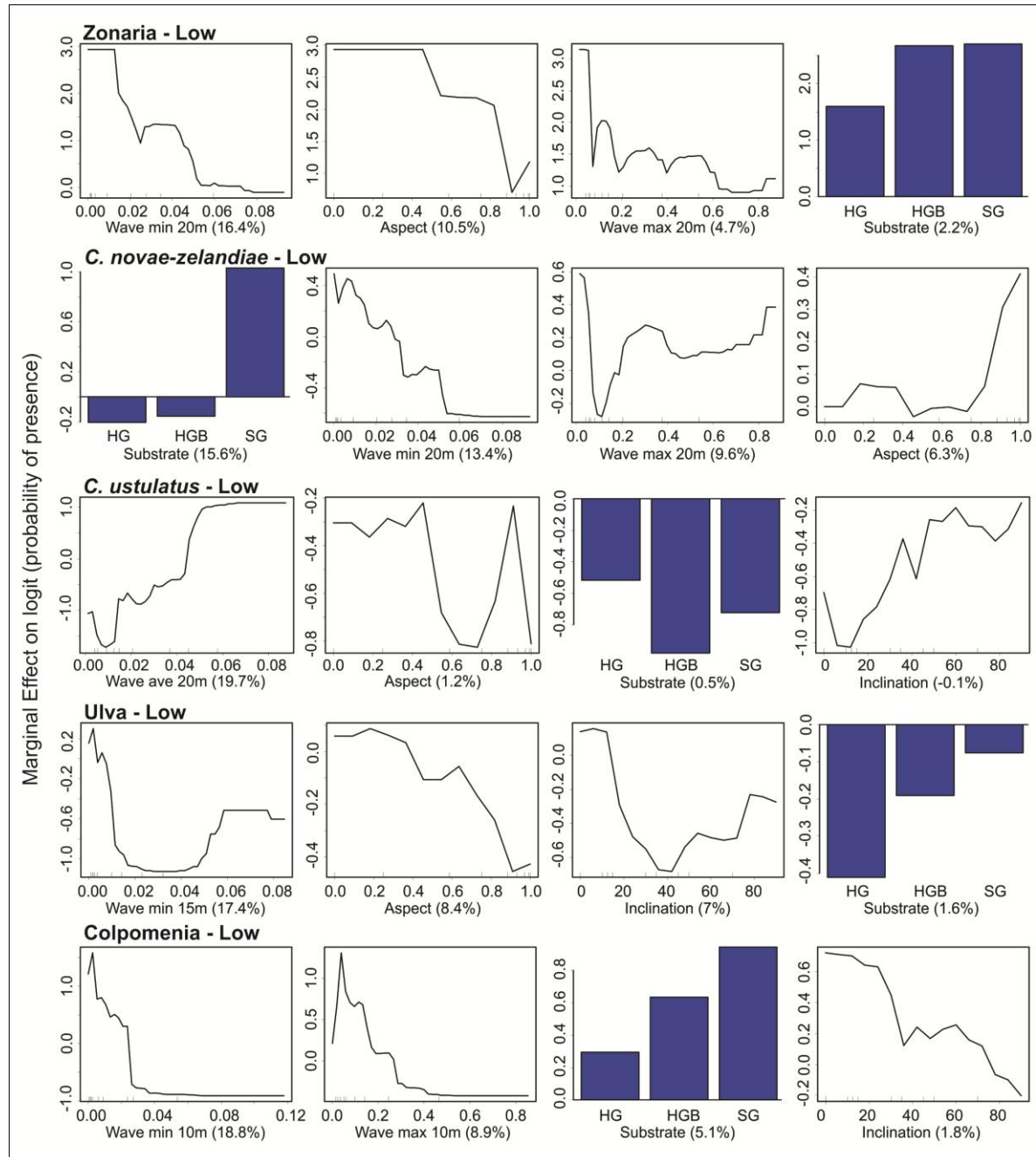


Figure 5.6. Partial dependency plots for understory/turfing and ephemeral algal species presence-absence based on relationships obtained from random forests analyses. Plotted functions illustrate the logistic transformed probability of each species being present as a function of each predictor for the top four predictors ranked by predictor importance. Values in parentheses next to x-axis labels indicate predictor importance.

The remaining macroalgal groups consisted of large brown algal species. Models for *C. maschalocarpum* had a low κ -value (0.33), indicating the majority of agreements were due to chance with most absences misclassified (Table 5.4). As a result partial dependency plots were difficult to interpret (Figure 5.7). Models for *X. gladiata* failed to accurately predict when this species would be present in the majority of cases (sensitivity 33.3%), but partial dependency plots indicate presences were most likely in mid wave-exposure locations on flat to moderately inclined surfaces (Appendix 3, Figure A3.5). Models for the remaining large brown algal species had κ -values in the range 0.69-0.8 indicating good agreement between model predictions and observations. Of the remaining species models predicted that *D. antarctica* was present only in the most wave-exposed locations, whereas *Cystophora* spp. and *U. pinnatifida* are predicted to occur only in wave-sheltered locations, favouring boulder and sandstone dominated substrates, respectively (Figure 5.7).

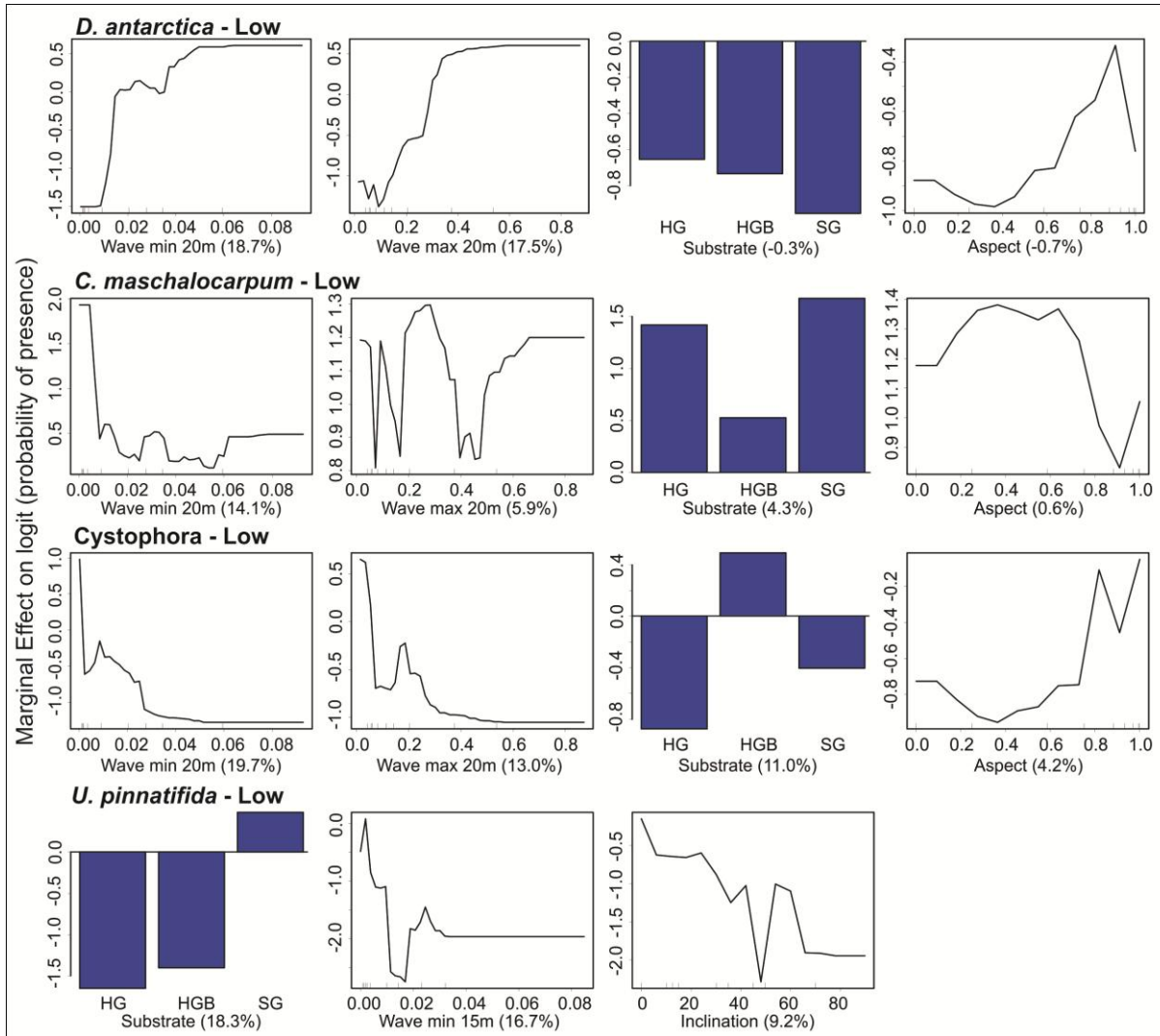


Figure 5.7. Partial dependency plots for canopy forming algal species presence-absence based on relationships obtained from random forests analyses. Plotted functions illustrate the logistic transformed probability of each species being present as a function of each predictor for the top four predictors ranked by predictor importance. Values in parentheses next to x axis labels indicate predictor importance.

5.3.4 – Predictive maps

The abundance/percent cover for *C. brunnea* and *Notoacmea* sp. are similar in having the greatest abundance at the most exposed locations on the forefront of intertidal platforms, whereas *Austrolittorina* spp. showed a similar distribution, but had greatest abundance in mid exposure locations away from the front of intertidal platforms, and lowest abundance in the most sheltered locations behind obstacles (Figure 5.8). Siphonaria abundance was predicted to be greatest at moderate exposure locations and least in very sheltered and exposed locations (Figure 5.8). *C. columna* abundance decreased from east to west (Figure 5.8).

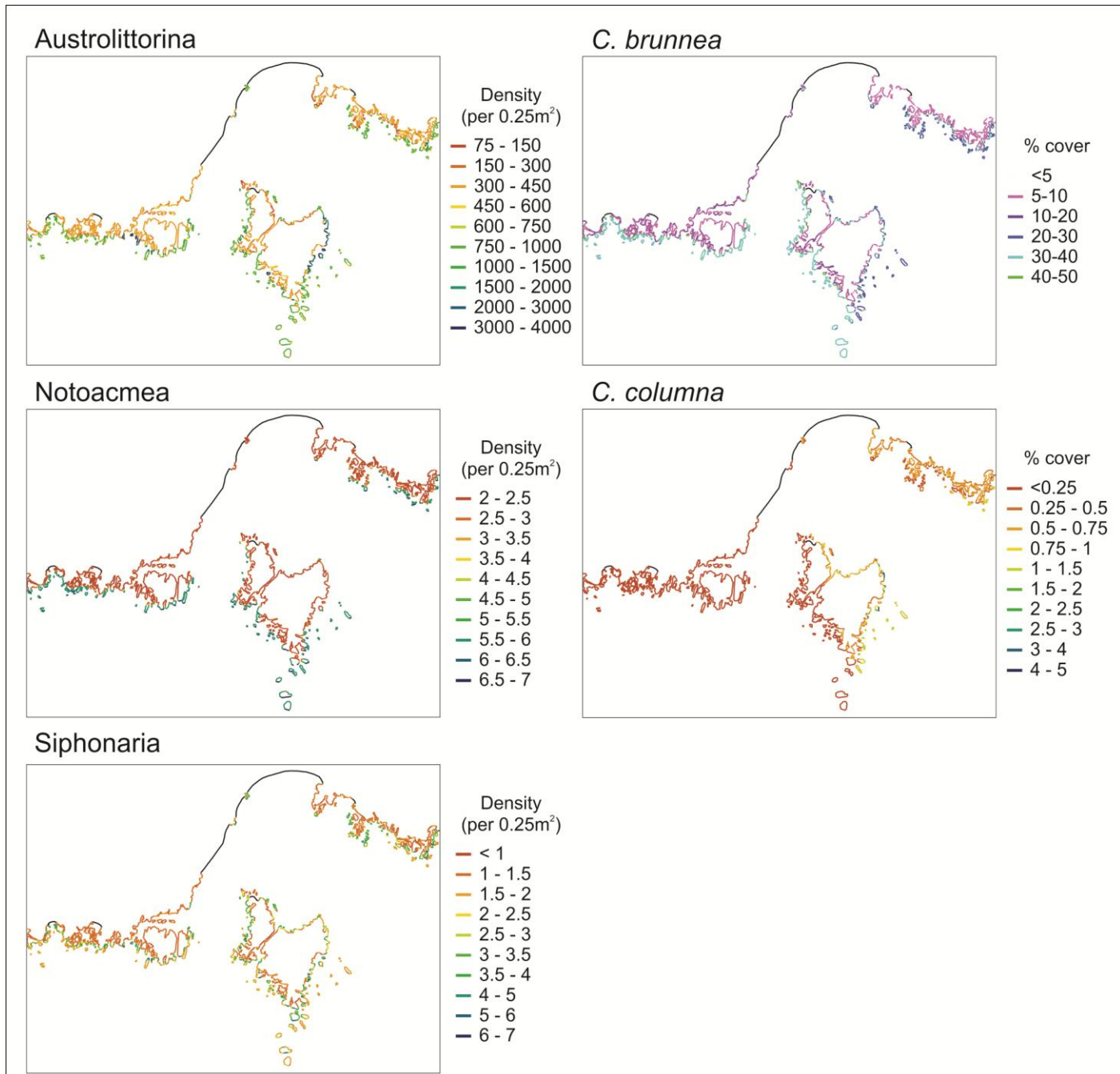


Figure 5.8. Maps illustrating the abundance and % cover for species in the high intertidal zone. Black lines in all figure panels indicate unsuitable habitat in the form of sand and/or gravel sections of coastline.

C. denticulata was predicted to be most abundant in exposed locations at the forefront of intertidal platforms and increased in abundance from east-west (Figure 5.9). This is in contrast to *C. radians*, which displays the opposite patterns of abundance (Figure 5.9). The encrusting alga *H. saxigenum* was predicted to be predominantly found at open wave-exposed locations at the tips of intertidal platforms (Figure 5.9).

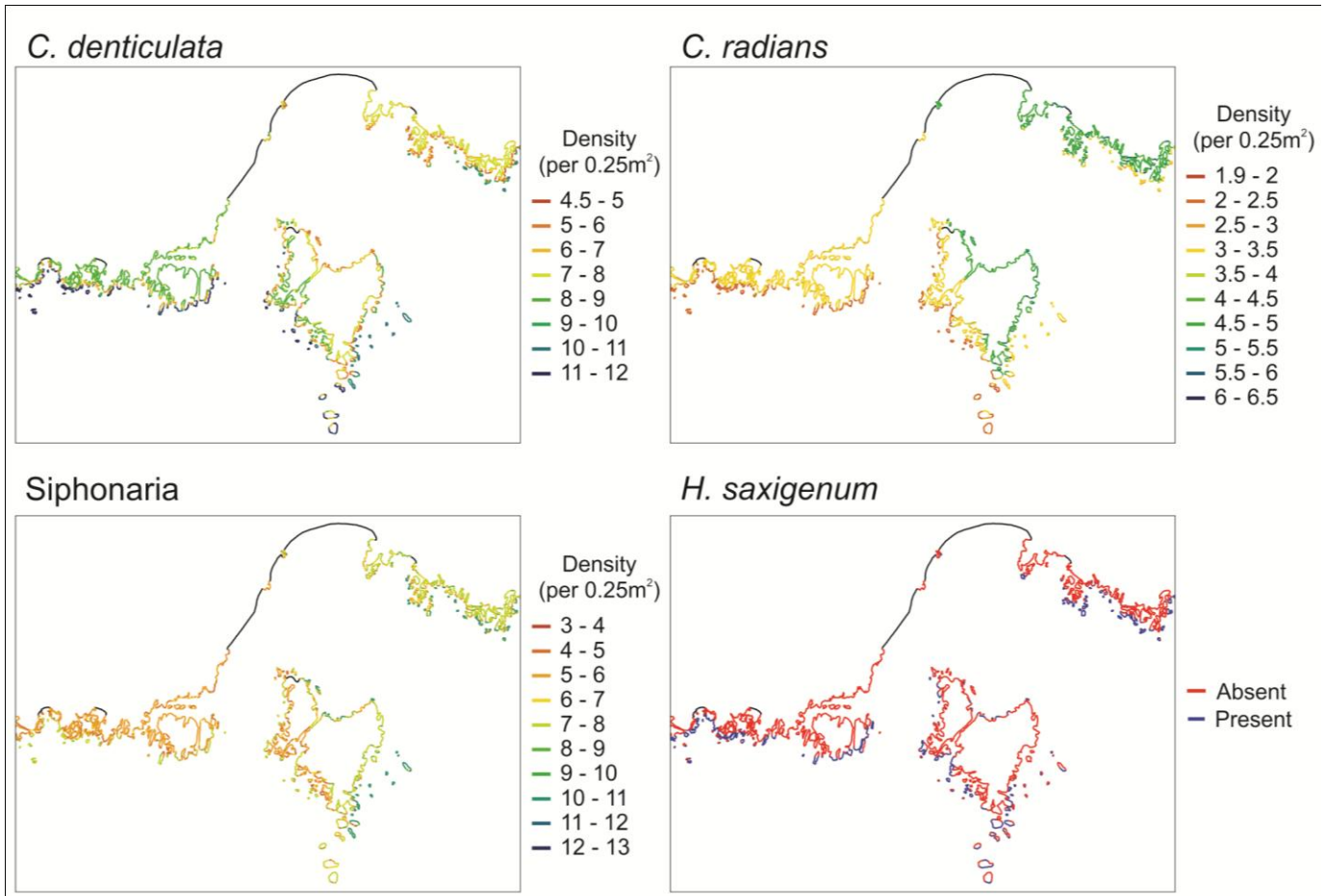


Figure 5.9. Maps illustrating the abundance of mobile invertebrate species and the presence-absence of the encrusting algae *Hapalospongidion saxigenum* in the mid intertidal zone. Black lines in all figure panels indicate unsuitable habitat in the form of sand and/or gravel sections of coastline.

The low intertidal algal species' distributions illustrate a shift in community from a diverse algal assemblage in sheltered locations to an assemblage consisting of only a few species at the most exposed locations (Figure 5.10). At the most sheltered locations all species except *D. antarctica* and *C. ustulatus* were predicted to be present. At mid exposure locations *Cystophora* spp., *Ulva* sp. and *Diplura* sp. become absent and at the most exposed locations at the tips of intertidal projections and intertidal islands a community consisting of coralline turf, *Zonaria* sp., *C. maschalocarpum*, *C. ustulatus* and *D. antarctica*, with no ephemeral species, was predicted (Figure 5.10).

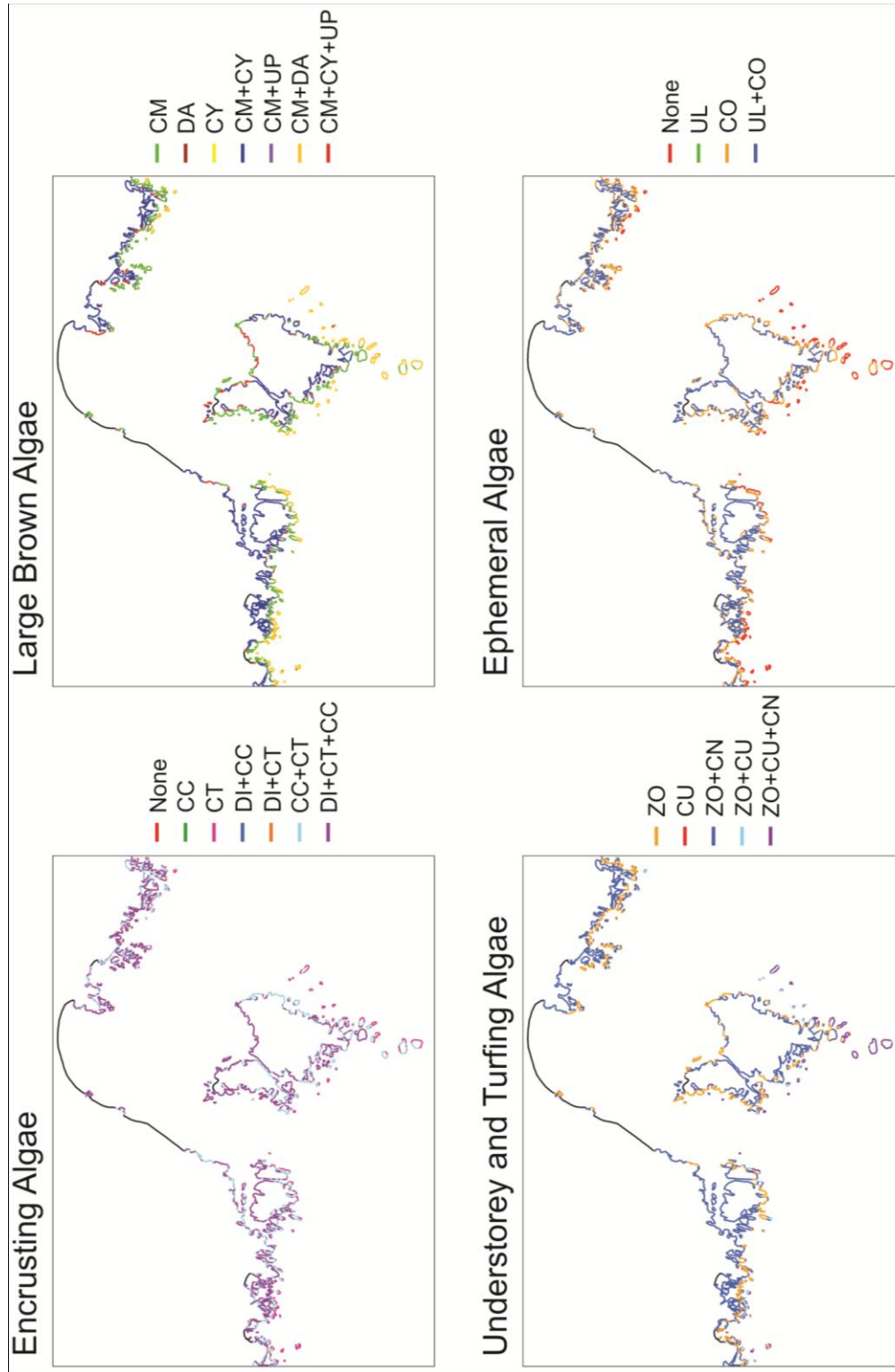


Figure 5.10. Maps illustrating the species composition, based on presence-absence, of different algal groups in the low intertidal zone. Abbreviations are CC – *Codium convolutum*, CT – coralline turf, DI – Diplura, ZO – *Zonaria* sp., CU – *Caulacanthus ustulatus*, CN – *Champia novae-zelandiae*, CM – *Carpophyllum maschalocarpum*, DA – *Durvillaea antarctica*, CY – *Cystophora* spp., UP – *Undaria pinnatifida*, UL – *Ulva* sp. and CO – Colpomenia. Black lines in all figure panels indicate unsuitable habitat in the form of sand and/or gravel sections of coastline.

5.4 – Discussion

Exhaustive biological surveys are logistically not feasible, and given the already high costs of performing field surveys there is a great incentive to increase the capacity of what monitoring data can reveal regarding ecological patterns (Nicholls 1989; Manel *et al.* 1999). As demonstrated here, predictive species distribution models can increase the spatial applicability of limited field surveys to achieve more widespread coverage. The increased use of machine learning routines (Robinson *et al.* 2011), such as BRT and RF, that are designed specifically for prediction (Elith & Leathwick 2009) have aided in the development of models to increase predictive capabilities, subsequently increasing the confidence that can be placed in the results of distribution modelling. Although not as frequently applied in marine ecological studies compared to terrestrial studies (Robinson *et al.* 2011), this study demonstrates that, in conjunction with wave model predictions, adequate predictive models can be developed for intertidal species on relatively fine spatial scales.

Explanation (how, why) and prediction (where, when) are two separate concepts, and whilst explanation may be sufficient for prediction, prediction based on the identification of correlative relationships (rather than causative relationships such as is the case for process-based species distribution modelling) (Morin & Thuiller 2009) is not always sufficient for explanation of the ecological process causing these patterns. Despite this many of the predictive relationships identified in this study are consistent with the ecology of these species.

5.4.1 – Abiotic associations

Of the two barnacle species examined both showed increased abundance with increasing wave exposure (Figure 5.3), which is consistent with earlier research for barnacles in general (e.g., Ballantine 1961; McQuaid & Branch 1985; Menge 2000a) and particularly for *Chamaesipho brunnea*, which is often a characteristic feature of exposed locations in New Zealand (Morton & Miller 1968; Raffaelli 1979). This may arise from the more frequent delivery of food through wave-induced flow (McQuaid & Lindsay 2000), and because barnacles in more wave-exposed locations are submerged more frequently than those in wave-sheltered locations, increasing the capacity for feeding (Menge 2000a). This may be particularly important in this area as it has been suggested that low particulate food concentration in the water column may be the reason why mussels are almost absent along the Wellington South Coast (Helson *et al.* 2007; Gardner 2008). Thus food availability may

be a limiting resource for mussels and barnacles that both rely on suspended particulate food matter. However, little black mussel (*Limnoperna pulex*) abundance was highest at the more wave exposed locations, but more importantly their abundance was greatest at locations with the highest *C. brunnea* % cover (see Appendix 3B). This suggests that *L. pulex* are capable of surviving under similar conditions as *C. brunnea* (however, a positive association between these species can also not be discounted). Furthermore, Gardner (2008) noted that the larger *Perna canalicula* died sooner when placed in Cook Strait water than the smaller *Mytilus galloprovincialis* and *Aulacomya maoriana* suggesting that the low particulate food concentration in Cook Strait water was insufficient to maintain larger individuals. Therefore food limitation may act to restrict the larger bodied mussels from colonising the south coast but smaller bodied individuals, such as *L. pulex* (and also *C. brunnea*), may be able to survive at lower food concentrations. If these food requirements also apply to barnacles then the combined effects of increased feeding times (due to more frequent submersion) and increased replenishment of local food availability (through increased water flow with wave action, McQuaid & Lindsay 2000) may explain the higher % cover of barnacles and *L. pulex* in wave-exposed locations. Other factors may also be important, such as increased barnacle recruitment and a reduction in mortality rates from desiccation/heat stress (due to splash and surge) and predation (due to predator dislodgement and a reduction in predator foraging times) at the more exposed locations (Menge 1983, 2000b). Interspecific competition is unlikely to be a determinant, however, because there were few, if any, other species present in the high intertidal zone, with the majority of space being bare rock.

Distance from the harbour was a strong predictor of abundance in both *Chamaesipho* species, with *C. brunnea* predicted to increase in abundance, whilst *C. columna* abundance was predicted to decrease (Figure 5.3). *C. columna* is the dominant species in Wellington Harbour occupying >50% of the available substrate in the high intertidal zone (Demello & Phillips 2011). Demello & Phillips (2011) also found that settlement of *Chamaesipho* individuals of both species on the south coast was considerably lower than in the harbour and displayed contrasting patterns, with the majority of settlers in the harbour consisting of individuals of *C. columna*, whereas settlers on the south coast were *C. brunnea* suggesting differential larval supply between the two areas. Similarly, Helson & Gardner (2004) found that planktonic larval densities of mussels were an order of magnitude higher in Wellington Harbour compared to the Wellington South Coast. Phillips & Hutchinson (2008) also demonstrated that, whilst the magnitude of mussel recruitment is similar between the two

regions (in a grazer exclusion experiment), the recruits were of different species between the two areas, with the blue mussel *M. galloprovincialis* recruiting to the harbour, whilst recruits to the south coast consisted of the little-black mussel *L. pulex*, suggestive of differential larval supply/recruitment between the two regions. Thus, the gradient in *C. columna* abundance may be the result of limited larval supply along the Wellington south coast, with sites closer to the harbour entrance receiving a greater or more consistent supply of *C. columna* larvae. With regards to *C. brunnea* the Wellington Harbour is unlikely to be a source of larvae given the low abundance and settlement of *C. brunnea* in the harbour (Demello & Phillips 2011). Given the predominant flow direction (NW to SE, Heath 1971) and potential sources of *C. brunnea* larvae, the gradient in *C. brunnea* abundance may also derive from larval dynamics, with *C. brunnea* larvae arriving on the South Coast from sources further into the Cook Strait. Larval transport acting in isolation would be unlikely to fully explain these relationships, however, because species would be able to successively colonise areas in a stepping-stone way through time. Previous studies, however, have also demonstrated a gradient in water column composition with decreasing suspended particulate matter and dissolved nutrients as distance from the harbour increases (Gardner 2000; Helson *et al.* 2007; Helson & Gardner 2007). If food is limiting then individuals in this area may have lower reproductive output, which in combination with low larval supply may limit their dispersal along this coast as has been suggested for a discontinuity in intertidal community structure along the Chilean coast (Navarrete *et al.* 2005). Therefore food limitation (as suggested by Helson *et al.* 2007 for mussels on Wellingtons south coast) in combination with larval supply differences may explain the patterns seen for *C. columna* and *C. brunnea*.

Notoacmea sp. and *Austrolittorina* spp. were also predicted to have higher abundances at higher wave exposures (Figure 5.4). *Notoacmea* sp. are predominantly found in the unoccupied space within beds of *C. brunnea* and so the increase in abundance with wave exposure is likely linked with increasing amounts of suitable habitat created by *C. brunnea* abundance at higher wave exposures. This may also apply to *Austrolittorina* spp. as littorinid snails have been shown to be associated with barnacle cover (Underwood & McFadyen 1983; Chapman 1994), due to the complex surface topographies created by living barnacles and the empty shells of recently deceased barnacles providing small-scale refuge from wave-shock (Underwood & McFadyen 1983; O'Donnell & Denny 2008). Wave exposure is also likely to reduce desiccation and heat stress (Harley & Helmuth 2003) and may also promote the biomass of biofilms (diatoms, microalgae), which has been shown to be higher in more wave-

exposed locations (Thompson *et al.* 2005), subsequently providing higher food availability for intertidal grazers. *Austrolittorina* spp. also exhibited a decrease in abundance at the highest wave energies (response to Wave max, Figure 5.4), which may be due to the increased probability of dislodgement of individuals at these locations (Trussell 1997). In addition, both *Notoacmea* sp. and *Austrolittorina* spp. were more abundant on flat surfaces compared to inclined surfaces (Figure 5.4), which may result from the reduction in wave forces experienced on horizontal versus vertical surfaces (Chapman 1995; Helmuth & Denny 2003) amongst other factors including increased energy expenditure staying attached to vertical compared to horizontal surfaces (Donovan & Taylor 2008).

At mid tidal heights opposing relationships were observed for *C. denticulata* compared to *C. radians* with regard to both wave exposure and distance from the harbour (Figure 5.4). Limpets of the genus *Cellana* in Australia experienced increased mortality when densities were experimentally manipulated above observed densities, indicating that *Cellana* densities may be self-regulating due to food limitation (Creese & Underwood 1982). Although speculative, there could be a trade off in abundance between these two species with *C. denticulata* more adapted to withstand higher wave forces and therefore becoming competitively dominant in more exposed locations. In addition, these two species may have become more specialised towards certain environmental niches in this area in order to reduce inter-specific competition. Manipulative studies would, however, be required to ascertain the true relationship, if any, between these species. Limpets in the Siphonaria group were predicted to be most abundant in the mid intertidal zone on relatively flat surfaces consisting of the sandstone dominated substrate type, a trait that they share with *C. radians* (Figure 5.4). This substrate has a coarser surface texture (akin to sandpaper), is far easier to incise marks and depressions on its surface and parts are more easily pried (even by hand, Kennedy & Beban 2005) away from larger formations than for the other substrate types. Surface texture has been shown to be an important cue for larval settlement (McGuinness & Underwood 1986; Tourneux & Bourget 1988; Menge *et al.* 2010) and also is likely to influence biofilm formation, with consequences for food availability and settlement (Crisp & Ryland 1960). The provision of microhabitats between the two substrate types (SG, HG) is also likely to differ (McGuinness & Underwood 1986). This may be particularly important for Siphonaria (mostly individuals of *Siphonaria australis*, although differentiation between *S. australis* and *Patelloida cortica* could not always be achieved) as this species has homing tendencies, and is therefore reliant upon the availability of suitable microhabitats for home scars.

The remaining species identified as characteristic of mobile invertebrate communities were modelled inadequately, achieving low predictive deviance ($D^2 \leq 0.2$). Availability of suitable microhabitats (cracks, crevices, ledges and overhangs) is likely to be an important predictor for these species as for other mobile invertebrates in the high intertidal (McGuinness & Underwood 1986; Gray & Hodgson 1998; Underwood 2004). Microhabitats provide both respite against desiccation stress (Gray & Hodgson 1998; Jones & Boulding 1999; Martins *et al.* 2010), predation (Mercurio *et al.* 1985; Marsh 1986) and wave forces (O'Donnell & Denny 2008) and thus are likely to be an important predictor of abundance. In particular, *Cellana ornata* are known to return to a home scar (Boyden & Zeldis 1979), whilst *S. pelliserpentis* were always observed clustered into cracks or grooves in the rock. In addition *C. denticulata* at high tidal heights are likely to be more susceptible to desiccation stress than at mid-tidal heights, and so individuals would only be present if suitable microhabitats were available in the high zone (Martins *et al.* 2010). Although large cracks and crevices were specifically avoided during sampling, there was considerable variation within the sampled plots of smaller features (cracks, overhangs, depressions, grooves) both with regard to the scale size of individual features (may select for individuals above or below a certain size) (Underwood 2004) as well as diversity of features (may allow a progression of shelter as individuals develop). Consequently, densities of these species, on the small-scales sampled, are likely to be influenced by the availability of suitable microhabitats and not quantifying this as a factor may explain the relative failure of the models for these species. In addition, the effective area of plots with higher surface complexity is larger than plots with lower surface complexity. Therefore this will have introduced considerable variability in abundances due to the variable effective area surveyed between plots with different surface complexities. This is likely to have also masked any relationships that may exist between the factors considered herein and mobile invertebrate abundance.

Models for macroalgal species in the high and mid intertidal performed poorly compared to the low intertidal macroalgal species (Table 5.4). Model results for the high intertidal alga *Porphyra* sp. failed to accurately predict any absences (specificity = 0%) with all agreement between predictions and observations due to chance rather than model performance ($\kappa=0$). The model failure in this case, and also for *C. maschalocarpum*, may largely derive from the high prevalence of these species, with only five and eight quadrats recording an absence for *Porphyra* sp. and *C. maschalocarpum*, respectively. In scenarios such as this there is little information within the data to inform the modelling process

regarding the conditions under which each species is absent, leading to inadequate predictive models (Manel *et al.* 2001). This also highlights the need to consider multiple metrics of model predictive ability, because based on OOB misclassification rates models for both of these species performed well, but performed poorly when considering specificity and Cohen's- κ (Manel *et al.* 1999; 2001). However, these results also indicate that *Porphyra* sp. and *C. maschalocarpum*, as well as CCA (observed in nearly all mid and low intertidal quadrats) are widespread species/groups, occurring in almost all conditions where sampling was performed.

High intertidal macroalgal species are likely to be predominantly limited by desiccation stress (Connell 1972; Lubchenco 1980). Whilst predictive accuracy was low for *Gelidium pusillum*, model predictions were consistent with this species preferring locations that remain well hydrated (predicted increased likelihood of presence with wave exposure, and on moderately inclined surfaces compared to walls that have greater drainage) in locations that are not fully exposed to the sun (predicted increased likelihood on E/W to S facing aspects, decreased likelihood on flat surfaces) (Gómez *et al.* 2004). The model results for CCA displayed a similar response to inclination and wave exposure, and along with observations that CCA in the high intertidal zone was limited to cracks/grooves in the rock where water is likely to pool indicate this group is also likely limited by desiccation/dehydration stress (see also Padilla 1984).

Similarly models for the mid intertidal algal species, mostly encrusting species, failed to attain high predictive accuracy. The exceptions was *H. saxigenum*, which was predicted to have a strong preference for the most exposed locations, as well as favouring HG and HGB substrates, which matches the description given in Adams (1994) of a species favouring hard, smooth substrates. The mid intertidal zone along Wellington's south coast is dominated by bare rock with an average availability across seasons of 68%, (seasonally between 64% and 74%), with bare rock, CCA and barnacles accounting for 89% (varied seasonally between 85% and 91%). Phillips & Hutchinson (2008) demonstrated that excluding limpets, which are numerically the dominant group in the mid intertidal, had a strong influence over all algal groups (filamentous, foliose, encrusting and microalgae) suggesting strong control of mid intertidal algal species by limpet grazing and that biological rather than physical factors may be the major determinant of macroalgal distributions in the mid intertidal (Underwood & Jernakoff 1981, 1984).

The predictive models revealed that low shore macroalgal communities are largely governed by wave exposure, with wave-related predictors (wave max, wave min, wave ave) having the greatest influence for 10 of the 15 species. There is a large body of literature describing the influences of wave forces on intertidal macroalgae (Gaylord *et al.* 1994; Blanchette 1997; Denny & Gaylord 2002; Pratt & Johnson 2002; Kitzes & Denny 2005) and many more demonstrating how these translate to differences in algal distribution (Bustamante & Branch 1996; England *et al.* 2008; Hill *et al.* 2010). The majority of algal species showed a decrease in the probability of presence with increasing wave action with only *C. ustulatus* and *D. antarctica* exhibiting an increase in probability (although there was some indication that *X. gladiata* is most likely to be found at intermediate wave exposures). Damage and dislodgement of species that are less well adapted to continually high wave energies is likely to explain some of this variation. However, acting alone this is unlikely to explain the absence of most species as these forces would preferentially select for smaller individuals of the same species (Gaylord *et al.* 1994; Denny & Gaylord 2002) and many species display morphological differences in wave sheltered compared to wave exposed locations that allow them to persist under both conditions (Gaylord *et al.* 1994; Blanchette 1997; Koehl 1999). *D. antarctica*, was however limited to the most wave-exposed locations, and has several adaptations allowing it to persist at these locations (Stevens *et al.* 2002). These adaptations include large holdfasts, stipes that join the holdfast at a flexible joint allowing for a high degree of movement, and elastic fronds that dissipate wave forces through extension rather than transmission of the drag forces to the holdfast (Koehl 1982; 1999; Stevens *et al.* 2002). However, during storms *D. antarctica* are broken (at the juncture of the stipe and the holdfast) or dislodged, frequently due to failure of the substrate to which they are attached (Stevens *et al.* 2002). Any free space that becomes available is likely to be available to any of the species considered in this study and so there must be other factors limiting the distribution of the species found only in wave-sheltered locations. Scouring or whiplash effects (Dayton 1975) are likely to limit most of these species from occupying this free space. *D. antarctica* fronds can reach lengths of 12 m and individual plants can have wet weights exceeding 70 kg (Stevens *et al.* 2002). *D. antarctica* fronds are therefore likely to cause considerable damage to individuals in the surrounding area from whiplash effects in heavy surf conditions (Dayton 1975; Santelices *et al.* 1980; Kim & DeWreede 1996; Schiel 2004) which occur regularly along Wellington's south coast (see Chapter 4). In particular, Taylor & Schiel (2005) note that in southern New Zealand there are few other species able to co-exist with *D. antarctica*

except for coralline and turfing red algae and it is able to exclude all other species of brown algae, which is consistent with model results. In addition, *D. antarctica* may be able to maintain its dominance at the most wave-exposed locations through the process of self-replacement (Taylor & Schiel 2005) that maintains sufficiently high densities to limit (through scouring) other species from colonising any free space.

Apart from wave forces, shade (relating to inclination and aspect) and substrate were important predictors in explaining macroalgal species distributions. In particular *C. convolutum*, displayed a preference for locations that do not experience full light intensity for extended periods (predicted primarily on inclined surfaces with E/W aspects), which is consistent with observations that distributions of *Codium* species are inversely related to the probability of desiccation stress (Trowbridge 1998). Of the substrate types available, most macroalgal species groups showed a preference for the SG (sandstone-dominated greywacke) substrate type. This substrate was present at two sites, Houghton Bay and Palmer Head, which differ with regard to wave exposure (Houghton Bay – exposed, Palmer Head – sheltered), distance from harbour and topography (Houghton Bay – a series of intertidal platforms rising sharply from water ~ 3-4 m deep, Palmer Head – rocky projections interspersed amongst a shallow pebble-gravel beach). Other than sharing similar substrate, these sites are both in close proximity to sandy bays, and so some of the substrate effect may derive from this rather than a direct effect of the substrate type itself, with further sampling required to confirm this relationship beyond the two sites included here. However, other studies (both experimental and observational) have demonstrated that substrate type can have a strong effect on community structure (McGuinness & Underwood 1986; Cattaneo-Vietti *et al.* 2002), which may result from the chemical composition of the different rock types, as well as surface texture as mentioned previously. However, this aspect of intertidal ecology remains poorly investigated and further experimental investigation is required to reveal the mechanisms by which it influences species community composition.

5.4.2 – Model limitations

Apart from species- or group-specific limitations already raised there are several, more general, limitations of this study. The aim of this study was to capture patterns of spatial, rather than temporal variation, with multiple survey data used to confirm that the observed spatial variation was consistent through time. Furthermore, an absence recorded in one survey may be a true absence (species cannot persist under the conditions at that

location), or may be a result of temporal variation, which may be random (non-process driven) or seasonal (particularly for ephemeral species that are present only during one or two seasons). The modelling results therefore illustrate where and under which conditions a species is capable of surviving, across all seasons, and therefore do not indicate that individuals of a certain species will always be there at any particular time. Although this represents a step up from using one-off survey data, which may be confounded by false absences, it falls short of a full spatio-temporal analysis that is capable of making predictions of spatial distributions for any particular season. Also, no measure of macroalgal abundance or biomass was used, partly because this varies seasonally, and therefore an average over time would likely misrepresent the patterns of spatial variability (e.g., a species in two locations could have the same time-averaged abundance, whilst at location 1 it could be due to large seasonal fluctuations in abundance, whereas at location 2 it could be relatively constant). This will be the focus of future work utilising the full dataset of macroalgal abundances.

Models were based on a relatively small sample size (in comparison to other species distribution models), and the area covered is unlikely to have captured all possible combinations of factors and species present within this area. In addition, as mentioned previously for *C. maschalocarpum* and *Porphyra* sp., some species are likely to be over-represented relative to their actual prevalence due to potential bias introduced as a result of the survey methodology. Surveys were intentionally restricted to ocean-facing rather than land-facing locations and also moderately open locations within each of these areas. Thus the most sheltered locations are unlikely to be adequately described and application of model predictions to these locations should be performed with caution. Further sampling would likely increase model accuracy and generality of model results, as well as providing an independent test of the models predictive capacity. Approaches similar to those employed here could provide useful information for marine spatial planning and management provided several important alterations to the data collection and modelling procedure. Firstly the data was collected from locations nested within nine separate locations. A vital improvement to this would be to sample from random locations along the shoreline, rather than from pre-defined “sites”, using a stratified random approach, with strata corresponding to a-priori zones with regard to exposure, distance etc. Within a “site” conditions are likely to be similar, and as such the species composition is likely to vary less between two locations within a site, versus two random locations. As a result, the number of characteristic species will be less

than with a random sampling strategy and the extent of conditions a species can occupy may not be as fully captured using this sampling regime versus a random sampling procedure. This introduces potential error into the analysis and therefore reduces the applicability of any subsequent modelling attempts. If further studies wish to adopt a similar approach as developed here, a stratified random sampling strategy would be recommended so that the full extent of conditions are captured, with uniform sample coverage across the range of predictor variables. This does require some prior knowledge of the major determinants of a systems state to identify adequate strata, but this could be identified using a literature search of similar systems and/or pilot studies of the study area. Secondly, as mentioned in Chapter 4 for the wave model, validation or independent test data should be collected so as to examine the true predictive capacity of the modelling procedure. This would give a truer indication of how robust the resultant maps are, which is of particular importance to spatial planning assessments. Finally, short of incorporating this data as a layer of information in a formal spatial planning application (i.e. MARXAN, Ball *et al.* 2009), a synthesis of the general features of the model results, such as species richness, diversity indices and presence of key or commercially important species, at a spatial scale applicable to management (i.e. on the scale of hundreds of metres or more) would greatly increase its usefulness to managers or decision-makers. The maps and resultant model plots provide this information, but at a scale and level of detail not amenable or immediately accessible to managers. This final stage would require stakeholder input into the goals of management to identify in what way the data can best be synthesised and would be a suitable subsequent analysis to apply to this data. These changes would ensure greater model coverage and accuracy, and also ensure that the results were easier to interpret and apply in a managerial sense.

5.4.3 – Conclusion

Despite these limitations the coupling of wave model predictions, physical topography and observations of intertidal species composition provide the basis for the development of multiple species-distribution models that can be used to make predictions on a relatively fine spatial scale. Whilst this section of shoreline has been studied in great detail with regard to the almost complete lack of mussels in the mid-intertidal zone (Gardner 2000; Helson & Gardner 2004, 2007; Helson *et al.* 2007; Gardner 2008; Demello & Phillips 2011), this study provides a quantitative description of the biological communities, and the physical factors that characterise this stretch of coastline. This will provide useful information with regard to future monitoring (where to establish monitoring sites based on predicted

similarity/dissimilarity in community composition) and as a predictive baseline for this section of coastline that can be used to determine the impacts of future changes to the marine environment in this area. This study also serves as an example of marine species distribution modelling and spatial mapping, which should be a vital first stage in the identification of optimal areas for marine conservation (Leslie 2005) and ecosystem management (Douvere 2008).

Chapter 6 – Looking ahead: Current themes and recent advances in marine protected area monitoring and application of findings in a monitoring framework

6.1 – Structure

In this thesis I have addressed questions related to monitoring programme design (Chapter 2 & Chapter 3) and methods for spatial and species distribution mapping (Chapter 4 & Chapter 5). The aim of this final chapter is to draw together these findings in the wider context of data collection relevant to the establishment and ongoing monitoring of marine protected areas (MPAs), and to relate the results and methods presented in Chapters 2 – 5 to ongoing and future fields of research.

Using the Web of Knowledge academic search engine a keyword search was performed to identify recent and ongoing fields of research, and to provide a holistic view of monitoring across marine species and biogeographic zones. The aim of this was to identify areas that are currently receiving much attention, whilst also highlighting areas that have been overlooked or require further research with regard to MPA effects and effectiveness. In particular I aim to identify factors that should be surveyed, and techniques to adequately survey them at all stages from initial surveys performed prior to MPA establishment through to assessing the long-term effects of MPAs. Areas of particular interest were studies that:

- Presented MPA effects over short and long timeframes as well as direct and indirect effects of protection to give an idea of the magnitude of these effects on these timescales.
- Give further consideration to larger spatial scale effects such as those associated with MPA networks, or meta-analyses of multiple MPAs.
- Describe new methodologies and how they can be applied to improve monitoring effectiveness.
- Identify additional avenues of research relevant to MPA effects, such as areas relevant to the planning stage of MPA placement and monitoring of changes other than those traditionally associated with MPA effects (i.e. beyond abundance, biomass and mean size of targeted species).

Finally, the overarching goal of this chapter is to combine all of this information, as well as results and methods from Chapters 2 – 5, into a framework to be used as a guideline for surveillance and monitoring of MPAs to further our understanding of MPA effects and to enhance management success in achieving stated or implicit goals in MPA designation.

This chapter is separated into four main sections. I will firstly describe the methods used to perform the keyword search and give an overview of the resulting articles. I will then present a framework incorporating multiple considerations relevant to MPA monitoring including the themes identified from the keyword search, along with methods, ideas and results presented in Chapters 2 – 5. I will then describe the separate components of this framework, making particular reference to current research findings, methods and ideas identified from the keyword search. Finally, I will describe how these components fit together within this framework as a series of guidelines and considerations for MPA establishment, monitoring and surveillance.

6.2 – Description of Web of Knowledge keyword search

To identify recent advances and themes associated with biological monitoring of MRs/MPAs, a review of the literature from the last five years was performed. The search was limited to the last five years to firstly limit the number of articles returned by the search terms and also so that recent advances and current themes were addressed. Using the Web of Knowledge online database, a keyword search using the search terms “marine”, “conservation” and “monitoring” was performed. Due to the large number of articles matching these search terms, multiple filters were applied to limit the number of resultant articles (Table 6.1).

Table 6.1. Search terms and filters applied in the Web of Knowledge literature search. Values in parentheses indicate the number of articles returned for that journal.

Filter area	Search Terms					
Topic	Marine	AND	Conservation	AND	Monitoring	
Document type	Article					
Language	English					
Years	2008	2009	2010	2011	2012	
Database	Web of Science					
Research domain	Science Technology					
Research areas	Environmental Sciences Ecology	Biodiversity Conservation	Marine Freshwater Biology	Fisheries	Zoology	
Journals	<i>Mar. Ecol. Prog. Ser.</i> (52)	<i>J. Appli. Ecol.</i> (10)	<i>Ecol. Appli.</i> (22)	<i>Coral Reefs</i> (9)	<i>J. Wild. Dis.</i> (6)	<i>Aquaculture</i> (1)
	<i>Mar. Poll. Bull.</i> (74)	<i>J. Exp. Mar. Biol. Ecol.</i> (13)	<i>Env. Cons.</i> (9)	<i>J. Fish Biol.</i> (8)	<i>Mar. Pol.</i> (6)	<i>Ecol. Soc.</i> (4)
	<i>Biol. Cons.</i> (37)	<i>Env. Man.</i> (15)	<i>Mar. Freshwat. Res.</i> (13)	<i>Afr. J. Mar. Sci.</i> (6)	<i>Aq. Ecos. Heal. Manage.</i> (4)	<i>N. Amer. J. Fish. Manage.</i> (5)
	<i>ICES J. Mar. Sci.</i> (29)	<i>Fish. Res.</i> (21)	<i>Anim. Cons.</i> (8)	<i>Aq. Liv. Res.</i> (9)	<i>Env. Biol. Fish.</i> (6)	<i>Chel. Cons. Biol.</i> (3)
	<i>PLoS ONE</i> (32)	<i>Rev. Biol. Trop.</i> (17)	<i>Coastal Manage.</i> (7)	<i>Ambio</i> (9)	<i>J. Shell. Res.</i> (10)	<i>Hydrobiologia</i> (6)
	<i>Oryx</i> (13)	<i>Aq. Cons. Mar. Freshwat. Ecos.</i> (29)	<i>Biod. Cons.</i> (7)	<i>Mar. Env. Res.</i> (4)	<i>Proc. Natl. Acad. Sci. U.S.A.</i> (7)	<i>NZ. J. Mar. Freshwat. Res.</i> (2)
	<i>Estuar. Coast. Shelf Sci.</i> (17)	<i>J. Coast. Res.</i> (20)	<i>Env. Monit. Ass.</i> (12)	<i>Fish. Manage. Ecol.</i> (6)	<i>Mar. Biol.</i> (8)	<i>Cons. Lett.</i> (3)
	<i>J. Mar. Biol. Ass. UK</i> (16)	<i>Cons. Biol.</i> (11)	<i>Can. J. Fish. Aq. Sci.</i> (11)	<i>J. Env. Manage.</i> (5)	<i>Mar. Mam. Sci.</i> (7)	<i>Wild. Res.</i> (3)

The abstracts of the articles meeting these requirements were reviewed and information regarding authorship (so that articles could be found later), publication date, focal species, group, or research area, and journal title were recorded (Table 6.2). In addition, several criteria based on *a priori* research questions and recurring themes were defined and each article was classified based on the content of the abstracts with regard to each of these criteria (Table 6.2).

Table 6.2. Fields recorded and the type of information recorded from each abstract of the articles returned using the search criteria given in Table 6.1.

Field	Requirements
First author	First-author's last name
Year	Publication year
Focal species group or research area	This could either be a general name of a species group, (e.g. <i>Fish - coastal</i> , <i>Fish - pelagic</i> , <i>Fish - sharks</i> , <i>Marine mammal - dolphins</i> , <i>Marine reptile - turtle</i>) or if the study was performed across multiple groups it was listed as <i>Ecosystem</i> (e.g. fish, kelp, invertebrate abundances). <i>Habitat</i> was used if the study was specifically identifying both biotic and/or abiotic habitat distributions. Alternatively <i>MPA design</i> , <i>Framework</i> and <i>Social</i> were used to identify studies concerned with MPA design, monitoring/management frameworks, and social studies respectively.
Journal	One of the journal names listed in Table 6.1
Relevant	Binary (Y/N) - if the article met any of the following criteria; monitoring of any of the following species or species group traits - abundances, spatio-temporal distribution, ecological processes, movement patterns; developed and/or tested - monitoring methodologies, indicators, indices, monitoring frameworks; monitored anthropogenic aspects including - opinion, anthropogenic impacts, community involvement. If N , the following fields were not recorded.
Monitoring results	Binary (Y/N) - was the study predominantly the presentation of the results of a monitoring program?
Methods	Binary (Y/N) - was the study focussed on developing and testing new monitoring methods, indices, indicators, remote sensing and other technological applications?
Power, precision, accuracy	Binary (Y/N) - were analyses of power, precision and/or accuracy described in the abstract regarding methodologies or techniques?
MR/MPA specific	Binary (Y/N) - was the study carried out in an MR, prior to MR designation, or meta-analytically across MRs?
MR/MPA mentioned	Binary (Y/N) - did the abstract specifically mention that the research had implications for MR design, effectiveness or placement?
Baseline	Binary (Y/N) - was the research carried out for baseline establishment, reconstruction, comparison to post-impact areas, or specifically states lack of baseline information in the abstract?
Spatial	Binary (Y/N) - did the research concern assessments of spatial distribution, movement patterns, habitat usage, or spatial distribution modelling?
Temporal	Binary (Y/N) - did the research aim to quantify or model interannual or seasonal temporal variability?
Management	Binary (Y/N) - was the research specifically for management including development of management frameworks?
Invasive	Binary (Y/N) - was the research aimed at monitoring the abundance and/or impact of invasive species?
Pollution	Binary (Y/N) - was the research aimed at monitoring the impact of pollution on biological communities?
Fishery	Binary (Y/N) - was the research related to fisheries?
Climate	Binary (Y/N) - was the research related to climate-change?
Description	Broad descriptive phrases assigned to each paper that could be one or more of; monitoring results – state, monitoring results – process, monitoring results – spatial mapping, monitoring results – movement/behavioural, monitoring results – baseline establishment, monitoring results – temporal, monitoring results – social, monitoring methods – framework, monitoring methods – indices, monitoring methods – indicators, monitoring methods – techniques, monitoring methods – statistical, monitoring programme establishment, call for monitoring, management or marine reserve establishment.
Summary	Brief descriptive summary of the information given in the abstract for later inspection
Importance	Rank (1-5) – subjective scoring system based on how innovative, relevant or unique the abstract seemed so that papers to be read in full could be prioritised later (5 – high, 1 – low)

6.3 – Overview of keyword search results

The keyword search detailed in Table 6.1 returned 632 journal articles and after reviewing all the abstracts, 425 were considered relevant to this discussion. Non-relevant articles were mostly related to fisheries stock assessments (41), experimental ecology, physiology or biology (40), water quality monitoring (36), monitoring of chemical pollutants (28), and terrestrial studies (22), with the remainder consisting of a mix of review articles, and other miscellaneous subjects that were not related to the monitoring of marine ecosystems. Most articles reported the results of monitoring programmes, whilst over 20% of the articles described research carried out in MPAs and nearly 40% identified that their research had MPA specific applications (Figure 6.1). Methodological considerations were explored in over 30% of relevant articles, but those that mentioned analyses of power specifically within the abstract were limited to only a small proportion of studies. Just under 20% of the relevant articles were reporting the establishment of baseline abundances (not specific to MPAs), spatial distributions or temporal variation (not specific to marine reserve or marine protected area studies), and made use of baseline data in a before-after, or full before-after-control-impact assessment (Figure 6.1). Of the thematic areas identified in Table 6.2, fisheries management was the most prominent area identified by the keyword search where monitoring would be applicable. Pollution and climate change were the focus of 11% and 5% of studies, respectively, while invasive species studies were not well represented in this sample of articles (6 articles in the 425 relevant articles – Figure 6.1).

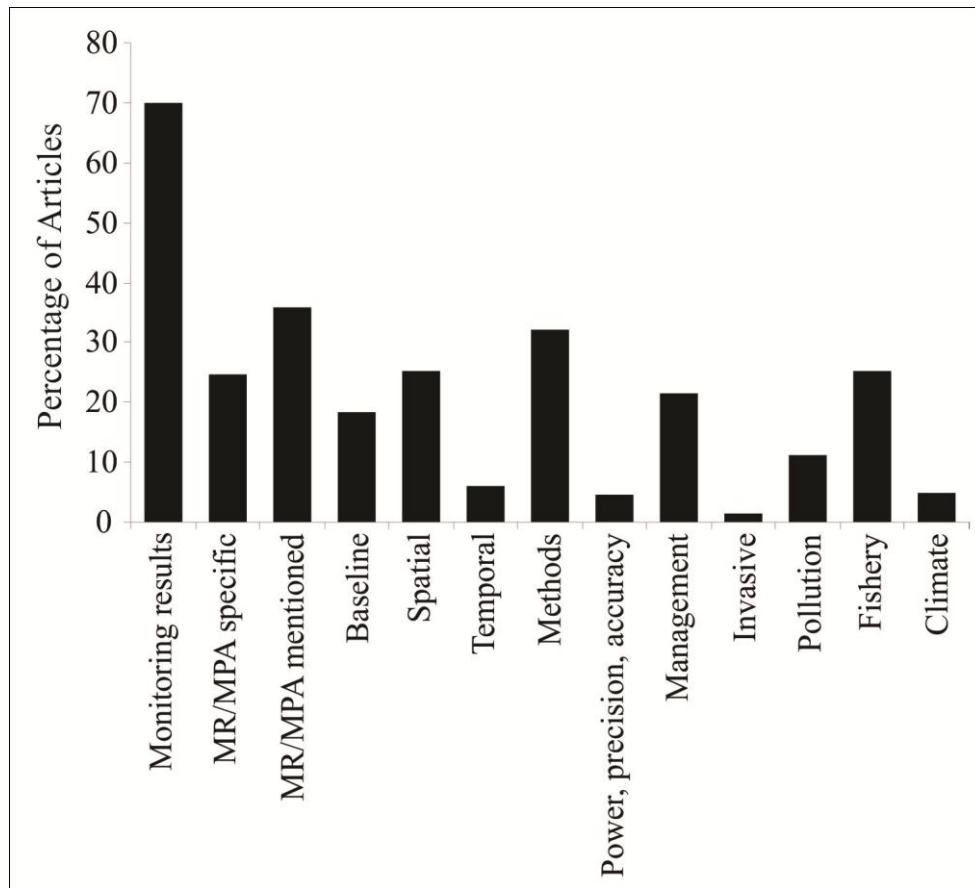


Figure 6.1. The percentage of relevant articles according to the criteria described in Table 6.2.

Further splitting these articles into more specific research areas indicated that most monitoring studies were focussed on state-level variables (e.g. abundance, biomass, and mean-size), rather than process variables (e.g. recruitment, grazing, predation and mortality) (Figure 6.2). Studies assessing species movement patterns were also prominent, with 39 articles assessing movement patterns across nearly all species groups identified in the keyword search (Figure 6.2). Methodological papers consisted of comparisons among techniques, the development and evaluation of indices, testing of species-specific indicators of ecosystem state and statistical methodologies to complement field studies (Figure 6.2). Finally, 27 articles discussed monitoring and/or management frameworks, and marine reserve establishment, presentation of baseline information and calls for greater monitoring were discussed in 11, 8 and 19 articles, respectively, while monitoring associated with socio-economic considerations constituted 19 of the relevant articles (Figure 6.2).

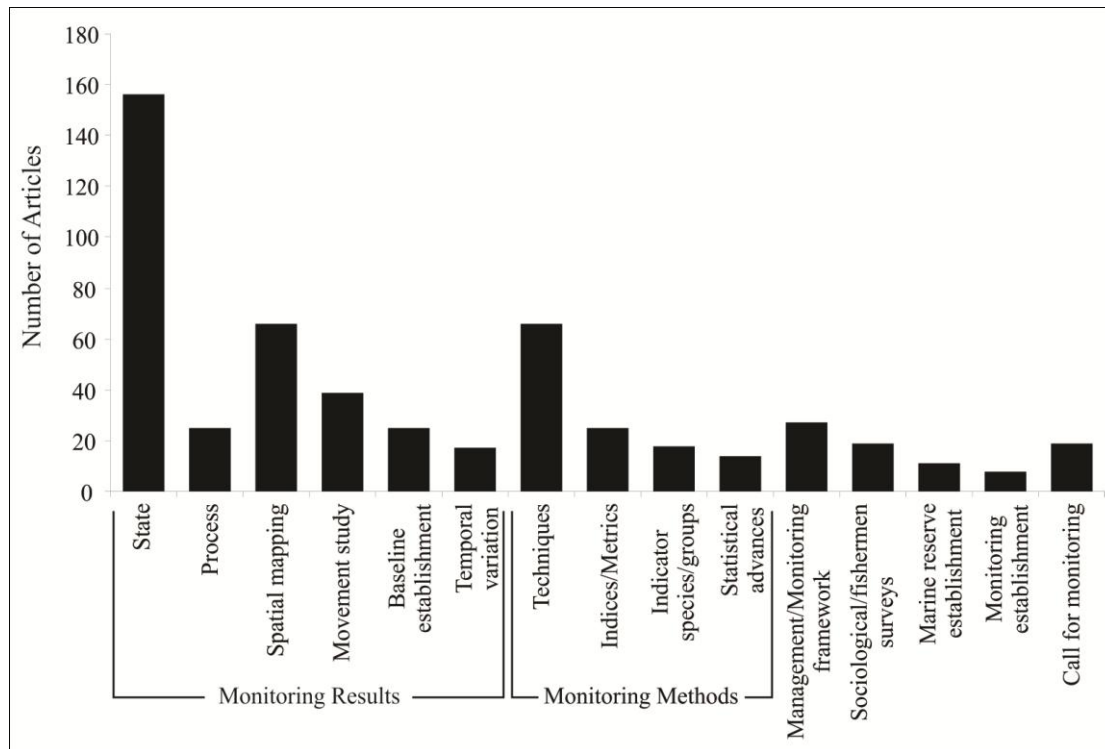


Figure 6.2. The number of relevant articles in specific areas of monitoring programme results, methods, frameworks and the establishment of marine reserves and monitoring programmes, along with the number of articles specifically calling for long-term monitoring of species and/or ecosystems.

The relevant articles covered many marine species groups including a wide range of fishes, marine mammals and benthic invertebrates, but the vast majority of studies researched Teleost fish species and species groups (Figure 6.3). Most studies focussed on ecosystem-wide monitoring were performed in tropical or coral reef environments, followed by temperate marine ecosystems (Figure 6.3). Forty-four of the relevant articles focussed neither on specific species nor ecosystems, but involved spatial assessments of habitat distributions (6 articles) and marine reserve/marine protected area spatial planning (8 articles), while the remaining articles were a mix of management, policy and sociological studies (Figure 6.3).

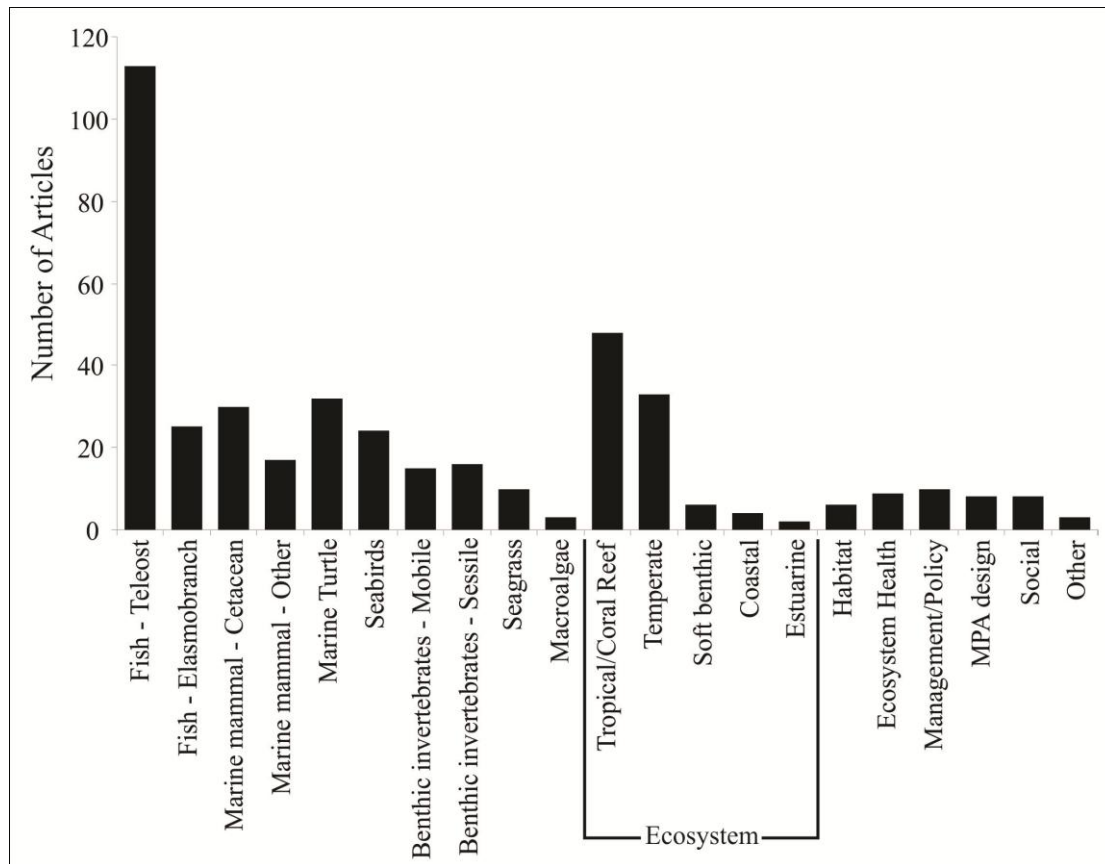


Figure 6.3. The number of relevant articles classified by research area, specifically regarding species groups, ecosystem type, and management/spatial planning studies.

Of the relevant articles, a further 107 articles were evaluated in more detail (ranked 4-5, based on the importance scoring, see Table 6.2) by accessing the full text and noting the aims, results and conclusions of these articles that may have been overlooked based on the abstract. Although this methodology is subjective, I believe it gave a good overview of the recent literature and current areas of research, as well as an idea of future trajectories in research fields across multiple taxonomic groups.

6.4 – Overview of monitoring framework

Based on the results and methods of the articles from the keyword search, and results and conclusions of Chapters 2-5, I constructed a framework as a guide for the monitoring of MPAs from prior to their inception through to assessing long-term changes in targeted species abundances, and wholesale shifts in ecosystem structure and functioning (Figure 6.4).

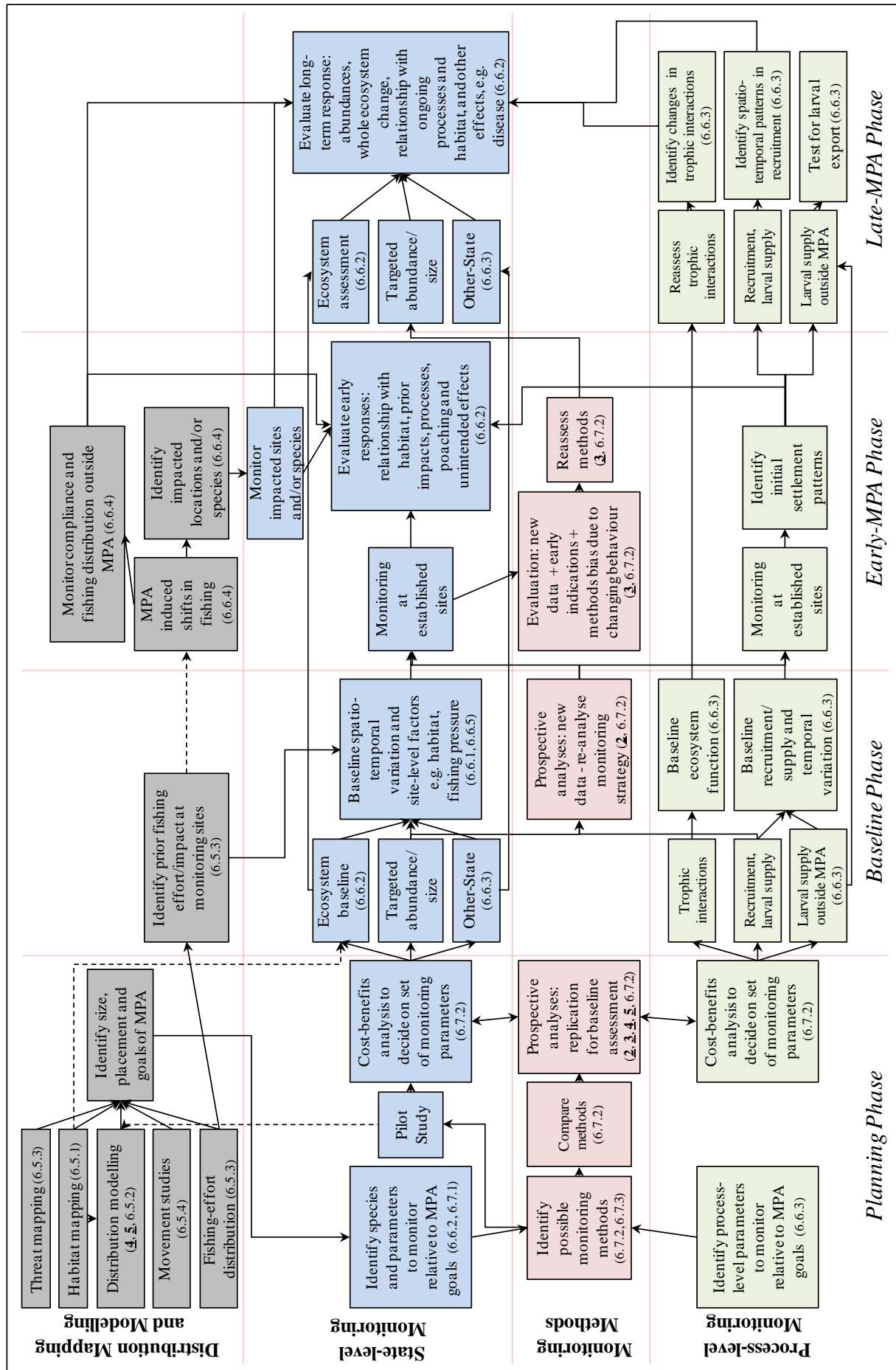


Figure 6.4. A general monitoring framework detailing the various stages of data collection and evaluation of MPA effects and monitoring effectiveness. Underlined and bold numerical values in brackets indicate where methods results and ideas developed in Chapters 2 – 5 are incorporated into this framework, whereas standard numeric values indicate the section number of this chapter where more detailed information can be found for each particular component of the diagram, respectively (previous page).

I will now discuss each of the components in detail, making particular reference to articles identified in the literature search, before proceeding to explain the framework in terms of how these components fit together as a cohesive guide for the establishment, and ongoing monitoring of MPAs. The following sections are roughly defined by the horizontal bands depicted in Figure 6.4, which are:

- (1) Spatial planning and distribution assessments
- (2) MPA baseline, short and long-term monitoring (includes state and process level monitoring)
- (3) Monitoring methodologies.

6.5 – Spatial planning and distribution studies

The science of MPA planning has advanced in recent years in an attempt to move away from *ad hoc* approaches (that may result in sub-optimal placement, Stewart *et al.* 2003), to instead rely on quantitative spatial assessments of species abundances, life-history and ecology to identify optimal placement of MPAs, either singularly or as part of a larger network (Leathwick *et al.* 2008a). These initial assessments can then be negotiated with stakeholders to decide on the placement of these areas that the majority of stakeholders agree upon, or can be used by a minister or area manager to make decisions based on lowest likely impact. Alternatively this information can be directly incorporated into zonation planning (Leslie 2005; Leathwick *et al.* 2008a) using software such as Marxan (Ball *et al.* 2009; Smith *et al.* 2009). The following sections provide a brief overview of methods and results presented in the literature for mapping or inferring the distribution of species, habitats, fishing and threats to ecosystems, and the various considerations highlighted within the literature associated with each of these.

6.5.1 – Habitat mapping and testing biological surrogacy

Habitat mapping was identified by several articles represented in the keyword search as being a necessary tool for conservation and marine spatial planning initiatives (Mumby *et al.* 2008; Fonseca *et al.* 2010). Several articles reported the habitat spatial variation patterns

on coral reefs (Fonseca *et al.* 2010; Cassata & Collins 2010; Scopélitis *et al.* 2010) and in temperate subtidal areas (Monk *et al.* 2008; Claudet *et al.* 2011). Habitat mapping usually involved a combination of methodologies including; remote sensing and satellite imagery (Fonseca *et al.* 2010; Cassata & Collins 2010; Scopélitis *et al.* 2010), aerial imagery (Cassata & Collins 2010), multibeam (Claudet *et al.* 2011), drop-cameras (Pelletier *et al.* 2012) and field-based ground-truthing using video transects (Cassata & Collins 2010), volunteer diver networks (Monk *et al.* 2008), local ecological knowledge (Scopélitis *et al.* 2010), and diver surveys (Claudet *et al.* 2011). Knowledge of the spatial distribution of different habitats is essential for effective conservation planning and spatial management, particularly where habitat-species associations are well understood so that habitat distribution can be used as a proxy for species distributions. Despite the need to protect habitats in their own right, habitat maps are often used in management and conservation planning as proxies or surrogates of species richness and diversity, without the direct knowledge of how the different habitats extant in a region contribute to the overall regional or local diversity. Two studies identified in the keyword search assessed the capability of habitats as surrogates for the spatial distribution of species richness and biodiversity, the protection or promotion of which is often the goal of establishing a MPA or MPA network. Mumby *et al.* (2008) tested the degree to which the distribution of 11 Caribbean coastal habitats provide useful planning information for fish and benthic species richness, functional roles of fish species and ecosystem processes to inform the selection of a MPA network. They found that the distributions of functional classes of fish were a good surrogate for overall fish species richness, as well as benthic species richness, while estimates of benthic species richness and ecosystem services and processes were ineffective as surrogates for overall species richness. Interestingly, Sutcliffe *et al.* (2012) performed a similar analysis assessing the effectiveness of biological surrogates, and found that no species group was a viable surrogate for any other in describing patterns of diversity on the Great Barrier Reef, and several taxonomic groups would need to be assessed to achieve greater representation of the underlying patterns in diversity. This suggests that although biological surrogacy can be used as a cost-effective tool for assessing distributional patterns of biodiversity (Mumby *et al.* 2008), it is not without its limitations and requires formal testing and incorporation of multiple metrics to identify potential pitfalls in its application.

6.5.2 – Distribution modelling

Species distribution modelling can be considered as a generalised extension of species-habitat associations (see 6.5.1 above), and includes the identification of relationships between physical factors and species abundances (see also Chapter 5). Species distribution modelling, while utilised extensively in terrestrial ecological research, is currently underutilised in marine research (Robinson *et al.* 2011). The keyword search, however, identified several studies that utilised a distribution modelling approach to predict the distribution of species and habitats. Those based on correlative approaches included Valle *et al.* (2011) that utilised ecological niche factor analysis (ENFA), coupled with LiDAR assessments of bathymetry to predict the distribution of seagrass beds, and to identify what areas would be best suited for restoration and protection, while Shephard *et al.* (2012) used linear models to model the distribution of elasmobranch species richness and biomass in the Celtic Sea. Other studies incorporated behaviour and trophic interactions to identify species distributions rather than basing distribution assessments on correlations with physical factors alone. Sveegaard *et al.* (2012) identified the distribution of mackerel and harbour porpoise, in relation to herring distributions that form a large part of their respective diets. Furthermore, Grecian *et al.* (2012) predicted the at-sea usage distributions of seabirds based on colony location, colony size (which is known to be a determinant of maximum foraging distance), foraging strategy and at-sea availability of food resources.

Pelagic ecosystems and predicting the at-sea distributions of species and species richness has historically been under studied due to the difficulty and cost of identifying pelagic species distributions (Louzao *et al.* 2011) that may also vary through time (Grantham *et al.* 2011). Therefore species distribution models are ideally suited to identifying pelagic protected areas. Leathwick *et al.* (2008a) identified pelagic fish species distributions in the waters surrounding New Zealand using a boosted regression tree approach relating individual species distributions to environmental and oceanographic predictors. Using this information and information regarding the economic value of these fisheries, they were able to identify a spatial zoning plan for pelagic marine protected areas that would meet several different conservation requirements while minimising the economic loss to fisheries. Furthermore, Louzao *et al.* (2011) used wandering albatross movement patterns to identify the time spent within certain grid-cells performing different activities (searching for food, feeding and overall time spent) and then related these to both static (bathymetry, distance to colony) and dynamic (e.g. sea-surface temperature, sea-level anomaly among others) parameters to

produce predictive models of spatial usage patterns to identify pelagic protected areas for this species. These all provide examples of how distribution modelling can be used to generate quantitative assessments of the spatial distribution of species that are otherwise difficult to ascertain, and are therefore an effective way to develop protected area plans and to implement effective conservation strategies.

6.5.3 – *Fishing effort distribution and threat mapping*

In addition to identifying MPA placement based on species distributions it is also essential to consider the level of anthropogenic impacts experienced across the network of possible locations. Many studies were focussed on quantifying the incidental effects of fisheries, such as bycatch (Gardner *et al.* 2008; Abbott & Haynie 2012; Amandè *et al.* 2012), and damage incurred to the seabed (Hall-Spencer *et al.* 2009; Reiss *et al.* 2009) to identify MPA areas. Incorporating separate assessments of the spatial distribution of fishing effort and species distributions was also used extensively to identify areas of overlap between fishing effort and species distributions, including species of marine mammals (Kelkar *et al.* 2010; Cronin *et al.* 2012), seabirds (Trebilco *et al.* 2008), turtles (Gaos *et al.* 2012), and sessile benthic species (Hall-Spencer *et al.* 2009). Identifying areas of overlap can be utilised in the design of MPAs, and in setting management processes, to both reduce bycatch and minimise damage to fragile ecosystems. This was taken one step further in a study performed by Selkoe *et al.* (2009) to prioritise areas for conservation by identifying the distribution and magnitude of 14 anthropogenic threats including invasive species, bottom and lobster-trap fishing, ship-based pollution, ship strike risks, marine debris, research related damage, and climate change effects of increased UV radiation, frequency of temperature anomalies and ocean acidity. Combining the distribution of these threats with habitat maps and expert guidance they produced maps of cumulative risk, which they suggested should be incorporated into any future assessments related to management, surveillance, permitting decisions and climate change monitoring. Similar assessments could, however, be applied in defining a network of MPAs, and with each MPA defined for specific purposes based on the nature and extent of the threats identified for these areas. In a complementary study Thompson & Dolman (2010) simulated the effects of different stressors on coral reefs, identifying that while coral reefs are able to recover from damage caused by cyclones and crown of thorns starfish outbreaks, the advent of mass bleaching leads to rapid and irreversible declines in hard coral cover and significant changes in community composition. Combining the methods presented in Selkoe *et al.* (2009) along with those in Thompson & Dolman (2010) has huge potential for

identifying conservation priorities and areas of concern in light of future climate change and continued anthropogenic degradation of the marine environment. While these studies were focussed on coral reef ecosystems, similar methods identifying the spatial distribution of anthropogenic threats along with assessments of the biological impact/recovery dynamics following these events threats could equally be applied in temperate, and polar marine settings to identify conservation priorities.

6.5.4 – *Species movement studies*

While distribution mapping and modelling are useful for identifying the placement of MPAs, for mobile species assessments of movement patterns become increasingly important. Due to reducing costs, miniaturisation and accessibility of acoustic tagging and receiver technology and satellite transmitters, there has been a surge in the number of tagging and movement studies in the last decade (Yeiser *et al.* 2008). From the keyword search 39 of the 425 studies were studies of species movement patterns, featuring studies of marine mammals (4), turtles (7), temperate bony-fish (9), tropical bony-fish (5), temperate sharks or rays (5) and tropical or reef sharks (4). From a conservation perspective these are essential for identifying whether a protected area of a given size or location is adequate for protecting a given species and also for identifying overlap between fishery areas and pelagic species distributions (discussed in section 6.5.3). Most of the fish- and shark-based studies were aimed at assessing the effectiveness of MPAs for these species by identifying home-range sizes (Afonso *et al.* 2008, 2009; Green & Starr 2011). However, the studies identified several factors that need to be considered when interpreting movement data for this purpose. Several studies identified consistent movement-pattern types in the fish they tagged that were related to social status of individuals (Afonso *et al.* 2008), variation between inshore and offshore populations (Afonso *et al.* 2009) or natural behavioural differences among individuals (Green & Starr 2011). There is also likely to be variation among life stages (e.g. ontogenetic shifts in habitat use - Murchie *et al.* 2010; Green & Starr 2011), and also among years (e.g. natural temporal variability - Schofield *et al.* 2010) requiring intensive tagging of multiple life-stages at different times to identify areas that sufficiently protect individuals throughout different life-history stages. Movement studies are also useful for identifying MPA placement because they can identify areas that are particularly important to different life stages, such as nursery areas (Yeiser *et al.* 2008) and spawning aggregation sites (Afonso *et al.* 2008), and can also identify natural barriers to movement. For example, Meyer *et al.* (2010) identified that several species of reef fish would not move across open sand areas, and tended to only move

along sections of continuous reef. The incorporation of these natural barriers into an MPA would provide a barrier against individuals straying into open fished areas. Incorporating these areas into a MPA network, possibly as small-scale MPAs, may enable the conservation of species that, due to their mobility, are not amenable to other forms of marine protection (e.g. Hamilton *et al.* 2011).

6.6 – MPA monitoring: baseline, short and long term monitoring

Monitoring of MPAs ideally should consist of several stages. The acquisition of spatially and temporally replicated baseline data is essential to identify the initial state of MPAs and to identify possible confounding factors that may affect the evaluation of MPA effectiveness, but historically baseline assessments have rarely been performed. Despite this, many studies have demonstrated rapid responses to reserve protection, and monitoring in the short term is a valuable way to demonstrate that marine reserves are effective. However, due to the relative youth of the majority of MPAs, there are few studies that are able to quantify the long-term effects of MPAs. In this section I will discuss ideas and findings from studies presenting results from one or more of these stages, as well as further considerations for MPA monitoring and assessments in the light of confounding factors, and also adaptations that are required as the field of MPA science moves from individual areas to networks of MPAs.

6.6.1 – MPA baselines

It has been widely acknowledged that pre-reserve baseline information is invaluable for assessing the effects of MPAs (Edgar *et al.* 2004), with many studies criticising early MPA assessments for their lack of baseline information (Willis *et al.* 2003b). From the keyword search eight studies used a before-after-control-impact (BACI) survey design, while six studies utilised before-after data and a further six studies described baseline surveys of marine reserves. This is in comparison to the meta-analysis performed by Stewart *et al.* (2009) using data prior to 2006 that only included one BACI study, suggesting that baseline data collection is becoming more prominent and is being used in more MPA assessments. Many articles identified in the keyword search, demonstrated the importance of baseline data, either directly or indirectly, by identifying factors that may otherwise have confounded the assessment of marine reserve effectiveness. These included differential responses due to pre-existing seascape level habitat variation (Claudet *et al.* 2011), the existence of natural environmental gradients across MPA and control sites (Pande & Gardner 2009), biogeographic variation (Hamilton *et al.* 2010), socio-political bias in reserve area selection

toward lower quality locations (Francini-Filho & de Moura 2008a; Edgar *et al.* 2009), pre-existing spatial distribution of target species (Karnauskas *et al.* 2011) and pre-existing gradients in biomass and/or body size when testing for spillover effects (Francini-Filho & de Moura 2008b). In the absence of baseline data there is a far greater potential for misinterpretation (e.g. when reserve and control sites span a gradient in abundance or where reserves are established to include a location that is *a priori* known to be particularly biodiverse, Pande & Gardner 2009, 2012) and failure to identify effects (e.g. when MPA sites are in lower quality locations than nearby control sites, Edgar *et al.* 2009). The collection of baseline data in MPA assessments is therefore a key part of establishing a powerful and accurate MPA monitoring programme, particularly where habitat variation and differential responses are likely to otherwise confound marine reserve assessments.

6.6.2 – Short- and long-term monitoring

The duration of MPA monitoring was mentioned in several studies highlighted by the keyword search. Results of several short-term studies (less than 10 years) varied in their ability to demonstrate changes due to MPA designation, with some unable to demonstrate effects on targeted species abundances (e.g. no demonstrable changes after 3 years - Edgar & Barrett 2012), while others demonstrated rapid responses to protection. For example, in a review across multiple reserves, distributed globally, Babcock *et al.* (2010) identified that direct effects were detected on average after five years of protection. Furthermore, Stewart *et al.* (2009) performed a global meta-analysis of temperate marine reserves and found that the median period from establishment to the detection of effects was 9.5 years. New Zealand specific meta-analyses have also demonstrated that species specific effects are evident within the first ten years (Pande *et al.* 2008; Diaz Guisado *et al.* 2012). Based on these findings, monitoring for the purpose of demonstrating the ability of marine reserves to increase abundance or biomass of targeted species should only proceed in the short term (~10 years) to achieve these targets. Demonstrating changes in the early years is often required to demonstrate to stakeholders that MPAs are effective. Therefore in the short term it would seem appropriate to establish monitoring at a high frequency (i.e. annual or biennial monitoring) to demonstrate these effects as soon as they become apparent. However, even within species, responses vary considerably among reserves, as demonstrated by Freeman *et al.* (2012) who found that rock lobster abundance in some NZ MRs immediately increased after establishment, but in others 12 years had elapsed before any changes could be detected. Due to the variability in responses among reserves this initial period may be as long as 15-20

years before direct effects become apparent. Indirect effects (i.e. changes to non-target species due to increases in predator biomass), however, are likely to take longer to manifest themselves, with Babcock *et al.* (2010) estimating that on average indirect effects were detected after 13 years, which was 36% longer than the direct effects observed within the same reserves. In addition, multiple studies carried out on temperate Australian reefs have demonstrated that effects associated with marine reserve protection are ongoing (Edgar & Stuart-Smith 2009; Edgar *et al.* 2009; Barrett *et al.* 2009), and require a much longer commitment to MPA monitoring than is currently employed in many MPAs. Furthermore, Edgar & Barrett (2012) argue that the short timescale often reported in meta-analyses of MPA effects (e.g. 9.5 years in Stewart *et al.* 2009) may be optimistic, given that publication bias in reporting marine reserve results selects for those studies which show significant effects. Large predatory species are also likely to take decades to recover given that many are long-lived, late maturing, and have been subjected to historical depletion and intense fishing pressure (Roberts *et al.* 2001). Therefore it may require anywhere between 10 and 40 years to establish the effects of marine reserves in restructuring trophic interactions (Edgar *et al.* 2009; Kellner *et al.* 2010; Edgar & Barrett 2012). Consequently, in addition to the short-term high frequency monitoring required to detect initial direct effects, longer-term monitoring, taking a more holistic approach (i.e. monitoring species beyond those considered commercially viable), is required to identify changes in abundance for species that may be affected indirectly by exclusion of fishing (Barrett *et al.* 2009; Pande & Gardner 2009, 2012) and for those that have undergone historical depletion. Long-term monitoring is also required to assess how multiple processes interact in nature to structure these communities in the absence of anthropogenic pressure (Hereu *et al.* 2012). The cost of long-term monitoring, however, is likely to be considerable unless the frequency of monitoring is low. However, if whole ecosystem changes are stable, then the frequency of monitoring can be reduced without impairing the ability of the monitoring to detect these changes, particularly if they are associated with wholesale shifts in habitat and community type (Shears & Babcock 2003). Even in these cases, however, stability is unlikely to last over sustained periods, with Babcock *et al.* (2010) identifying that on average the duration of stable periods were ~ six years for direct effects and ~ nine years for indirect effects, and further suggest that monitoring in the long-term should take place with less than five years between sampling periods to capture sudden shifts away from its previous state. Trained volunteer diver networks, as utilised across southern Australian reserves (Edgar *et al.* 2009) and in Italy for

biodiversity monitoring (Goffredo *et al.* 2010), are a promising development that may help to reduce costs significantly, enabling greater spatial and temporal replication enabling monitoring in the long-term to be performed (however see Section 6.7.3 for the advantages and benefits of volunteer and community monitoring schemes).

Several studies have identified that changes are ongoing, even after decades of protection (Shears & Babcock 2003; Edgar *et al.* 2009) indicating that long-term monitoring is required to address the ongoing effects of removing extractive processes, and whether MPAs can restore areas to a pristine or more natural state. However, making judgments regarding what represents a natural state is a challenging task given the shifting baseline syndrome (Pinnegar & Engelhard 2008) and the lack of pristine ecosystems with which to make valid comparisons (although see Vroom *et al.* 2010). Several studies in the keyword search were concerned with reconstructing historical baselines, which may have particular utility with regards to identifying what should be considered an un-impacted state. Taylor *et al.* (2011) reconstructed baselines for the Poor Knights Islands Marine Reserve in New Zealand based on divers' perceptions spanning the 60 years prior to MR establishment and related these to concurrent scientific surveys. Not only does this give an indication of the extent of degradation prior to establishment, but it provides a decadal-scale indication of how shifting baselines are likely to influence judgments of what constitutes a natural state (Pinnegar & Engelhard 2008), which due to historical overfishing may require a much broader time frame for examining the impacts of fishing on marine ecosystems (e.g. Fortibuoni *et al.* 2010). Where possible, historical reconstructions can be used to measure the long-term response of marine ecosystems in the absence of extractive practices (e.g. Taylor *et al.* 2011). In addition, they can also be useful in identifying under what circumstances' fishing is responsible for irreversible shifts in ecosystem composition as MPAs may achieve a stable state different from that of historical reconstructions due to hysteresis and irreversible shifts in ecosystem function (Hughes *et al.* 2005). Identifying these effects should be an additional long-term aim of MPAs and in particular of no-take areas where anthropogenic effects can be completely isolated.

6.6.3 – Monitoring beyond abundance, biomass and size

The keyword search also highlighted many articles associated with identifying and quantifying differences in factors beyond those usually investigated in MPA studies, i.e. abundance, biomass and/or size. Process level variables such as recruitment, larval supply

and settlement (Aburto-Oropeza *et al.* 2010; Aiken & Navarrete 2011; Freeman *et al.* 2012; Hereu *et al.* 2012), predation and grazing (Hereu *et al.* 2012, Ling & Johnson 2012) were the subjects of several studies. In particular, monitoring of larval supply and recruitment within MPAs could explain differences in MPA response. Freeman *et al.* (2012) identified large disparities in the timing and magnitude of changes in rock lobster abundance inside New Zealand MPAs, which the authors attributed to differential settlement and/or recruitment pulses. Specifically monitoring larval supply and recruitment dynamics could be utilised to manage expectations of individual marine reserves (i.e. a low rate of recovery may be expected for locations that receive low larval supply) and to identify time-lags in the response of certain MPAs, that may be associated with irregular pulses of recruitment (Freeman *et al.* 2012). In addition, marine reserves as fisheries management tools are partially established for the purpose of seeding the surrounding areas, and for this reason, and to validate MPA networks supporting viable metapopulations, Aiken & Navarrete (2011) suggested that monitoring of MPAs should extend to monitoring the abundance and recruitment of fisheries target species up to distances of the long-distance dispersal potential of these species. However, this will also require consideration of the likelihood of detecting any changes, which may be feasible for species with short pelagic larval durations (PLD) such as abalone that have a PLD of ~ 3-15 days (Leighton 1974; Stephens *et al.* 2006), but unlikely for species with longer dispersal capabilities such as rock lobsters (*Jasus edwardsii*) that have a PLD of 12-24 months (Booth 1994). Modelling dispersal dynamics from MPAs could also be used to identify monitoring sites where increasing recruitment is likely to be detected based on local hydrodynamics and population sources within MPAs (e.g. Stephens *et al.* 2006). Recruitment dynamics can also interact with trophic interactions that are likely to be different inside MPAs. Hereu *et al.* (2012) identified that the consequences of recruitment pulses of urchins were damped inside MRs because of predation by lobsters, which were larger and more abundant inside MRs, and because of density-dependent recruitment, with urchin recruitment higher in areas with greater urchin abundance. Furthermore, Ling & Johnson (2012) found that urchin survival was partially mediated inside MPAs by availability of suitable shelter. Thus, monitoring of recruitment and its interplay with trophic dynamics, as well as additional factors such as habitat, can be used to inform expectations of MPA responses for different species. Monitoring of process level variables, however, requires a different approach to that of monitoring ecosystem state. Green *et al.* (2011) described the establishment and initial results of a monitoring framework specifically designed to monitor

coral reef state and process variables, involving a mix of fixed monitoring stations (process-level), and random sampling (state-level) at a variety of spatial scales. Similar approaches could be adopted in MPA studies, but would need to be optimised for the monitoring of vagile as well as sessile species, perhaps through the use of SMURFs (Standard Monitoring Units for the Recruitment of Fishes - Ammann 2004; White & Caselle 2008) for monitoring larval fish supply and sampling standardised plots for mobile invertebrate recruits (López *et al.* 1998).

Aside from the monitoring of processes inside MPAs, other factors identified in the keyword search were associated with monitoring of disease prevalence (Freeman & MacDiarmid 2009; Wootton *et al.* 2012) and behavioural changes (Parsons *et al.* 2010) inside MPAs. Disease monitoring is particularly important where the primary goal of an MPA is as a fishery closure, where it is expected to contribute to the surrounding area via adult spillover. Wootton *et al.* (2012) found that prevalence of diseases of the European lobster inside a no-take-zone in the UK was higher than outside, possibly due to higher population densities. However, Freeman & MacDiarmid (2009) found that bacterial infections in NZ rock lobsters were less prevalent inside MRs, most probably due to reduced handling by fishermen. Despite the differences in response, monitoring of individual health is important, particularly when fisheries benefits are expected from marine closures (Wootton *et al.* 2012). Finally, behavioural changes should also be monitored inside MRs, partially associated with changing attitudes towards divers, affecting survey bias (Willis *et al.* 2000) and also because of direct changes to behavioural patterns as a result of reserve status (Parsons *et al.* 2010). Parsons *et al.* (2010) performed a tagging study on the New Zealand snapper *Pagrus auratus* and identified two behavioural strategies, one with a small home range, and another that had a bimodal home range, spanning a much larger area. Of the tagged fish, all individuals tagged inside the MR displayed small home-range behaviour, while this behaviour was only displayed by half of the fish tagged outside the reserve, suggesting that the marine reserve has selected for individuals that do not frequently go outside of the reserve boundaries. This has worrying implications as selectivity for less mobile behaviour is an unwanted consequence of MR status and may impair the value of MRs as fishery tools with regards to adult spillover, but may be beneficial with regards to larval export as the more sessile reserve population is more comprehensively protected. Monitoring movement patterns in other reserves would clarify whether this is a widespread effect and over what timescale these effects become apparent.

6.6.4 – Fishing effort outside MPAs and compliance

Monitoring of fishing effort and compliance were identified in several studies regarding MPAs. In several cases poaching events were observed during regular monitoring, and these events were linked to dramatic decreases in abundance of targeted species (Linares *et al.* 2012; Francini-Filho & de Moura 2008a). Identifying these events is not only important for locating specific areas where policing effort should be increased, but can also be directly incorporated into MPA assessments in explaining the lack of demonstrable ecological effects (e.g. Fujitani *et al.* 2012). Monitoring to identify the spatial distribution of factors related to successful conservation, such as fishing effort (Stelzenmüller *et al.* 2008) and threats to ecosystem health (Selkoe *et al.* 2009) were also represented in the keyword search. Stelzenmüller *et al.* (2008) used a distribution modelling approach for assessing the spatial distribution of fishing effort with regard to distances from ports and MPAs as well as depth and other physical factors and found that fishing effort was concentrated around five no-take zones in the Mediterranean. While the authors identified that the increased fishing effort could be due to increased catch around no-take zone boundaries, it could also be attributed to fishermen's expectations of increased adult fish export from the reserves and so is not a direct indication of biomass export. Nevertheless this has important consequences for the assessment of spillover effects through the detection of gradients in biomass or size across marine reserve boundaries (Francini-Filho & de Moura 2008b), as these border zones may become depleted of fish, so confounding the detection of spillover effects (Stelzenmüller *et al.* 2008). Changes in fishing effort at the boundaries of MPAs are also likely to have direct consequences for species that frequently cross them. For example, Babcock *et al.* (2010) argued that initial changes in lobster abundance within the Cape Rodney-Okakari Point Marine Reserve in northern New Zealand led to an increase in fishing effort along the seaward MR boundary. This coincided with declines in lobster abundance within the MR, as it is also known that these lobsters perform onshore-offshore movements making them prone to legal fishing beyond the MR boundaries. In addition, monitoring the changes in fishermen's behaviour can provide information about the unintended consequences of MPA designation. Abbott & Haynie (2012) monitored the changes in the spatial distribution, gear type and fishing effort after a fisheries area closure in the Bering Sea. The changes in fishing behaviour led to increases in bycatch of halibut, highlighting the need to anticipate behavioural adaptations by fishermen, or to introduce management measures that are robust to such changes. Although identifying the areas where the negative consequences of MR

designation occur (i.e. displacement of fishing effort, shifts to alternate species) is a challenging task (marine reserve boundaries are set, but changing fishing effort requires monitoring of fishing fleet behaviour to identify impacted sites), this should be part of MR assessments to identify whether MRs have an overall positive effect when taking into account all changes attributable to MR designation.

6.6.5 – MPA networks

While the vast majority of studies reported the results of monitoring individual MPAs, several studies identified the effectiveness of MPA networks, and continental scale analyses of multiple reserves, which will become more important as MPAs move away from single isolated areas into larger networks of interconnected areas (Edgar & Stuart-Smith 2009; Hamilton *et al.* 2010; Edgar & Barrett 2012). These studies identified several adaptations to monitoring programmes that need to be adopted in order to identify and understand changes that are occurring in these areas. For large networks biogeography is likely to play an important role in governing the individual responses displayed across a MPA network (Hamilton *et al.* 2010). Hamilton *et al.* (2010) performed a network-wide analysis of the Channel Islands marine reserve network, which spans a biogeographic boundary between its eastern and western group of marine reserves. By considering biogeographic variation and grouping MPA sites according to fish community structure resultant analyses were more sensitive to MPA effects. Furthermore, Edgar & Stuart-Smith (2009) performed a continental analysis of Australian MRs and documented that differences in a number of important factors are likely to influence the outcome of MR protection, including:

- Biogeography
- Local environmental conditions, e.g. currents, exposure
- Distances of monitored sites from MR boundaries
- Time since establishment
- Differences in species and community composition
- Pre-existing fishing effort
- Level of compliance
- Level of resource extraction of surrounding areas
- Size and shape of MR
- Larval supply and source-sink dynamics
- Accessibility of MR for adult immigration and emigration

While many of these effects are relatively constant for a single reserve (and therefore do not introduce much variability into responses), they are likely to vary considerably across MPA networks, to the point where overall effects may be masked simply by the level of variability in responses introduced by these effects. While Hamilton *et al.* (2010) successfully incorporated biogeographic variation into their monitoring and analysis strategy, it remains a challenge for researchers to quantify and incorporate the above effects into MR monitoring programmes, so that individual responses can be explained and attributed to one of the above effects, within a larger network setting.

6.7 – Monitoring methodologies

Methodologies vary in their effectiveness among species, and also among locations (see Chapters 2 and 3). In this section I will discuss studies that present both new technological advances in monitoring techniques, but also considerations of metrics and indices of ecosystem state, considerations for replication and frequency of monitoring, the testing and utilisation of volunteer networks and participatory monitoring, and finally monitoring and management frameworks.

6.7.1 – Indices and metrics

There were 25 articles identified using the keyword search that were either performing research defining adequate indices or metrics, or utilising indices to assess ecosystem state, or health. Indices are most often defined for systems where a holistic approach to defining ecosystem health (i.e. considering all aspects of the community) is required. Identifying adequate metrics however requires a formal test of alternative metrics and identification of a minimum set of metrics required to represent the specific targets of MPAs (e.g. using factor analysis as in Greenstreet *et al.* 2012). Metrics must also have adequate baselines or benchmark figures, based on non-impacted or pristine ecosystems (e.g. Vroom *et al.* 2010 and discussion in section 6.6.2). However for many areas, adequate control locations are unlikely to exist, due to heterogeneity in environmental conditions and the pervasive and long term nature of human impacts. Villnäs & Norkko (2011) addressed this issue to identify reference conditions and a simple metric of benthic status based on average regional diversity. Furthermore, based on a long-term dataset they were able to identify reference conditions for different areas, and also levels of acceptable deviation away from these reference states that are indicative of environmental degradation. Incorporating these measures along with an appropriate management decision framework (statistical process

control, based on manufacturing quality control frameworks have recently also been applied in an ecological context, Mesnil & Petitgas 2009) has particular utility within management contexts.

6.7.2 – *Monitoring techniques*

Multiple technological advancements were described in the literature for monitoring different aspects of subtidal communities. Although some of these simply presented new technologies, for example rotating high-definition drop cameras (Pelletier *et al.* 2012), and use of multibeam data to identify grouper “holes” as a proxy for spawning abundance (Wall *et al.* 2011), the majority were comparisons of methods, particularly regarding; differences in the species they were capable of monitoring (e.g. between baited and unbaited remote underwater video, Bernard & Götz 2012), ability to measure fish sizes (e.g. Laser calibrated underwater video versus diver estimation, Heppell *et al.* 2012) and precision of alternate methodologies or protocols in determining species densities (e.g. among stationary counts, belt transects and diver tow video surveys, McCauley *et al.* 2012). However, many studies, rather than rely on single methodologies, concluded that a suite of monitoring techniques and methods were often required, as each method had its own strengths and weaknesses (Seytre & Francour 2008; Bernard & Gotz 2012). In particular, many studies focussed on the importance of habitat in governing fish assemblage composition and abundances (Claudet *et al.* 2011), as well as monitoring to assess entire ecosystem change (see section 6.6.2). Achieving this would require a much broader suite of monitoring protocols including UVC, hydroacoustics, multibeam data, RUVs, and drop cameras (Cassata & Collins 2010; Murphy & Jenkins 2010; Pelletier *et al.* 2011; 2012).

Identifying the amount of replication that is required is made even more important if resources are spread across multiple monitoring techniques. Several studies from the keyword search were identified as performing analyses of statistical power to optimise survey design (Jackson *et al.* 2008; Sims *et al.* 2008; Molloy *et al.* 2010; Teilmann *et al.* 2010). While the specific applications varied, these studies highlighted the importance of considering when is the best time to sample populations (Jackson *et al.* 2008; Sims *et al.* 2008) that may be particularly important for species that undergo large-scale movements (e.g. rock lobster inshore/offshore, Kelly 2001) and also the importance of repeated surveys within each year (Teilmann *et al.* 2010). Repeated surveys (i.e. surveys performed on separate days within each year and/or season) are useful in that they allow year to year variation, associated with

recruitment, growth and mortality, to be separated from day to day variation that is more likely to be associated with sea state, atmospheric conditions or presence of predator/prey on the survey date (Thompson & Mapstone 2002; McClanahan *et al.* 2007). Performing repeated surveys and assessing whether they are necessary for individual species groups as part of a pilot study should be a necessary component of monitoring programme design. Monitoring frequency across years is also a valid consideration (e.g. Smith *et al.* 2008 identified that annual monitoring is sufficient to detect persistent signs of stress in a coral reef ecosystem, but would not be sufficient to resolve patterns of transient stress) for MPAs as monitoring may be able to give initial indications of otherwise undetected poaching, disease and spread of invasive species that may require swift management actions, and monitoring at higher frequencies is more likely to detect these changes early, such that management actions are more successful.

6.7.3 – *Volunteer monitoring networks and participatory monitoring*

Volunteer monitoring is an attractive prospect and although the initial establishment and organisation is time-intensive it is a relatively cost-effective means for collecting data, particularly across continental spatial scales (Edgar & Stuart-Smith 2009; Goffredo *et al.* 2010). To ensure quality and reliability of data volunteer collected data need to be validated against data collected by scientific divers (e.g. Edgar & Stuart-Smith 2009). However, recreational divers who are dedicated and have undergone some training are able to collect data with similar accuracy and precision as that of scientific divers (Reef Life surveys, see Edgar & Stuart-Smith 2009), and although this limits the numbers of participants (only the most dedicated divers were selected to partake in monitoring for Reef life surveys) it provides some guarantees regarding data quality. Recreational diver surveys and questionnaires have also been used in biodiversity assessments (e.g. Goffredo *et al.* 2010). The major drawback of this means of data collection is few recreational divers are willing to dive at poor quality sites, and consequently biodiversity assessments are likely to be biased towards more attractive or high quality locations. However, Goffredo *et al.* (2010) also noted that in addition to the benefits of broad scale data collection, involvement of divers in scientific studies increases diver awareness, and may consequently contribute to increasing compliance within MPAs. This is also one of the main arguments for participatory or community driven monitoring, as it is a means for involving the people who are most influential in the governance of MPAs directly into assessments of their effectiveness (Léopold *et al.* 2009). Strategies providing some means of training, and utilising techniques that the local

community know and trust (Seytre & Francour 2008), can provide the data required for scientific investigation while enforcing belief in protection measures and marine closures (Léopold *et al.* 2009; Fox *et al.* 2012). Particularly where monitoring and the whole process of implementing management strategies are handled through local communities, simplified analyses and clearly established management steps are required to enable adequate monitoring and marine management. For example, Rouphael *et al.* (2011) in collaboration with park managers identified that a monitoring and management plan consisting of data collection followed by confidence interval estimation and comparison to pre-defined thresholds provided an adequate means to identify potential damage to hard-corals due to snorkelers within a MPA. Furthermore, additional review and evaluation stages, involving the collection of additional information once a potential, but not definite, effect was noted, and consultation with scientific advisors, were incorporated such that at any stage there were clear processes and protocols once an effect was potentially noticed. Simple methods, such as those presented in Rouphael *et al.* (2011), which are grounded in solid scientific assessments, provide powerful means to achieve adequate management and also provide a means for local communities, who often lack scientific training, to become more involved in the management of marine ecosystems, with subsequent impacts on compliance and the state of coastal marine environments (Fox *et al.* 2011).

6.8 – Description of monitoring framework

The framework itself is split into four time periods, two phases prior to MPA establishment, and two phases after. The main target for data collection in the planning phase is to provide suitable information regarding the distribution of species and habitats across broad spatial scales to inform decisions pertaining to the placement and size of an MPA, or series of MPAs. During the planning phase initial broad-scale assessments of the spatial distribution of habitats, species and threats is carried out. Distribution modelling using methods such as those presented in Chapters 4 and 5 can be utilised in this phase to make assessments of species/habitat distributions that can be incorporated into zonation assessments for MPA placements, while mapping of habitats, threats and fishing effort provide additional information with regard to the degree of anthropogenic pressure across the entire seascape. During this phase discussions regarding the key aims and goals of MPA protection (i.e. whether it is to protect or promote diversity, individual species abundances, fisheries management), should take place and at this point the monitoring protocol for measuring these responses, both in the short and the long-term, should be discussed along

with prospective analyses (i.e. precision and/or accuracy of measured variables for different monitoring methods, and amounts of replication) to identify suitable monitoring protocols for baseline assessments. Although at this stage the amount of data available to perform prospective analyses to identify suitable levels of replication and coverage is likely to be small (quite possibly zero), examples of retrospective and prospective analyses of monitoring effectiveness, such as those presented in Chapters 2 and 3, could be used to identify an initial monitoring protocol for species that have similar abundances (based on initial pilot studies performed during the planning phase) and display similar behaviour to the species for which the prospective analyses are to be performed. In addition, distribution modelling information (such as in Chapter 4 and 5) may be used to identify areas that are likely to have similar communities prior to MPA establishment (useful for identifying similar sites inside and outside the MPA that could be used to establish a paired BACI design - Osenberg *et al.* 1994), and also to identify potential sites that have different species and/or communities so that monitoring coverage incorporates all of the communities within the wider area to give a complete view of MPA effects among community types. Based on these prospective analyses, an initial monitoring protocol can be established for the collection of baseline information.

The aim of monitoring in the baseline phase is to establish information regarding the initial abundance, biomass and size of individuals along with variables that are likely to influence the rate and magnitude of responses at individual MPA sites, such as prior fishing effort, habitat (at various spatial scales i.e. Claudet *et al.* 2011) and also if possible the level of larval supply/recruitment at MPA sites. Further considerations include entire ecosystem assessments (i.e. information regarding non-target species that may be affected indirectly, rather than just target species) as well as identifying trophic interactions, because these are likely to change as a result of direct and indirect effects. Ideally, baseline information should be gathered over a period of years, so that levels of natural variation in monitored attributes can be assessed such that initial MPA effects can be distinguished from natural variability. It should be noted that the collection of comprehensive baseline information should be prioritised to enable adequate examination of MPA effects in the future. MPA effects can include simple single species responses (Davidson 1991) or can manifest as a shift in the entire community (Shears & Babcock 2003) affecting multiple species. The collection of comprehensive baseline information across species and habitats will provide the necessary data to provide a strong analysis of the full extent of MPA effects, irrespective of how they

manifest within a specific ecosystem. At this stage, due to the additional information available from baseline monitoring, a more comprehensive assessment of future monitoring protocols can be made, such as presented in Chapter 2, to identify subsequent monitoring in the short and long-term.

Monitoring after the establishment of an MPA is here split into two distinct phases. Due to the evidence suggesting that MPA effects can be rapid (section 6.6.2) relatively high-frequency monitoring should be performed at this time to identify direct responses, which may be critical in demonstrating that the MPA is “working” to various stakeholders and to advocate for further MPAs. In addition, data that can be used to supplement state-level monitoring should be collected, such as identifying the shifts in fishing behaviour (e.g. increased fishing effort along MPA boundaries may influence responses exhibited at nearby MPA sites - Stelzenmüller *et al.* 2008; Babcock *et al.* 2010), poaching and monitoring of process variables, to explain the rate of change (or lack thereof due to lack of recruitment, Freeman *et al.* 2012) within the MPA, or even to make projections about responses in the coming years (e.g. Aburto-Oropeza *et al.* 2010). Furthermore, to truly assess the effect of establishing an MPA the shifts in fishing behaviour outside the MPA need to be addressed, even to the extent of identifying sites where fishing effort has increased as a result of MPA protection, so that these can be monitored and subsequently incorporated into assessments of MPA effects (e.g. Abbott & Haynie 2012). Behavioural changes introducing bias in monitoring protocol (e.g. Willis *et al.* 2000; Davidson 2001) and changes in abundance due to MPA designation should be identified at this stage to assess whether methodologies remain effective and need to be updated if they no longer meet monitoring requirements (for example analyses such as those presented in Chapter 3 to identify changes in replication). The frequency and duration of monitoring in the early MPA phase is likely to be governed primarily by logistical and cost constraints. However, given that direct effects are often evident within the first decade following MPA designation (Stewart *et al.* 2009; Babcock *et al.* 2010), 10 years of monitoring on an annual or biennial basis would seem like a suitable target that can be adjusted based on the likelihood of changes occurring in this period informed by levels of prior anthropogenic pressure and species life-history and further by initial responses in the early years of monitoring.

The primary aim of monitoring in the final stage is to maintain monitoring of target species for the purpose of assessing ongoing progress with regard to historical baselines (e.g.

Taylor *et al.* 2011) or pristine locations (e.g. Vroom *et al.* 2010). Indirect effects are also likely to become evident over longer time periods, and direct effects may stabilise, continue in the same direction, or may reverse due to changes in trophic structure/habitat as a result of trophic cascades (Babcock *et al.* 2010). Thus, in this stage, periodic ecosystem assessments should be incorporated into monitoring plans to identify how the structure and functioning of the ecosystem differs from its baseline state as a means to identify the extent and nature of changes to ecosystems as a result of anthropogenic influences. In addition, fisheries expectations of MPAs, such as spillover of adults and larval export, are more likely to be evident in latter stages because of accumulation of more and larger individuals inside MPAs. Thus, monitoring of these effects by identifying gradients in biomass across MPA boundaries (Francini-Filho & de Moura 2008b) or tagging studies (Parsons *et al.* 2010) for spillover, and testing for changes in larval supply at external sites (Aiken & Navarrete 2011) are more likely to identify these changes at this latter stage than in earlier stages. This stage is likely to be ongoing for many decades after MPA designation, and requires a commitment to long-term monitoring and evaluation of effects, as well as rigorous scientific study of the connections among the various factors influencing MPA effectiveness. As suggested by Babcock *et al.* (2010) monitoring frequency should also be maintained with less than five years between monitoring occasions such that chance events, such as recruitment pulses and/or die-off of certain species due to disease, are captured. In addition relatively frequent monitoring is also essential for identifying otherwise unobserved poaching events (Linares *et al.* 2012) and the effects of fishing MPA boundaries (Babcock *et al.* 2010) both of which are likely to increase as MPAs age.

The monitoring framework presented here should be treated not as an exhaustive list of necessary data collection, but should rather be treated as a guideline for stakeholders to consult with specific research questions in mind. Depending on these research questions, specific aspects of the framework are likely to be a priority, whilst others are likely to be unrelated to these research questions. The framework should also not be viewed as a one-way or linear series of steps, as assessments of the MPA and the MPA monitoring should be used to reassess past decisions, and be used update the state of the MPA (e.g. shifting from restricted fishing to full no-take, or an expansion or reduction of the MPA size) depending on the evidence to support the ongoing changes in light of the stakeholders aims and goals. This ensures that both the MPA, and the monitoring thereof remains relevant to stakeholders.

6.9 – Conclusion

In this final chapter I have drawn together current research findings and methodological considerations, as well as results and methods from Chapters 2 – 5, to construct a guideline framework for collection of data relevant to MPAs. Chapters 2 and 3 highlight the importance of performing prospective and retrospective analyses of monitoring performance to identify suitable monitoring procedures, while Chapters 4 and 5 provide novel methods for examining the spatial distribution of marine species and the biogenic habitats they occupy. This final point is an important consideration when designing MPAs and can be further incorporated into monitoring programme design to ensure that monitoring is representative of all habitats and species within the MPA. This chapter not only draws these findings into a consistent framework, but presents new information sourced across biogeographic and taxonomic groups, to provide a suitable basis for the monitoring of MPAs. In addition this framework incorporates components that may enable the explanation of the many differences among MPA responses (as highlighted by Stewart *et al.* 2009) in light of conditions, such as prior fishing pressure and larval supply, that are likely to effect the responses they exhibit, further advancing the state of MPA science.

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Appendix 1 – Supporting material and additional results for Chapter 3

Table A1.1. AIC and Log-likelihood values of model fits to the species-reserve specific datasets with site*date as a factor. Headings refer to the assumed error distribution. *Best models based on AIC and log-likelihood.

Reserve	Species	AIC			Log-Likelihood		
		Normal	Poisson	Negative Binomial	Normal	Poisson	Negative Binomial
Tonga Island	<i>Latridopsis ciliaris</i>	4039.4	1917.9	1770.1*	-1878.7	-818.9	-744.0*
	<i>Notolabrus celidotus</i>	9642.6	8709.2	7563.3*	-4680.3	-4214.6	-3640.7*
	<i>Nemadactylus macropterus</i>	9400.2	6123.8	3930.4*	-4559.1	-2921.9	-1824.2*
	<i>Parapercis colias</i>	4677.9	2607.4	2470.9*	-2198.0	-1163.7	-1094.5*
Long Island	<i>Latridopsis ciliaris</i>	2915.0	1387.2	1323.7*	-1300.5	-537.6	-504.9*
	<i>Notolabrus celidotus</i>	15619.0	23373.0	13384.0*	-7652.5	-11530.4	-6534.9*
	<i>Nemadactylus macropterus</i>	6124.8	1052.9	783.3*	-2905.4	-370.4	-234.7*
	<i>Parapercis colias</i>	10080.0	9477.6	8681.9*	-4882.8	-4582.8	-4183.9*
Horoirangi	<i>Latridopsis ciliaris</i>	1455.6	545.9	486.1*	-650.8	-196.9	-166.1*
	<i>Notolabrus celidotus</i>	4824.6	4564.9	4375.7*	-2335.3	-2206.5	-2110.9*
	<i>Nemadactylus macropterus</i>	5294.0	2653.9	1375.8*	-2570.0	-1250.9	-610.9*
	<i>Parapercis colias</i>	1265.6	813.5	808.6*	-555.8	-330.8	-327.3*

Table A1.2. The proportion of within site counts that were considered to be overdispersed compared to a poisson distribution, by comparing the within site variance to that expected if the counts were poisson random variables using a chi-squared test ($\text{dof.} = n_{\text{transects}} - 1$).

Species	Reserve	Frequency of overdispersal (per region)	Frequency of overdispersal (per species)
<i>Latridopsis ciliaris</i>	Long Island	0.24	0.25
	Tonga Island	0.25	
	Horoirangi	0.24	
<i>Notolabrus celidotus</i>	Long Island	0.83	0.61
	Tonga Island	0.50	
	Horoirangi	0.37	
<i>Nemadactylus macropterus</i>	Long Island	0.24	0.41
	Tonga Island	0.50	
	Horoirangi	0.35	
<i>Parapercis colias</i>	Long Island	0.55	0.38
	Tonga Island	0.27	
	Horoirangi	0.10	

Table A1.3. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Long Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Blue Cod	3	6	1	48.2	0.16	0.027	53.4	0.16	0.029	15.6	0.34	0.051	15.8	0.34	0.052
		3	8	1	52	0.16	0.028	53	0.16	0.029	21.2	0.30	0.048	20.2	0.30	0.045
		3	10	1	49.2	0.16	0.024	54.4	0.16	0.027	23.2	0.28	0.043	24.4	0.27	0.043
		3	12	1	49.4	0.16	0.029	56.8	0.16	0.025	29.2	0.25	0.046	28.8	0.25	0.035
		3	16	1	54.6	0.15	0.026	54.8	0.16	0.026	32	0.23	0.039	28	0.23	0.035
		4	6	1	55.6	0.15	0.025	54.6	0.15	0.025	19.4	0.30	0.047	19.6	0.30	0.051
		4	8	1	57.6	0.15	0.026	58.4	0.15	0.024	24.4	0.26	0.040	22.6	0.26	0.040
		4	10	1	54.4	0.15	0.025	57.2	0.15	0.026	28.6	0.24	0.039	26	0.24	0.038
		4	12	1	60.2	0.15	0.025	61	0.15	0.026	29.2	0.22	0.036	33.2	0.22	0.036
		4	16	1	55.8	0.15	0.025	58.4	0.15	0.025	37.2	0.20	0.035	38.2	0.20	0.035
		5	6	1	59	0.14	0.027	60.4	0.14	0.022	22.4	0.27	0.041	24	0.27	0.042
		5	8	1	57.2	0.14	0.024	63.6	0.14	0.022	27.4	0.24	0.039	29	0.24	0.037
		5	10	1	62.4	0.14	0.025	59.2	0.14	0.023	30.6	0.22	0.036	35.6	0.22	0.035
		5	12	1	61.4	0.14	0.024	61	0.14	0.024	35.8	0.20	0.031	35.4	0.20	0.036
		5	16	1	60.8	0.14	0.020	61	0.14	0.024	42.2	0.19	0.031	41.2	0.19	0.030
		6	6	1	60.4	0.14	0.023	59.4	0.14	0.025	25.8	0.25	0.039	25.4	0.25	0.043
		6	8	1	62.6	0.14	0.024	61.8	0.14	0.024	27.8	0.22	0.035	31	0.22	0.039
		6	10	1	60.6	0.14	0.024	62.4	0.13	0.025	35.8	0.20	0.035	37	0.20	0.036
		6	12	1	65.2	0.13	0.023	60.8	0.14	0.022	41.6	0.19	0.032	39.2	0.19	0.032
		6	16	1	61.2	0.14	0.024	65	0.14	0.024	43.6	0.17	0.029	46.6	0.17	0.031
		8	6	1	64	0.13	0.022	64.2	0.13	0.021	33	0.22	0.035	30.2	0.22	0.032
		8	8	1	67.8	0.13	0.021	64.6	0.13	0.022	39	0.19	0.031	36.8	0.20	0.031
		8	10	1	64.2	0.13	0.025	67.2	0.13	0.021	43.2	0.18	0.031	44.2	0.18	0.028
		8	12	1	65	0.13	0.024	66.2	0.13	0.023	46	0.17	0.029	42.4	0.17	0.030
		8	16	1	65	0.13	0.024	66	0.13	0.023	49.4	0.16	0.025	50.2	0.16	0.027

Table A1.4. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Long Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Blue Cod	3	6	2	37.8	0.29	0.042	30.4	0.28	0.040	14	0.63	0.077	10.8	0.64	0.076
		3	8	2	34.2	0.28	0.037	35.6	0.27	0.036	15	0.55	0.070	15	0.56	0.062
		3	10	2	32.8	0.27	0.042	31.4	0.27	0.038	16.2	0.50	0.064	13.2	0.50	0.056
		3	12	2	36.8	0.28	0.036	35	0.28	0.037	17.4	0.47	0.055	20.4	0.45	0.059
		3	16	2	31.8	0.28	0.035	36.8	0.27	0.037	19.2	0.43	0.054	19.6	0.42	0.053
		4	6	2	37.4	0.26	0.037	36.4	0.26	0.037	14	0.55	0.063	15.6	0.57	0.072
		4	8	2	39.6	0.25	0.038	37.2	0.25	0.034	19.4	0.48	0.062	16.4	0.49	0.062
		4	10	2	36.4	0.26	0.036	39.4	0.25	0.036	18.4	0.44	0.055	18.4	0.43	0.056
		4	12	2	35.4	0.25	0.034	39.4	0.24	0.036	23.6	0.41	0.055	21.2	0.41	0.055
		4	16	2	39	0.25	0.034	42.8	0.24	0.038	23.4	0.38	0.052	23.8	0.38	0.047
		5	6	2	41.4	0.24	0.032	40.2	0.23	0.038	14.2	0.50	0.060	14.8	0.52	0.062
		5	8	2	42.2	0.23	0.036	39	0.23	0.032	18.8	0.45	0.055	16.6	0.44	0.056
		5	10	2	39	0.23	0.034	39.8	0.23	0.034	19.2	0.41	0.049	17.4	0.41	0.050
		5	12	2	40.2	0.23	0.032	43.8	0.23	0.034	21.2	0.38	0.047	20.6	0.38	0.047
		5	16	2	46	0.23	0.038	39.2	0.24	0.034	27.4	0.34	0.048	25.6	0.34	0.043
		6	6	2	39.4	0.23	0.036	46.2	0.22	0.036	17	0.47	0.057	18	0.47	0.059
		6	8	2	43.2	0.22	0.031	40.6	0.23	0.032	19	0.41	0.053	20	0.41	0.050
		6	10	2	40	0.23	0.035	43	0.22	0.030	25	0.37	0.052	22.2	0.37	0.048
		6	12	2	42.8	0.22	0.030	45.8	0.21	0.035	24	0.34	0.047	22.6	0.35	0.042
		6	16	2	41.4	0.22	0.034	45	0.23	0.034	26.8	0.31	0.045	28.2	0.32	0.040
		8	6	2	48.2	0.21	0.031	48.4	0.20	0.030	21.8	0.40	0.048	18.8	0.41	0.051
		8	8	2	44	0.21	0.032	50	0.21	0.033	23.2	0.36	0.049	23.8	0.36	0.049
		8	10	2	51.4	0.20	0.031	46.8	0.20	0.032	22.4	0.34	0.042	23.8	0.33	0.042
		8	12	2	45	0.21	0.032	42.6	0.20	0.033	28.6	0.31	0.043	26.2	0.31	0.040
		8	16	2	45.6	0.21	0.031	49.4	0.21	0.032	32.4	0.28	0.037	30.4	0.28	0.036

Table A1.5. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Long Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Blue Cod	3	6	3	41.4	0.34	0.040	39.8	0.33	0.036	14.2	0.78	0.076	16.4	0.75	0.073
		3	8	3	35.6	0.33	0.033	38.4	0.32	0.038	17.2	0.66	0.064	15.2	0.66	0.062
		3	10	3	37	0.33	0.038	39	0.32	0.037	19.2	0.61	0.058	21.4	0.60	0.063
		3	12	3	40.4	0.32	0.034	39	0.33	0.034	20.2	0.55	0.056	20	0.57	0.057
		3	16	3	41.8	0.33	0.035	41.6	0.32	0.033	22.2	0.50	0.048	26	0.50	0.050
		4	6	3	40.4	0.31	0.035	44.8	0.29	0.032	14.8	0.68	0.063	15.8	0.68	0.062
		4	8	3	44.2	0.31	0.033	41.2	0.29	0.035	17	0.61	0.055	21.4	0.60	0.059
		4	10	3	44.4	0.30	0.031	45.2	0.29	0.033	19.8	0.55	0.049	20.6	0.55	0.059
		4	12	3	41.8	0.30	0.031	43.2	0.29	0.030	23	0.51	0.047	19.2	0.50	0.043
		4	16	3	47.6	0.29	0.032	41.4	0.29	0.034	23.6	0.47	0.045	27.6	0.45	0.046
		5	6	3	44.4	0.29	0.034	43.6	0.28	0.030	19.6	0.62	0.057	16.6	0.64	0.058
		5	8	3	44.8	0.28	0.033	53	0.27	0.030	20	0.55	0.052	19.6	0.55	0.051
		5	10	3	50.8	0.27	0.033	47.4	0.27	0.031	25.6	0.49	0.053	23.8	0.50	0.045
		5	12	3	49.2	0.27	0.031	47.6	0.27	0.031	23.8	0.46	0.052	25.4	0.46	0.047
		5	16	3	49.2	0.28	0.029	46.2	0.27	0.033	26	0.42	0.040	29.2	0.42	0.043
		6	6	3	45.8	0.27	0.032	48	0.25	0.031	20.2	0.58	0.052	20.6	0.58	0.055
		6	8	3	48.2	0.27	0.031	48	0.26	0.029	22.2	0.51	0.049	24.8	0.51	0.048
		6	10	3	46.6	0.27	0.031	49.8	0.25	0.029	28	0.46	0.043	29.8	0.46	0.045
		6	12	3	47.6	0.26	0.032	50.2	0.26	0.031	33	0.42	0.046	28	0.43	0.043
		6	16	3	52.2	0.26	0.030	51.6	0.25	0.030	33.8	0.38	0.040	31.8	0.39	0.040
		8	6	3	48.8	0.25	0.032	47.2	0.24	0.029	19.6	0.51	0.047	22.6	0.52	0.052
		8	8	3	52.6	0.24	0.031	54.4	0.23	0.026	26.8	0.46	0.045	25	0.44	0.039
		8	10	3	52.2	0.24	0.030	51	0.24	0.033	28	0.41	0.036	27.4	0.41	0.044
		8	12	3	52	0.23	0.029	54.2	0.22	0.029	33.6	0.38	0.037	33.6	0.38	0.040
		8	16	3	52.8	0.24	0.030	53.6	0.24	0.032	36.8	0.35	0.041	37.2	0.34	0.038

Table A1.6. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Tonga Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Blue Cod	3	6	1	14.6	0.34	0.050	23.6	0.30	0.043	13.6	0.47	0.071	11.2	0.43	0.062
		3	8	1	20.6	0.32	0.051	20	0.29	0.043	11.6	0.42	0.062	13	0.39	0.055
		3	10	1	19.4	0.31	0.045	20.6	0.28	0.040	13.2	0.40	0.057	13.8	0.37	0.052
		3	12	1	20.8	0.30	0.047	22	0.28	0.045	17	0.37	0.060	14	0.35	0.054
		3	16	1	22.4	0.29	0.046	23.4	0.28	0.039	18.4	0.34	0.053	14.6	0.32	0.043
		4	6	1	18.4	0.30	0.051	24.2	0.27	0.042	14.6	0.41	0.066	15.4	0.38	0.059
		4	8	1	22.4	0.28	0.043	23.8	0.26	0.040	12.2	0.37	0.055	17.2	0.35	0.057
		4	10	1	26.4	0.27	0.043	24.6	0.25	0.040	16	0.34	0.052	18.2	0.32	0.045
		4	12	1	24.8	0.27	0.045	29.6	0.25	0.039	17.4	0.32	0.047	19.2	0.30	0.043
		4	16	1	25.8	0.26	0.042	29.2	0.24	0.037	22.2	0.30	0.048	24.6	0.28	0.046
		5	6	1	25.6	0.27	0.041	27	0.24	0.037	15	0.37	0.058	16.6	0.34	0.051
		5	8	1	23.2	0.26	0.036	31	0.23	0.038	18.8	0.32	0.049	19.2	0.31	0.044
		5	10	1	29.2	0.25	0.038	28.6	0.23	0.038	19.2	0.31	0.051	20	0.29	0.046
		5	12	1	29.2	0.24	0.039	30.8	0.22	0.033	20.2	0.29	0.043	22.6	0.27	0.045
		5	16	1	30.6	0.23	0.034	32.6	0.22	0.034	24.6	0.27	0.043	23.4	0.26	0.042
		6	6	1	26	0.25	0.036	32	0.22	0.034	17	0.34	0.051	18.6	0.31	0.048
		6	8	1	26.6	0.24	0.037	36	0.21	0.033	21.8	0.30	0.050	16.2	0.29	0.039
		6	10	1	29.8	0.23	0.036	31.2	0.21	0.033	22.4	0.28	0.044	21.6	0.27	0.041
		6	12	1	35	0.22	0.036	32.8	0.21	0.032	24.4	0.27	0.040	24.2	0.25	0.041
		6	16	1	36.4	0.21	0.034	35	0.20	0.032	27.8	0.25	0.040	27.2	0.24	0.036
		8	6	1	32	0.22	0.033	36.2	0.20	0.031	19.4	0.29	0.044	22.4	0.27	0.039
		8	8	1	37.4	0.21	0.031	38.4	0.19	0.029	23.4	0.26	0.043	28	0.25	0.037
		8	10	1	38.6	0.20	0.029	40.1	0.18	0.028	28	0.25	0.039	27.8	0.23	0.035
		8	12	1	39	0.20	0.031	41.8	0.18	0.027	29.2	0.24	0.038	33.8	0.22	0.038
		8	16	1	37.2	0.19	0.029	44.8	0.18	0.028	30.6	0.22	0.032	36	0.21	0.035

Table A1.7. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Blue Cod	3	6	2	10.8	0.63	0.076	13.2	0.57	0.073	11	0.86	0.100	12	0.83	0.094
		3	8	2	13	0.58	0.067	12.8	0.54	0.067	11.2	0.77	0.092	9.2	0.75	0.092
		3	10	2	12.4	0.57	0.064	16	0.53	0.063	10.2	0.71	0.090	11	0.66	0.077
		3	12	2	13.2	0.56	0.064	10.4	0.52	0.061	13.2	0.69	0.083	10.2	0.65	0.074
		3	16	2	11.4	0.54	0.062	15.8	0.51	0.062	12	0.65	0.075	10.4	0.62	0.071
		4	6	2	12.2	0.56	0.071	13	0.52	0.055	8.2	0.78	0.088	13.4	0.72	0.092
		4	8	2	13.6	0.54	0.066	16	0.49	0.060	9.8	0.68	0.081	11	0.65	0.081
		4	10	2	14	0.51	0.056	15.8	0.48	0.058	11	0.63	0.071	11.8	0.62	0.067
		4	12	2	18.2	0.50	0.065	15.2	0.47	0.058	11	0.62	0.067	16.4	0.57	0.069
		4	16	2	13.2	0.48	0.058	15.4	0.44	0.055	10.6	0.57	0.058	12.6	0.54	0.067
		5	6	2	18.2	0.51	0.062	19	0.46	0.059	11	0.70	0.084	13	0.65	0.082
		5	8	2	13.4	0.48	0.049	17.6	0.45	0.049	11.6	0.62	0.068	12.2	0.59	0.062
		5	10	2	18.6	0.47	0.054	18.6	0.42	0.051	13.4	0.57	0.069	13	0.56	0.068
		5	12	2	15.6	0.45	0.051	18.4	0.42	0.049	15.8	0.56	0.065	14.8	0.53	0.059
		5	16	2	16.6	0.44	0.053	17	0.42	0.046	13.6	0.51	0.063	13.8	0.48	0.053
		6	6	2	14	0.47	0.057	20.6	0.43	0.052	11.6	0.63	0.073	11.8	0.59	0.068
		6	8	2	17.4	0.45	0.056	16	0.41	0.049	13	0.57	0.068	12.6	0.55	0.061
		6	10	2	17	0.43	0.053	21.8	0.39	0.044	16	0.55	0.063	16	0.50	0.058
		6	12	2	17.4	0.42	0.045	22	0.38	0.046	14.6	0.50	0.062	13.8	0.49	0.059
		6	16	2	20.6	0.41	0.047	23	0.39	0.048	16.6	0.48	0.057	16.2	0.45	0.054
		8	6	2	18.6	0.42	0.048	24.6	0.37	0.044	11.8	0.57	0.067	14	0.52	0.062
		8	8	2	18.2	0.39	0.047	23.8	0.36	0.039	13.2	0.51	0.061	14.8	0.48	0.055
		8	10	2	21.2	0.38	0.044	20.8	0.35	0.039	17.4	0.47	0.060	15.6	0.45	0.047
		8	12	2	26.6	0.37	0.045	21	0.35	0.044	16.6	0.45	0.055	19.6	0.43	0.050
		8	16	2	20.8	0.35	0.039	19.8	0.34	0.037	19	0.42	0.050	18	0.39	0.048

Table A1.8. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Blue Cod	3	6	3	12.4	0.79	0.069	14.8	0.69	0.066	14.2	1.08	0.111	13.8	0.96	0.089
		3	8	3	13.2	0.74	0.064	15.8	0.66	0.058	12.2	0.99	0.090	12	0.90	0.087
		3	10	3	11.2	0.70	0.061	15	0.65	0.060	10.4	0.89	0.087	13	0.84	0.076
		3	12	3	15.4	0.68	0.065	15	0.64	0.056	14.4	0.83	0.079	13.6	0.81	0.080
		3	16	3	16	0.67	0.057	19.2	0.62	0.065	10.8	0.79	0.072	13	0.75	0.069
		4	6	3	13.8	0.70	0.065	15.8	0.63	0.057	12.2	0.97	0.079	14.2	0.86	0.082
		4	8	3	13.8	0.68	0.058	18.6	0.60	0.054	12.6	0.87	0.080	13	0.82	0.074
		4	10	3	19	0.63	0.058	18.2	0.58	0.059	12.4	0.80	0.070	14.4	0.73	0.067
		4	12	3	18.2	0.63	0.059	20.4	0.57	0.053	16.2	0.77	0.068	13	0.72	0.060
		4	16	3	15.8	0.60	0.059	18.4	0.57	0.051	12.4	0.70	0.064	16.4	0.65	0.055
		5	6	3	13.2	0.65	0.055	19	0.57	0.049	10.6	0.89	0.078	11.4	0.80	0.068
		5	8	3	17.2	0.62	0.052	18.4	0.55	0.047	12.6	0.79	0.067	11.4	0.74	0.058
		5	10	3	16.4	0.59	0.052	22.4	0.53	0.052	14.2	0.73	0.064	16	0.69	0.064
		5	12	3	18.6	0.57	0.051	19.2	0.53	0.045	14.4	0.69	0.067	14.4	0.63	0.056
		5	16	3	20	0.54	0.050	20.4	0.52	0.048	18.6	0.63	0.057	17.4	0.63	0.054
		6	6	3	18.6	0.58	0.052	25	0.51	0.050	11.6	0.79	0.069	14	0.76	0.070
		6	8	3	20	0.56	0.048	22.2	0.50	0.044	16.8	0.73	0.065	12.2	0.69	0.055
		6	10	3	23.6	0.54	0.052	20.8	0.50	0.044	15.6	0.67	0.059	16.8	0.62	0.058
		6	12	3	20	0.52	0.042	22.4	0.48	0.040	17.4	0.63	0.057	17.2	0.61	0.053
		6	16	3	24.8	0.50	0.045	23.4	0.47	0.046	21.2	0.59	0.053	17.8	0.57	0.049
		8	6	3	18.8	0.52	0.045	25.4	0.47	0.040	13.8	0.71	0.060	14.8	0.66	0.055
		8	8	3	21.6	0.49	0.044	24	0.44	0.039	16.8	0.63	0.058	19	0.58	0.056
		8	10	3	23	0.48	0.040	25.6	0.43	0.039	18.6	0.60	0.055	22.2	0.56	0.051
		8	12	3	26.4	0.45	0.043	29.6	0.42	0.038	18.8	0.56	0.051	19.2	0.54	0.048
		8	16	3	27.6	0.45	0.040	29.6	0.42	0.037	18.4	0.53	0.045	26	0.50	0.049

Table A1.9. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Horoirangi Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Blue Cod	3	6	1	12.2	0.49	0.083	13	0.45	0.069	12	0.61	0.100	11.2	0.55	0.087
		3	8	1	14.4	0.47	0.081	14.2	0.44	0.072	11.4	0.57	0.077	11.2	0.51	0.087
		3	10	1	12	0.47	0.074	14.2	0.43	0.073	11	0.53	0.087	11.6	0.48	0.077
		3	12	1	15	0.45	0.077	14.4	0.43	0.066	10.2	0.51	0.084	15.4	0.48	0.084
		3	16	1	13.2	0.44	0.070	12.8	0.42	0.068	12.6	0.47	0.077	12.6	0.46	0.072
		4	6	1	13.2	0.44	0.072	13.6	0.41	0.068	12	0.55	0.091	12.2	0.48	0.083
		4	8	1	16	0.42	0.070	17.4	0.38	0.066	14	0.50	0.088	13.2	0.45	0.071
		4	10	1	14.4	0.41	0.069	14.4	0.38	0.062	15.6	0.46	0.067	15.8	0.44	0.073
		4	12	1	16.8	0.40	0.068	18	0.38	0.068	11.8	0.44	0.066	12.4	0.42	0.071
		4	16	1	16	0.40	0.069	14.4	0.38	0.058	14.8	0.42	0.073	15.6	0.40	0.074
		5	6	1	17.2	0.40	0.066	14.2	0.36	0.058	15.4	0.49	0.069	14.8	0.44	0.072
		5	8	1	17.2	0.38	0.064	18	0.35	0.060	13.2	0.44	0.065	14.4	0.41	0.069
		5	10	1	15.2	0.37	0.062	16.6	0.35	0.060	16.2	0.42	0.070	14.6	0.39	0.060
		5	12	1	17.8	0.36	0.061	16	0.34	0.053	15.2	0.40	0.070	14.4	0.39	0.065
		5	16	1	17.6	0.36	0.060	17.4	0.34	0.053	13.6	0.38	0.060	17.6	0.37	0.063
		6	6	1	20.2	0.37	0.068	19.8	0.34	0.058	12	0.45	0.068	14.4	0.41	0.065
		6	8	1	16.4	0.36	0.058	15.6	0.33	0.053	16.4	0.41	0.070	18	0.38	0.068
		6	10	1	18.8	0.34	0.058	17.2	0.32	0.058	14.6	0.40	0.066	18.6	0.36	0.062
		6	12	1	15.2	0.34	0.060	19.2	0.33	0.058	15.8	0.38	0.060	15.8	0.35	0.060
		6	16	1	16.6	0.33	0.057	19.4	0.32	0.058	17.4	0.35	0.059	20.6	0.34	0.055
		8	6	1	19.2	0.33	0.060	21.4	0.31	0.054	18.4	0.39	0.068	18.2	0.36	0.064
		8	8	1	19.6	0.31	0.052	22.8	0.30	0.053	19.6	0.36	0.066	17	0.34	0.061
		8	10	1	22.2	0.31	0.055	23.6	0.30	0.052	19.4	0.34	0.059	18.6	0.33	0.053
		8	12	1	20.6	0.31	0.054	18.8	0.30	0.046	18.4	0.33	0.061	16.6	0.31	0.056
		8	16	1	23	0.30	0.055	23.4	0.29	0.050	17.4	0.33	0.057	23.2	0.30	0.054

Table A1.10. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Blue Cod	3	6	2	8.4	0.92	0.116	13	0.82	0.107	11	1.09	0.143	8.6	1.03	0.137
		3	8	2	13	0.89	0.114	12.2	0.82	0.119	9.6	1.08	0.139	8.2	0.95	0.114
		3	10	2	12.8	0.83	0.113	13.4	0.79	0.102	11.6	0.93	0.122	11.6	0.91	0.120
		3	12	2	13	0.83	0.103	10.6	0.79	0.102	10.6	0.91	0.121	9.2	0.90	0.111
		3	16	2	13	0.81	0.101	15.6	0.76	0.097	10.6	0.86	0.114	12.8	0.85	0.108
		4	6	2	13.2	0.82	0.092	13.6	0.75	0.097	13.2	1.04	0.120	11	0.91	0.120
		4	8	2	14.6	0.78	0.109	12.2	0.71	0.095	9.4	0.92	0.112	12.8	0.85	0.112
		4	10	2	15.8	0.74	0.099	12.6	0.71	0.093	13.8	0.86	0.113	12	0.83	0.105
		4	12	2	13.8	0.74	0.094	14	0.70	0.097	12.6	0.81	0.092	10.8	0.80	0.101
		4	16	2	11.6	0.73	0.087	13.6	0.69	0.087	14	0.76	0.088	12.8	0.74	0.104
		5	6	2	13.4	0.78	0.101	14.6	0.69	0.083	9.8	0.93	0.108	13.8	0.86	0.104
		5	8	2	13.6	0.72	0.093	13.6	0.66	0.089	10.6	0.85	0.108	12.4	0.78	0.092
		5	10	2	13.2	0.69	0.091	14	0.66	0.082	12	0.79	0.106	13.2	0.73	0.095
		5	12	2	14.2	0.68	0.086	16.2	0.62	0.093	10.2	0.75	0.098	12	0.72	0.086
		5	16	2	12.4	0.64	0.081	14.6	0.62	0.084	13.6	0.71	0.099	13.8	0.69	0.087
		6	6	2	11.4	0.70	0.085	13.2	0.63	0.083	15.2	0.83	0.111	12	0.77	0.104
		6	8	2	14.6	0.67	0.091	15.2	0.60	0.077	11.6	0.76	0.093	14.6	0.71	0.102
		6	10	2	14.8	0.65	0.086	14.4	0.61	0.087	16.8	0.72	0.095	11	0.68	0.083
		6	12	2	12.8	0.62	0.084	14.2	0.59	0.080	14.2	0.69	0.093	14.2	0.67	0.086
		6	16	2	14.2	0.61	0.077	12.4	0.60	0.079	13.2	0.66	0.090	16.4	0.61	0.084
		8	6	2	17.6	0.60	0.076	18.8	0.55	0.075	12.4	0.74	0.091	12.6	0.68	0.096
		8	8	2	15.2	0.58	0.073	15.2	0.54	0.074	12.6	0.67	0.091	14.2	0.63	0.082
		8	10	2	17	0.57	0.080	18.4	0.53	0.072	16	0.63	0.088	15.8	0.60	0.086
		8	12	2	18.4	0.54	0.083	16.6	0.52	0.077	14.6	0.61	0.083	13.6	0.59	0.084
		8	16	2	16.4	0.54	0.074	17	0.52	0.074	17.4	0.58	0.078	17	0.56	0.072

Table A1.11. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue cod using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Blue Cod	3	6	3	13.8	1.18	0.108	14.2	1.05	0.106	11.4	1.35	0.135	13.6	1.26	0.123
		3	8	3	10.6	1.07	0.104	12.8	0.97	0.089	11.4	1.23	0.119	11.8	1.20	0.118
		3	10	3	13	1.05	0.097	15	0.95	0.097	14.2	1.15	0.113	16.2	1.09	0.109
		3	12	3	14	0.97	0.099	12.2	0.95	0.093	13	1.15	0.113	14	1.07	0.113
		3	16	3	14.6	0.98	0.101	13	0.92	0.093	14	1.08	0.102	14.4	1.01	0.106
		4	6	3	11.4	1.00	0.098	13.8	0.91	0.091	12.2	1.29	0.113	11	1.14	0.116
		4	8	3	12.4	0.96	0.101	14	0.86	0.096	13.4	1.15	0.112	9.6	1.04	0.095
		4	10	3	15	0.91	0.094	13.8	0.85	0.082	13.4	1.05	0.103	14	0.99	0.109
		4	12	3	16	0.91	0.094	14.4	0.84	0.085	11.8	1.02	0.099	12.2	0.97	0.097
		4	16	3	16.8	0.88	0.096	15	0.81	0.079	13.4	0.96	0.099	14.4	0.90	0.106
		5	6	3	13	0.93	0.091	19	0.85	0.084	13.4	1.18	0.117	13.6	1.03	0.101
		5	8	3	15.6	0.89	0.097	17.4	0.83	0.087	11.8	1.07	0.093	13.2	0.93	0.093
		5	10	3	13.6	0.86	0.082	18	0.79	0.086	13.2	0.98	0.097	17	0.92	0.093
		5	12	3	15.4	0.83	0.082	16	0.78	0.079	13.4	0.93	0.091	14.6	0.88	0.085
		5	16	3	17	0.81	0.077	18.2	0.77	0.085	12.8	0.88	0.087	15.2	0.83	0.077
		6	6	3	15	0.87	0.093	17.8	0.77	0.079	12.2	1.07	0.104	13.6	0.97	0.099
		6	8	3	16.8	0.82	0.091	16.4	0.74	0.073	16.2	0.96	0.100	13.8	0.87	0.092
		6	10	3	18	0.80	0.087	17.8	0.74	0.080	16	0.90	0.092	18.4	0.83	0.084
		6	12	3	17.6	0.78	0.079	14.8	0.73	0.074	15.2	0.88	0.089	15	0.82	0.080
		6	16	3	16	0.75	0.075	17.8	0.70	0.078	15.6	0.81	0.090	16.6	0.77	0.078
		8	6	3	16.4	0.75	0.076	21.2	0.67	0.075	12.4	0.92	0.083	13.6	0.83	0.083
		8	8	3	19.2	0.71	0.076	22.4	0.66	0.074	16.2	0.86	0.082	15.6	0.78	0.081
		8	10	3	21	0.68	0.076	18.8	0.65	0.068	17.4	0.78	0.080	19.2	0.74	0.082
		8	12	3	17.4	0.68	0.075	20.8	0.65	0.067	20	0.77	0.087	18.8	0.71	0.074
		8	16	3	19.2	0.67	0.069	20	0.62	0.072	20.2	0.71	0.074	21.6	0.67	0.077

Table A1.12. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Long Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Blue Moki	3	6	1	10	0.50	0.068	13.4	0.38	0.060	7.6	0.61	0.088	10.6	0.52	0.080
		3	8	1	11.6	0.45	0.064	16.4	0.35	0.057	8.8	0.53	0.085	13.6	0.45	0.074
		3	10	1	11.6	0.41	0.061	17	0.33	0.052	12.2	0.49	0.075	15	0.40	0.065
		3	12	1	13	0.40	0.052	18	0.32	0.050	10.8	0.45	0.067	12.2	0.38	0.060
		3	16	1	15.8	0.35	0.054	20.2	0.30	0.045	13.4	0.40	0.060	14	0.36	0.053
		4	6	1	13.4	0.44	0.065	16.6	0.34	0.047	11.6	0.55	0.077	15.2	0.45	0.069
		4	8	1	12	0.38	0.056	16.4	0.31	0.045	12.2	0.47	0.072	12	0.40	0.055
		4	10	1	14.4	0.36	0.051	20	0.28	0.043	10.4	0.43	0.058	16.8	0.36	0.054
		4	12	1	18.2	0.34	0.055	22.6	0.28	0.044	12.2	0.40	0.061	18.6	0.33	0.050
		4	16	1	18.4	0.31	0.045	22.6	0.27	0.039	15	0.35	0.053	19.4	0.31	0.049
		5	6	1	14.2	0.39	0.056	17.6	0.30	0.043	10.4	0.49	0.071	11.6	0.40	0.058
		5	8	1	14.2	0.35	0.047	21.8	0.28	0.040	12.8	0.42	0.056	16	0.35	0.052
		5	10	1	18.6	0.32	0.047	26.2	0.26	0.037	17.2	0.38	0.057	16.2	0.32	0.047
		5	12	1	18.4	0.30	0.043	27.8	0.25	0.038	17.2	0.35	0.053	18.8	0.30	0.045
		5	16	1	23	0.28	0.042	27	0.24	0.032	18	0.33	0.052	20.8	0.28	0.044
		6	6	1	18.2	0.35	0.051	23	0.27	0.042	13.8	0.44	0.063	13.4	0.37	0.052
		6	8	1	17.4	0.32	0.039	25.2	0.26	0.038	11.6	0.38	0.056	19	0.33	0.050
		6	10	1	18.2	0.29	0.039	27.2	0.24	0.034	18.6	0.35	0.056	20	0.30	0.043
		6	12	1	23.2	0.27	0.038	29.8	0.23	0.031	18	0.32	0.046	20	0.28	0.039
		6	16	1	27.4	0.25	0.037	33.6	0.22	0.031	20.2	0.28	0.041	23.8	0.26	0.040
		8	6	1	19.4	0.30	0.042	28.6	0.24	0.030	14.4	0.38	0.053	16.2	0.32	0.043
		8	8	1	25.6	0.27	0.043	33.8	0.22	0.033	15.6	0.34	0.047	23.2	0.28	0.044
		8	10	1	27.8	0.25	0.038	36.2	0.21	0.029	20	0.31	0.048	24.8	0.26	0.035
		8	12	1	32.8	0.24	0.037	40.2	0.20	0.030	20.6	0.28	0.040	30.2	0.24	0.035
		8	16	1	31	0.22	0.031	38.6	0.19	0.026	23.8	0.25	0.036	33.2	0.22	0.031

Table A1.13. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Long Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Blue Moki	3	6	2	8.2	0.99	0.108	10.2	0.75	0.086	6.4	1.23	0.126	8.4	1.01	0.116
		3	8	2	7	0.88	0.106	10.8	0.68	0.077	10	1.02	0.122	9.4	0.87	0.097
		3	10	2	9.4	0.81	0.087	11.2	0.64	0.075	10.6	0.92	0.108	10.2	0.79	0.091
		3	12	2	11.6	0.75	0.077	10.6	0.62	0.071	10.6	0.87	0.104	7.2	0.74	0.093
		3	16	2	9.4	0.69	0.070	11.4	0.57	0.065	12.2	0.76	0.094	9.8	0.67	0.077
		4	6	2	9	0.84	0.091	9	0.68	0.073	6.6	1.03	0.113	9.2	0.91	0.102
		4	8	2	11	0.71	0.085	9.4	0.60	0.061	9.2	0.87	0.106	9.4	0.76	0.085
		4	10	2	11	0.69	0.076	12	0.58	0.064	10	0.80	0.090	8	0.72	0.080
		4	12	2	11	0.65	0.072	10.6	0.53	0.060	9.4	0.76	0.084	10.6	0.65	0.074
		4	16	2	11.8	0.59	0.064	14	0.51	0.059	9.2	0.68	0.079	12.6	0.59	0.066
		5	6	2	9.8	0.75	0.076	9.4	0.60	0.063	8	0.93	0.088	8.2	0.79	0.087
		5	8	2	9	0.66	0.070	11.4	0.53	0.062	8.8	0.82	0.088	9.2	0.70	0.077
		5	10	2	12.4	0.63	0.071	13.2	0.52	0.055	10.6	0.72	0.083	13.6	0.63	0.075
		5	12	2	12.4	0.57	0.063	12.8	0.48	0.050	10.6	0.66	0.077	11.4	0.59	0.065
		5	16	2	11.4	0.54	0.060	16.4	0.46	0.052	12	0.60	0.066	13.6	0.54	0.058
		6	6	2	10.8	0.67	0.078	11.4	0.55	0.062	9.2	0.86	0.092	9.2	0.71	0.076
		6	8	2	11	0.61	0.071	11	0.51	0.054	8.8	0.75	0.078	10.2	0.62	0.063
		6	10	2	14	0.55	0.060	14.8	0.48	0.050	10	0.66	0.075	12	0.58	0.070
		6	12	2	11.6	0.53	0.057	15	0.45	0.048	8.8	0.62	0.066	13.4	0.55	0.064
		6	16	2	13.6	0.49	0.050	17.8	0.42	0.045	14.2	0.56	0.066	14.4	0.50	0.060
		8	6	2	9.8	0.60	0.059	15.6	0.48	0.051	10.4	0.73	0.079	10.6	0.62	0.071
		8	8	2	13	0.53	0.055	18.6	0.43	0.050	13	0.64	0.067	10.8	0.57	0.062
		8	10	2	15.6	0.49	0.054	15.6	0.41	0.046	13.2	0.59	0.071	13.2	0.50	0.054
		8	12	2	16.4	0.46	0.043	21.2	0.39	0.043	10.8	0.54	0.062	13.6	0.47	0.057
		8	16	2	16	0.42	0.047	19.2	0.37	0.038	16.4	0.49	0.051	15.4	0.44	0.048

Table A1.14. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Long Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Blue Moki	3	6	3	10	1.32	0.103	10	0.97	0.080	9.8	1.57	0.128	8.6	1.24	0.109
		3	8	3	11.6	1.15	0.093	10.2	0.85	0.070	10	1.35	0.107	7.6	1.08	0.091
		3	10	3	10.6	1.01	0.086	14.8	0.80	0.068	13	1.19	0.103	11.6	0.98	0.091
		3	12	3	13.2	0.96	0.078	11.4	0.75	0.068	10.6	1.14	0.089	12.6	0.91	0.082
		3	16	3	12.8	0.83	0.077	13.8	0.70	0.055	10.6	0.97	0.087	12	0.85	0.073
		4	6	3	10.2	1.13	0.091	12.8	0.82	0.070	9.6	1.38	0.122	9.6	1.04	0.086
		4	8	3	10.8	0.94	0.085	12.2	0.76	0.065	7.8	1.20	0.097	9.2	0.94	0.083
		4	10	3	10.8	0.87	0.076	15.4	0.70	0.062	8.4	1.05	0.077	11.4	0.84	0.068
		4	12	3	8.8	0.81	0.068	14.6	0.65	0.057	12.8	0.94	0.071	10.6	0.83	0.069
		4	16	3	10.8	0.77	0.061	12.4	0.62	0.056	9.4	0.86	0.069	14.6	0.72	0.064
		5	6	3	11.4	0.97	0.077	14.2	0.74	0.064	7.6	1.21	0.089	9.4	0.99	0.086
		5	8	3	8	0.86	0.069	15	0.67	0.059	8.8	1.05	0.082	12.8	0.84	0.071
		5	10	3	14.4	0.81	0.064	17.2	0.62	0.055	10	0.94	0.080	14.4	0.81	0.067
		5	12	3	13	0.72	0.060	18	0.60	0.052	12	0.87	0.067	13.2	0.73	0.067
		5	16	3	12.8	0.69	0.056	17.8	0.57	0.047	13.2	0.76	0.067	13.8	0.68	0.060
		6	6	3	12	0.90	0.075	16.4	0.68	0.058	8	1.15	0.086	10.2	0.90	0.068
		6	8	3	13.8	0.78	0.063	16	0.62	0.058	11.4	0.96	0.082	11.4	0.78	0.057
		6	10	3	8.2	0.73	0.056	15.2	0.58	0.051	12.6	0.86	0.071	12	0.70	0.066
		6	12	3	14.8	0.68	0.060	14.4	0.58	0.043	11.8	0.77	0.068	14.2	0.68	0.058
		6	16	3	16	0.62	0.052	20.8	0.53	0.044	15.8	0.71	0.055	17.2	0.62	0.053
		8	6	3	11.6	0.76	0.063	18.8	0.59	0.045	10.6	0.97	0.074	10.8	0.79	0.061
		8	8	3	13.4	0.66	0.058	21	0.55	0.043	10.8	0.81	0.062	16.8	0.70	0.059
		8	10	3	17	0.64	0.051	21.8	0.52	0.045	13	0.75	0.060	15	0.63	0.052
		8	12	3	14.6	0.58	0.045	22.2	0.50	0.041	10.6	0.68	0.051	17.8	0.60	0.055
		8	16	3	22	0.54	0.046	24	0.46	0.036	13.8	0.63	0.049	16.4	0.53	0.044

Table A1.15. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Tonga Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Blue Moki	3	6	1	14.6	0.43	0.073	13.6	0.37	0.056	10.2	0.55	0.083	12	0.49	0.073
		3	8	1	15.8	0.41	0.066	16.6	0.37	0.056	11.2	0.49	0.079	11	0.44	0.071
		3	10	1	14.2	0.39	0.058	17.2	0.35	0.056	11.4	0.46	0.071	13.2	0.42	0.067
		3	12	1	16.2	0.38	0.065	17.6	0.34	0.053	11	0.44	0.070	15	0.40	0.066
		3	16	1	14.4	0.36	0.057	19.8	0.33	0.058	11	0.41	0.062	16.2	0.38	0.064
		4	6	1	15.2	0.38	0.059	17	0.32	0.053	10	0.48	0.075	12.2	0.44	0.068
		4	8	1	16.4	0.35	0.061	17.2	0.32	0.048	14	0.42	0.067	14.4	0.39	0.066
		4	10	1	17.8	0.35	0.053	19.2	0.31	0.050	12.4	0.40	0.067	13.8	0.37	0.061
		4	12	1	19	0.33	0.060	20.6	0.31	0.048	16.2	0.38	0.060	15	0.35	0.058
		4	16	1	19.6	0.32	0.059	19.8	0.30	0.052	18	0.35	0.056	17.8	0.33	0.052
		5	6	1	21.8	0.34	0.062	21.8	0.30	0.047	13.2	0.43	0.063	14.2	0.38	0.062
		5	8	1	20.6	0.32	0.054	21.2	0.28	0.050	15.8	0.39	0.057	14.8	0.35	0.054
		5	10	1	20.2	0.31	0.045	22.4	0.28	0.045	14	0.36	0.055	16.6	0.34	0.055
		5	12	1	19	0.30	0.051	24.4	0.27	0.041	16	0.34	0.052	21.2	0.32	0.053
		5	16	1	20.6	0.28	0.047	26	0.27	0.043	20	0.33	0.051	21	0.30	0.051
		6	6	1	21.2	0.31	0.049	24.2	0.27	0.044	14.8	0.39	0.060	18.4	0.35	0.055
		6	8	1	22	0.29	0.049	30.8	0.27	0.046	18.6	0.35	0.059	18	0.32	0.055
		6	10	1	22.2	0.28	0.046	24.6	0.26	0.045	16.8	0.33	0.049	21.4	0.31	0.050
		6	12	1	23.4	0.28	0.045	26.2	0.25	0.043	20.2	0.31	0.054	22	0.29	0.046
		6	16	1	23	0.27	0.043	27.4	0.25	0.042	20	0.29	0.050	22	0.28	0.048
		8	6	1	22.8	0.28	0.044	24.8	0.24	0.040	20.6	0.34	0.057	19.4	0.31	0.048
		8	8	1	28	0.26	0.041	32.2	0.23	0.041	20.4	0.31	0.051	20.8	0.28	0.044
		8	10	1	26.2	0.25	0.038	28.4	0.23	0.039	23.6	0.29	0.048	26.2	0.27	0.044
		8	12	1	27	0.24	0.040	29.8	0.23	0.040	28.2	0.28	0.046	26.4	0.26	0.043
		8	16	1	29	0.24	0.039	30.8	0.22	0.040	27.8	0.26	0.044	26.8	0.25	0.042

Table A1.16. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Blue Moki	3	6	2	12.8	0.81	0.103	13.2	0.71	0.088	9.6	1.08	0.126	11.4	0.93	0.116
		3	8	2	12	0.77	0.091	13.6	0.66	0.087	10.2	0.92	0.114	12.4	0.81	0.099
		3	10	2	12.6	0.70	0.085	12.2	0.66	0.075	11	0.85	0.108	8.8	0.77	0.092
		3	12	2	13.4	0.67	0.083	16	0.63	0.073	10.2	0.79	0.094	9.2	0.75	0.087
		3	16	2	13	0.66	0.073	15.2	0.62	0.076	12.6	0.73	0.095	11.6	0.71	0.094
		4	6	2	10.8	0.73	0.086	13	0.63	0.077	9.4	0.90	0.104	12.8	0.82	0.098
		4	8	2	16.6	0.65	0.092	13.4	0.59	0.071	12.4	0.82	0.100	12.2	0.74	0.099
		4	10	2	13.4	0.64	0.078	14	0.58	0.068	11.8	0.74	0.093	12.6	0.68	0.090
		4	12	2	16.6	0.61	0.085	16.2	0.56	0.074	10.8	0.70	0.084	12.8	0.67	0.084
		4	16	2	14.6	0.60	0.079	15.2	0.55	0.080	12.8	0.66	0.076	11.8	0.62	0.084
		5	6	2	12	0.65	0.078	15.6	0.56	0.071	12.4	0.82	0.100	12.2	0.73	0.096
		5	8	2	13.6	0.61	0.075	12.2	0.54	0.061	11.8	0.74	0.085	11.8	0.67	0.084
		5	10	2	13.6	0.57	0.066	13	0.54	0.063	12.6	0.70	0.089	13.2	0.63	0.073
		5	12	2	14.6	0.57	0.070	15.2	0.51	0.061	14	0.66	0.086	15.2	0.60	0.074
		5	16	2	16.2	0.54	0.072	15.6	0.50	0.062	16.4	0.61	0.078	15.6	0.57	0.073
		6	6	2	14.6	0.58	0.080	19	0.51	0.071	13.2	0.75	0.091	10	0.69	0.086
		6	8	2	17	0.54	0.074	16.4	0.50	0.065	11.4	0.67	0.083	13.4	0.63	0.074
		6	10	2	17.6	0.52	0.069	19.4	0.49	0.058	12.8	0.63	0.076	15.6	0.58	0.070
		6	12	2	18.4	0.52	0.064	19.2	0.49	0.061	15.2	0.59	0.076	14	0.56	0.069
		6	16	2	18.6	0.50	0.064	16.6	0.46	0.057	14	0.55	0.073	13.8	0.52	0.065
		8	6	2	17.4	0.53	0.068	21.6	0.46	0.060	12.8	0.65	0.076	15.4	0.60	0.076
		8	8	2	16.6	0.49	0.063	20.4	0.44	0.060	15.8	0.60	0.071	19.6	0.54	0.076
		8	10	2	18.4	0.46	0.061	20.2	0.43	0.062	16.2	0.56	0.068	13.8	0.51	0.058
		8	12	2	16.8	0.46	0.058	19	0.41	0.057	15	0.52	0.064	17	0.49	0.061
		8	16	2	20.4	0.43	0.058	19.6	0.41	0.056	18.8	0.48	0.067	17.2	0.46	0.059

Table A1.17. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Blue Moki	3	6	3	12.4	0.98	0.085	12.8	0.86	0.085	12.8	1.31	0.131	10.8	1.09	0.098
		3	8	3	11.2	0.93	0.086	17.4	0.80	0.082	13.4	1.09	0.117	12.8	0.98	0.097
		3	10	3	13.4	0.89	0.091	12.8	0.81	0.075	8.4	1.03	0.098	13	0.94	0.087
		3	12	3	13.6	0.85	0.086	16	0.77	0.080	15.2	0.96	0.098	14.4	0.89	0.090
		3	16	3	15.6	0.81	0.084	14.4	0.73	0.068	15.2	0.93	0.087	13	0.84	0.087
		4	6	3	16	0.87	0.085	16.8	0.78	0.070	10.2	1.16	0.097	14.8	1.00	0.103
		4	8	3	15.4	0.82	0.079	13.8	0.73	0.068	13.4	1.02	0.095	11.8	0.91	0.089
		4	10	3	13.8	0.79	0.076	18.2	0.70	0.062	15.4	0.94	0.093	15.2	0.84	0.085
		4	12	3	15.6	0.77	0.072	16.6	0.70	0.060	11	0.87	0.081	12.6	0.79	0.079
		4	16	3	18.2	0.72	0.070	16.2	0.68	0.061	14.6	0.81	0.079	16.4	0.78	0.070
		5	6	3	13.4	0.82	0.074	18.4	0.70	0.067	10	1.03	0.101	12.2	0.94	0.088
		5	8	3	14.6	0.75	0.065	19.2	0.64	0.064	13.4	0.91	0.085	15.4	0.82	0.077
		5	10	3	16	0.72	0.074	19.2	0.65	0.064	13.4	0.86	0.081	16.6	0.78	0.077
		5	12	3	16.2	0.69	0.065	19.4	0.63	0.059	16.2	0.82	0.079	14.8	0.73	0.062
		5	16	3	19.6	0.66	0.068	19.4	0.61	0.061	17.6	0.76	0.073	13.4	0.70	0.060
		6	6	3	14.2	0.73	0.070	16.2	0.64	0.064	10.6	0.93	0.085	15.2	0.84	0.079
		6	8	3	19.6	0.69	0.066	22	0.62	0.065	14.2	0.85	0.078	14.8	0.78	0.068
		6	10	3	17.6	0.67	0.062	17.6	0.60	0.057	14.6	0.80	0.076	15.8	0.71	0.069
		6	12	3	16.4	0.64	0.065	19.6	0.58	0.056	21.6	0.74	0.076	14.2	0.70	0.057
		6	16	3	20	0.62	0.060	18	0.56	0.055	18	0.70	0.072	16.2	0.64	0.066
		8	6	3	18.6	0.66	0.059	23.6	0.56	0.057	12	0.83	0.070	16.2	0.74	0.070
		8	8	3	19.8	0.61	0.059	21.6	0.54	0.053	13.6	0.74	0.064	18.6	0.67	0.062
		8	10	3	20	0.60	0.055	25	0.53	0.056	16.2	0.70	0.062	18.2	0.63	0.063
		8	12	3	23.2	0.58	0.054	23.2	0.52	0.050	16.6	0.65	0.064	16.4	0.62	0.055
		8	16	3	24.6	0.54	0.056	23.6	0.51	0.053	20.2	0.60	0.064	19.8	0.59	0.056

Table A1.18. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Horoirangi Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Blue Moki	3	6	1	7.6	0.62	0.080	9	0.45	0.066	5.6	0.72	0.098	7.6	0.56	0.073
		3	8	1	7.4	0.55	0.070	13.4	0.40	0.062	6.8	0.62	0.089	11	0.48	0.073
		3	10	1	10.2	0.48	0.072	15.6	0.36	0.058	8	0.56	0.079	11.4	0.43	0.063
		3	12	1	11.4	0.45	0.064	15.6	0.34	0.049	11.6	0.51	0.071	10.4	0.41	0.058
		3	16	1	14	0.40	0.062	17.2	0.31	0.048	14.4	0.45	0.065	18.2	0.36	0.056
		4	6	1	9	0.55	0.075	11.2	0.39	0.049	7.6	0.63	0.088	12.2	0.50	0.071
		4	8	1	10.2	0.46	0.061	18	0.34	0.049	6.8	0.54	0.080	11.6	0.42	0.066
		4	10	1	12.2	0.43	0.058	20.2	0.32	0.048	11.6	0.48	0.064	15.8	0.38	0.060
		4	12	1	15	0.40	0.054	22.6	0.30	0.049	11.4	0.45	0.067	16.8	0.35	0.053
		4	16	1	16.4	0.35	0.050	20	0.28	0.044	16.6	0.39	0.055	19.6	0.32	0.050
		5	6	1	8.2	0.48	0.068	18.6	0.35	0.056	7.6	0.58	0.067	12	0.45	0.067
		5	8	1	14	0.42	0.057	20.2	0.31	0.044	9	0.50	0.072	15.4	0.38	0.057
		5	10	1	15.8	0.37	0.052	26	0.29	0.043	16.2	0.43	0.064	16.2	0.34	0.048
		5	12	1	15.4	0.35	0.049	26.2	0.27	0.042	15.8	0.39	0.061	19.6	0.31	0.046
		5	16	1	17.2	0.31	0.043	26.4	0.25	0.037	18	0.35	0.051	22.4	0.28	0.040
		6	6	1	8.6	0.44	0.059	19.8	0.32	0.044	8.4	0.52	0.067	11.8	0.40	0.060
		6	8	1	14.4	0.38	0.052	23.8	0.29	0.043	9.6	0.46	0.057	18.8	0.35	0.050
		6	10	1	17	0.34	0.049	25.4	0.26	0.039	14.8	0.40	0.053	16.8	0.31	0.048
		6	12	1	20	0.32	0.046	29	0.25	0.035	16.4	0.37	0.049	19.2	0.30	0.042
		6	16	1	22.8	0.28	0.040	31	0.22	0.032	17.8	0.32	0.043	25	0.26	0.039
		8	6	1	13	0.38	0.051	20.6	0.28	0.036	8.8	0.47	0.059	18.6	0.35	0.055
		8	8	1	18.4	0.33	0.043	27.6	0.25	0.036	13.8	0.38	0.053	19.2	0.30	0.042
		8	10	1	21	0.30	0.041	33.8	0.23	0.031	15.6	0.34	0.049	21.4	0.27	0.036
		8	12	1	21.6	0.28	0.042	35.8	0.21	0.033	19	0.31	0.047	25.2	0.25	0.038
		8	16	1	26.4	0.25	0.034	41.2	0.20	0.027	27	0.28	0.041	36.4	0.23	0.034

Table A1.19. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Blue Moki	3	6	2	6.8	1.21	0.123	6.4	0.88	0.094	5.6	1.54	0.158	9.8	1.09	0.130
		3	8	2	8.4	1.05	0.111	8.6	0.79	0.086	6.8	1.23	0.119	9.6	0.96	0.112
		3	10	2	9	0.94	0.102	10.2	0.71	0.081	9.6	1.04	0.122	8.6	0.85	0.092
		3	12	2	8.2	0.85	0.098	12.4	0.67	0.078	9	0.96	0.114	8.6	0.80	0.089
		3	16	2	9.8	0.77	0.077	10.4	0.59	0.065	10.2	0.83	0.096	11.8	0.69	0.092
		4	6	2	8.4	1.07	0.119	9.6	0.78	0.078	5.6	1.29	0.130	8.4	0.96	0.105
		4	8	2	7.2	0.92	0.098	10.4	0.69	0.076	8.2	1.06	0.120	7.6	0.81	0.088
		4	10	2	9	0.81	0.089	12.4	0.63	0.071	7.8	0.90	0.098	10	0.73	0.079
		4	12	2	12.4	0.75	0.085	13.6	0.60	0.066	9.6	0.84	0.094	11	0.69	0.078
		4	16	2	9.6	0.68	0.076	13.6	0.52	0.061	9.6	0.73	0.079	14.4	0.61	0.071
		5	6	2	8.6	0.93	0.095	12	0.70	0.076	5.2	1.11	0.110	8.6	0.85	0.090
		5	8	2	7.6	0.80	0.085	10.8	0.61	0.059	6.2	0.94	0.097	11.4	0.75	0.082
		5	10	2	12.6	0.73	0.080	13.6	0.56	0.059	7.8	0.86	0.097	10.2	0.66	0.067
		5	12	2	9.8	0.66	0.073	13.8	0.53	0.057	10	0.76	0.082	12.6	0.61	0.070
		5	16	2	12.4	0.59	0.065	16.8	0.48	0.056	14.4	0.65	0.076	12.8	0.54	0.061
		6	6	2	5.4	0.85	0.077	11.4	0.64	0.062	6.4	1.02	0.104	10	0.79	0.082
		6	8	2	9.2	0.74	0.078	11	0.56	0.058	8.4	0.85	0.078	11.6	0.67	0.077
		6	10	2	10.4	0.65	0.075	16.4	0.51	0.057	9.4	0.74	0.079	10.4	0.62	0.068
		6	12	2	11.6	0.59	0.065	13.6	0.48	0.051	6.8	0.70	0.075	12.6	0.56	0.075
		6	16	2	11.4	0.55	0.058	19.6	0.43	0.046	12.4	0.60	0.064	16.4	0.50	0.054
		8	6	2	8.4	0.72	0.077	14	0.55	0.056	6.6	0.88	0.083	10.4	0.68	0.072
		8	8	2	13.4	0.65	0.071	16.4	0.49	0.056	10.2	0.74	0.071	11	0.59	0.061
		8	10	2	15.4	0.58	0.059	19.2	0.44	0.049	10.8	0.65	0.068	13.2	0.55	0.060
		8	12	2	12.4	0.52	0.052	20.6	0.42	0.051	13	0.60	0.060	16.8	0.49	0.051
		8	16	2	17.2	0.47	0.048	19.6	0.38	0.043	16	0.53	0.058	18.6	0.44	0.047

Table A1.20. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of blue moki using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Blue Moki	3	6	3	8.4	1.68	0.109	8.8	1.17	0.099	7.2	1.86	0.127	10.4	1.38	0.120
		3	8	3	7.8	1.41	0.117	9.2	0.98	0.077	8.4	1.59	0.122	10.6	1.13	0.099
		3	10	3	10.8	1.20	0.104	11.6	0.90	0.077	9.6	1.42	0.117	9.4	1.04	0.094
		3	12	3	9.6	1.14	0.091	11.8	0.81	0.072	10.6	1.24	0.099	12.2	0.99	0.083
		3	16	3	8.8	1.00	0.077	13.6	0.74	0.068	14.8	1.06	0.091	12.4	0.85	0.078
		4	6	3	9	1.43	0.097	9.6	0.95	0.078	8.2	1.62	0.140	7.6	1.15	0.092
		4	8	3	8.6	1.19	0.098	11.6	0.83	0.073	8	1.33	0.117	10.8	1.01	0.087
		4	10	3	9.4	1.04	0.089	12.2	0.77	0.063	10.6	1.22	0.092	9.8	0.90	0.077
		4	12	3	12.4	0.95	0.084	13.4	0.72	0.060	10	1.07	0.085	13	0.84	0.069
		4	16	3	13.2	0.84	0.070	15.6	0.66	0.055	11.2	0.92	0.077	16.8	0.74	0.068
		5	6	3	8.6	1.23	0.096	11.8	0.86	0.077	5.4	1.44	0.117	11.6	1.08	0.085
		5	8	3	12.6	1.08	0.092	15.2	0.76	0.063	10.6	1.29	0.101	10.4	0.93	0.076
		5	10	3	9.2	0.93	0.073	15.8	0.68	0.057	7	1.10	0.077	13.4	0.83	0.078
		5	12	3	12.8	0.89	0.063	16.6	0.66	0.054	11	0.94	0.077	14.2	0.76	0.063
		5	16	3	17.2	0.77	0.065	17.4	0.60	0.053	9.2	0.83	0.067	15.4	0.69	0.059
		6	6	3	8.6	1.11	0.092	11	0.78	0.059	7.8	1.31	0.093	12.4	0.96	0.083
		6	8	3	9.8	0.96	0.075	14.4	0.70	0.063	11.6	1.06	0.075	12.2	0.83	0.070
		6	10	3	9.8	0.86	0.064	18.6	0.64	0.054	12	0.98	0.081	12.6	0.76	0.061
		6	12	3	12.2	0.77	0.058	19.6	0.60	0.047	12.6	0.87	0.069	13.8	0.68	0.057
		6	16	3	14.8	0.69	0.053	22.4	0.55	0.043	14	0.76	0.063	14	0.62	0.051
		8	6	3	11.4	0.97	0.074	12.8	0.70	0.051	8.8	1.15	0.077	10.2	0.84	0.068
		8	8	3	10.2	0.83	0.062	16.4	0.59	0.048	10.4	0.95	0.067	13	0.74	0.057
		8	10	3	13	0.74	0.054	20.4	0.55	0.044	12.4	0.86	0.063	14.6	0.67	0.059
		8	12	3	13.6	0.69	0.050	22.8	0.51	0.041	13.4	0.77	0.064	16.2	0.61	0.049
		8	16	3	17	0.61	0.049	26.6	0.47	0.039	15	0.68	0.053	22.4	0.56	0.045

Table A1.21. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Long Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Spotty	3	6	1	30.6	0.23	0.037	27.6	0.23	0.035	12.2	0.38	0.056	15	0.39	0.056
		3	8	1	27.6	0.22	0.035	32.8	0.23	0.039	16.6	0.35	0.055	15.6	0.35	0.053
		3	10	1	31.8	0.23	0.038	28.6	0.23	0.036	17.8	0.33	0.050	21	0.32	0.053
		3	12	1	28.4	0.23	0.038	34.2	0.23	0.039	16.8	0.31	0.045	19.8	0.31	0.045
		3	16	1	32.4	0.23	0.038	30.4	0.22	0.036	21.6	0.28	0.041	22.8	0.29	0.043
		4	6	1	39.6	0.21	0.031	34.4	0.20	0.034	18.8	0.33	0.054	13.2	0.34	0.049
		4	8	1	38.4	0.20	0.029	38.8	0.20	0.032	17.8	0.31	0.047	20.2	0.30	0.044
		4	10	1	35.8	0.20	0.033	37	0.20	0.034	22.4	0.28	0.044	24	0.28	0.048
		4	12	1	38	0.20	0.033	36.4	0.20	0.031	23	0.27	0.041	25.4	0.27	0.044
		4	16	1	33.2	0.20	0.031	37	0.20	0.031	24.8	0.25	0.041	22.6	0.25	0.036
		5	6	1	43.4	0.19	0.030	38.6	0.19	0.032	18.4	0.31	0.050	15.8	0.31	0.042
		5	8	1	40.8	0.19	0.032	39.2	0.19	0.027	20	0.27	0.041	20.8	0.27	0.044
		5	10	1	39.4	0.19	0.032	38.6	0.18	0.030	24	0.26	0.042	24.4	0.26	0.041
		5	12	1	40.6	0.18	0.034	37.2	0.18	0.029	30.2	0.24	0.037	27.4	0.25	0.036
		5	16	1	40.2	0.19	0.027	38.6	0.19	0.030	29.8	0.23	0.035	27.6	0.23	0.033
		6	6	1	44.6	0.17	0.031	48	0.18	0.029	19.6	0.29	0.048	19.6	0.28	0.042
		6	8	1	41.8	0.17	0.028	44.4	0.17	0.029	25.2	0.25	0.040	24.4	0.26	0.040
		6	10	1	46.4	0.17	0.026	42.4	0.17	0.028	28.8	0.24	0.036	29	0.24	0.038
		6	12	1	45.4	0.17	0.028	44	0.18	0.029	29.4	0.22	0.035	29.6	0.23	0.033
		6	16	1	45	0.17	0.026	41.8	0.17	0.027	32.2	0.21	0.033	33.2	0.21	0.037
		8	6	1	49.6	0.16	0.027	50.6	0.16	0.026	24.8	0.25	0.037	26.2	0.25	0.039
		8	8	1	47.6	0.16	0.026	50.6	0.16	0.028	28.6	0.22	0.035	29.6	0.22	0.035
		8	10	1	48.4	0.16	0.026	55.8	0.16	0.025	35.2	0.21	0.035	35.6	0.21	0.037
		8	12	1	49.2	0.16	0.025	51.4	0.16	0.026	37.8	0.20	0.032	38	0.20	0.029
		8	16	1	49.8	0.16	0.026	48.6	0.16	0.027	36	0.19	0.029	39	0.18	0.030

Table A1.22. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Long Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Spotty	3	6	2	17.2	0.42	0.052	18.6	0.42	0.050	13	0.71	0.091	12	0.72	0.091
		3	8	2	19.2	0.42	0.048	18.8	0.40	0.050	10.4	0.64	0.075	13.4	0.65	0.076
		3	10	2	22.4	0.43	0.053	19.2	0.42	0.052	8.8	0.61	0.066	13.8	0.59	0.074
		3	12	2	19.2	0.42	0.056	22.2	0.41	0.052	10.6	0.58	0.065	15	0.56	0.068
		3	16	2	22.4	0.43	0.055	21.2	0.41	0.056	15	0.52	0.065	14	0.53	0.063
		4	6	2	23.2	0.38	0.049	23.2	0.37	0.048	12.2	0.64	0.077	11.2	0.64	0.072
		4	8	2	22	0.38	0.046	22.6	0.38	0.046	15.8	0.57	0.067	11.6	0.58	0.060
		4	10	2	21.8	0.38	0.049	18.2	0.39	0.047	14.4	0.53	0.065	14.2	0.53	0.063
		4	12	2	22	0.37	0.045	22.6	0.37	0.048	16	0.51	0.066	12.2	0.51	0.060
		4	16	2	22.2	0.37	0.045	23.6	0.37	0.049	17.2	0.47	0.057	14.2	0.47	0.056
		5	6	2	25.6	0.35	0.045	23.6	0.34	0.045	13.6	0.58	0.067	7.4	0.58	0.059
		5	8	2	22.6	0.34	0.041	25	0.34	0.042	13.6	0.52	0.063	15	0.52	0.063
		5	10	2	23.8	0.34	0.044	26.2	0.34	0.044	13.8	0.49	0.058	15.2	0.49	0.051
		5	12	2	25.8	0.34	0.044	23.4	0.34	0.042	16.8	0.47	0.054	16	0.46	0.054
		5	16	2	23	0.35	0.043	24.6	0.34	0.041	17.6	0.43	0.051	15.6	0.43	0.053
		6	6	2	26	0.33	0.043	31	0.32	0.042	13	0.53	0.062	13.8	0.54	0.061
		6	8	2	28.2	0.32	0.040	25.8	0.32	0.042	13.8	0.49	0.059	15.4	0.48	0.057
		6	10	2	29.6	0.32	0.043	26.6	0.32	0.039	19.6	0.44	0.055	19.4	0.45	0.057
		6	12	2	27.8	0.32	0.040	25	0.32	0.042	17.4	0.42	0.049	18.2	0.43	0.055
		6	16	2	26.6	0.32	0.045	30.2	0.31	0.042	21.8	0.40	0.046	21.6	0.39	0.052
		8	6	2	28.8	0.28	0.038	29.8	0.28	0.041	14.4	0.47	0.057	17.4	0.47	0.054
		8	8	2	28.8	0.28	0.037	30.6	0.28	0.038	18.2	0.43	0.055	18	0.42	0.050
		8	10	2	33	0.28	0.040	31.2	0.28	0.037	20.2	0.39	0.048	21	0.39	0.049
		8	12	2	35.4	0.28	0.034	30.2	0.28	0.040	22.4	0.38	0.043	20.2	0.37	0.045
		8	16	2	30.4	0.28	0.038	30	0.28	0.038	22	0.35	0.042	22.2	0.35	0.045

Table A1.23. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Long Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Spotty	3	6	3	20.6	0.51	0.044	22.2	0.52	0.050	14.4	0.87	0.078	10.2	0.91	0.081
		3	8	3	21.8	0.51	0.051	22.8	0.51	0.049	13.4	0.79	0.069	11.6	0.77	0.068
		3	10	3	20.6	0.51	0.046	19.2	0.51	0.046	13.8	0.73	0.071	15	0.75	0.068
		3	12	3	22.6	0.50	0.047	23	0.51	0.052	16.2	0.69	0.063	18.2	0.68	0.065
		3	16	3	21	0.51	0.046	25	0.51	0.049	18.6	0.65	0.060	18.2	0.62	0.053
		4	6	3	22.8	0.45	0.044	28.4	0.46	0.044	12.2	0.78	0.068	14.2	0.78	0.069
		4	8	3	28	0.46	0.041	21.8	0.46	0.041	14.2	0.70	0.059	13	0.71	0.060
		4	10	3	25.4	0.46	0.047	26.8	0.46	0.045	14.2	0.65	0.055	15.6	0.65	0.059
		4	12	3	20.4	0.47	0.042	23.2	0.46	0.045	16.4	0.63	0.057	16.4	0.62	0.056
		4	16	3	25.6	0.46	0.048	27.8	0.46	0.045	23.2	0.56	0.056	16.6	0.59	0.053
		5	6	3	27	0.43	0.040	27.2	0.42	0.041	14.4	0.73	0.064	15.2	0.73	0.064
		5	8	3	26.6	0.42	0.043	25.8	0.43	0.037	16.4	0.65	0.055	15.4	0.65	0.053
		5	10	3	29	0.42	0.039	29.2	0.42	0.040	18.2	0.61	0.056	17.8	0.60	0.057
		5	12	3	28.2	0.42	0.040	30.2	0.42	0.039	18.6	0.57	0.052	16.6	0.56	0.054
		5	16	3	30	0.42	0.043	26.4	0.41	0.039	19.2	0.54	0.048	18.6	0.53	0.047
		6	6	3	29	0.40	0.041	27	0.39	0.040	16	0.67	0.060	14.8	0.67	0.061
		6	8	3	33	0.40	0.042	28.4	0.41	0.036	18.4	0.59	0.054	19	0.59	0.054
		6	10	3	31.2	0.39	0.035	31.2	0.39	0.040	18.4	0.56	0.052	18.6	0.55	0.049
		6	12	3	30	0.40	0.040	33.2	0.38	0.038	19.2	0.53	0.049	17.6	0.52	0.043
		6	16	3	30	0.39	0.038	30.6	0.39	0.038	23.2	0.48	0.046	24.4	0.50	0.049
		8	6	3	33.4	0.35	0.036	33.6	0.35	0.037	18.2	0.59	0.055	18.4	0.58	0.049
		8	8	3	34.2	0.35	0.035	33	0.35	0.033	17	0.53	0.041	19.4	0.53	0.048
		8	10	3	34.4	0.35	0.037	34.8	0.34	0.034	20.2	0.49	0.047	23	0.49	0.048
		8	12	3	36.2	0.35	0.040	34	0.34	0.034	23.2	0.47	0.042	22	0.47	0.044
		8	16	3	34.8	0.35	0.037	36.4	0.34	0.037	25	0.44	0.040	31	0.44	0.043

Table A1.24. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Tonga Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Spotty	3	6	1	27.6	0.25	0.038	28.2	0.24	0.037	15.6	0.39	0.059	15.4	0.39	0.063
		3	8	1	27.2	0.24	0.037	27.6	0.24	0.038	14.4	0.35	0.057	15.4	0.34	0.051
		3	10	1	30	0.24	0.042	26.6	0.23	0.038	16.6	0.33	0.050	19.2	0.32	0.054
		3	12	1	29.4	0.24	0.038	29.8	0.23	0.039	19	0.31	0.050	17.6	0.31	0.048
		3	16	1	32	0.23	0.041	31.2	0.23	0.039	19.4	0.30	0.040	22.4	0.29	0.047
		4	6	1	29.8	0.22	0.037	34.6	0.22	0.034	16.2	0.34	0.054	18	0.34	0.051
		4	8	1	32.4	0.22	0.034	33.8	0.21	0.036	20.8	0.31	0.050	20.6	0.31	0.048
		4	10	1	28.6	0.22	0.035	31.8	0.22	0.036	21.2	0.29	0.047	20.2	0.29	0.043
		4	12	1	36.6	0.22	0.035	32.6	0.22	0.034	20.8	0.27	0.043	25.6	0.27	0.044
		4	16	1	33.2	0.21	0.038	34.2	0.21	0.036	26.8	0.26	0.048	25.2	0.26	0.044
		5	6	1	33	0.21	0.032	38.8	0.20	0.032	16.4	0.31	0.051	21.4	0.31	0.050
		5	8	1	35.6	0.20	0.031	34.8	0.20	0.037	22	0.28	0.043	17.8	0.28	0.039
		5	10	1	35.6	0.21	0.032	35	0.20	0.035	22.8	0.27	0.044	23	0.26	0.040
		5	12	1	37.4	0.20	0.031	36.2	0.20	0.033	26.2	0.25	0.043	27.8	0.25	0.037
		5	16	1	32.4	0.20	0.032	35.8	0.20	0.031	26.6	0.24	0.040	28.2	0.23	0.043
		6	6	1	37.6	0.19	0.033	37.2	0.19	0.031	24.2	0.29	0.047	19.2	0.28	0.046
		6	8	1	33.8	0.20	0.030	43.2	0.19	0.033	24.2	0.26	0.042	23.2	0.26	0.040
		6	10	1	39.8	0.19	0.031	39.8	0.19	0.033	23.8	0.25	0.038	28.6	0.24	0.040
		6	12	1	39.8	0.19	0.030	35.8	0.19	0.032	26.4	0.24	0.034	25	0.23	0.036
		6	16	1	39.2	0.19	0.031	39.4	0.19	0.032	31.6	0.22	0.037	30.6	0.22	0.034
		8	6	1	40.8	0.19	0.032	38.6	0.18	0.032	25.2	0.25	0.041	26	0.25	0.040
		8	8	1	41.6	0.19	0.031	41.8	0.18	0.029	28.2	0.23	0.039	32.2	0.23	0.038
		8	10	1	40.2	0.18	0.028	44.6	0.18	0.029	30.8	0.22	0.035	33.4	0.22	0.036
		8	12	1	41.2	0.18	0.032	45.4	0.18	0.028	32.8	0.21	0.033	31.6	0.21	0.034
		8	16	1	40.2	0.18	0.030	43	0.18	0.026	36.6	0.20	0.036	30.4	0.20	0.037

Table A1.25. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Spotty	3	6	2	18.8	0.45	0.056	19.6	0.43	0.058	11.8	0.72	0.092	14.4	0.70	0.086
		3	8	2	18.4	0.44	0.056	18.8	0.43	0.057	14.2	0.64	0.080	10.8	0.64	0.072
		3	10	2	16.6	0.44	0.053	18.6	0.42	0.052	15	0.61	0.074	13.4	0.60	0.070
		3	12	2	18	0.43	0.056	21.8	0.42	0.057	12	0.58	0.069	12.8	0.58	0.073
		3	16	2	19.8	0.42	0.055	18.4	0.43	0.050	12.2	0.53	0.064	15.8	0.53	0.064
		4	6	2	17.4	0.40	0.052	20.4	0.39	0.050	11	0.64	0.076	11.6	0.64	0.078
		4	8	2	22.4	0.40	0.052	21	0.38	0.049	12.6	0.57	0.073	15.2	0.58	0.077
		4	10	2	21.2	0.39	0.053	22.2	0.38	0.048	15.6	0.56	0.070	15.6	0.53	0.074
		4	12	2	22.8	0.38	0.053	16	0.39	0.049	13.4	0.52	0.059	15.2	0.52	0.063
		4	16	2	21.4	0.38	0.046	23	0.37	0.052	17	0.48	0.059	17.2	0.48	0.061
		5	6	2	22.2	0.37	0.047	23.4	0.35	0.046	10	0.58	0.067	12.8	0.58	0.073
		5	8	2	24	0.37	0.052	24	0.35	0.047	14.8	0.52	0.071	15.4	0.53	0.063
		5	10	2	26.6	0.36	0.054	25.4	0.35	0.044	16.8	0.49	0.059	11	0.49	0.054
		5	12	2	24.6	0.35	0.046	24.8	0.36	0.046	13.6	0.48	0.060	16.6	0.47	0.064
		5	16	2	20.4	0.36	0.049	24.6	0.35	0.045	17.8	0.44	0.052	17.4	0.43	0.059
		6	6	2	23.8	0.34	0.048	26.6	0.34	0.046	14.4	0.55	0.063	11.2	0.54	0.061
		6	8	2	22.8	0.34	0.042	23.8	0.32	0.043	16	0.49	0.063	18.4	0.49	0.062
		6	10	2	23	0.33	0.044	29.2	0.32	0.048	19.6	0.46	0.062	17.8	0.45	0.058
		6	12	2	27.4	0.33	0.044	24.4	0.33	0.044	18.4	0.44	0.058	15.8	0.43	0.053
		6	16	2	25.8	0.32	0.047	26	0.33	0.046	17.4	0.42	0.052	19.4	0.41	0.050
		8	6	2	27.6	0.30	0.041	25.8	0.31	0.045	17.4	0.47	0.057	17.8	0.48	0.062
		8	8	2	27.6	0.31	0.042	27.6	0.31	0.044	19.8	0.44	0.055	19.2	0.42	0.056
		8	10	2	27.8	0.30	0.045	28.2	0.30	0.040	21.8	0.40	0.055	22.4	0.40	0.049
		8	12	2	27.8	0.30	0.041	29.6	0.30	0.044	21.4	0.38	0.050	19.6	0.39	0.054
		8	16	2	25.2	0.31	0.045	29.2	0.29	0.043	21.6	0.36	0.047	26.4	0.36	0.048

Table A1.26. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Spotty	3	6	3	21.6	0.53	0.053	23.4	0.53	0.051	10.8	0.88	0.077	11.4	0.89	0.081
		3	8	3	19.6	0.53	0.055	22.8	0.53	0.054	13.4	0.80	0.076	13.8	0.79	0.071
		3	10	3	18.6	0.53	0.049	19.2	0.51	0.046	15.8	0.75	0.068	16.8	0.74	0.071
		3	12	3	25	0.52	0.054	22.8	0.51	0.049	16.8	0.69	0.061	18.4	0.69	0.069
		3	16	3	20.8	0.52	0.050	21.6	0.53	0.051	16.8	0.65	0.066	15.4	0.64	0.063
		4	6	3	27.4	0.49	0.049	24.6	0.48	0.046	12	0.80	0.069	14.6	0.79	0.075
		4	8	3	24.4	0.49	0.046	24.4	0.46	0.045	13.2	0.71	0.065	13.8	0.72	0.068
		4	10	3	24	0.48	0.047	23.2	0.47	0.045	13.6	0.69	0.058	15.4	0.67	0.060
		4	12	3	22.2	0.47	0.050	21.2	0.49	0.052	16.6	0.63	0.061	15.4	0.62	0.060
		4	16	3	22.4	0.48	0.046	24.8	0.45	0.049	24	0.58	0.066	23.4	0.59	0.059
		5	6	3	25	0.45	0.049	25.2	0.44	0.042	15.8	0.73	0.066	14.6	0.72	0.063
		5	8	3	25.2	0.44	0.050	28.8	0.43	0.048	16	0.66	0.058	16.2	0.66	0.057
		5	10	3	25.6	0.44	0.046	28.2	0.43	0.044	17.8	0.61	0.054	21.4	0.60	0.057
		5	12	3	28.4	0.43	0.046	29.6	0.43	0.047	20.8	0.58	0.059	20.8	0.57	0.056
		5	16	3	26.4	0.44	0.044	29.8	0.43	0.048	18.2	0.54	0.052	20	0.54	0.058
		6	6	3	29	0.41	0.048	29.6	0.41	0.045	14.8	0.68	0.062	17.2	0.66	0.063
		6	8	3	34.8	0.40	0.045	28.8	0.40	0.044	17.4	0.61	0.054	18.4	0.59	0.060
		6	10	3	26.8	0.41	0.045	28.6	0.40	0.039	18.4	0.56	0.061	23.2	0.56	0.057
		6	12	3	30.4	0.40	0.039	30.4	0.39	0.046	24	0.54	0.057	20.6	0.52	0.051
		6	16	3	29.6	0.40	0.046	29.8	0.41	0.045	21	0.51	0.050	23.2	0.49	0.051
		8	6	3	30.6	0.37	0.041	32.4	0.37	0.039	17.8	0.59	0.058	18.6	0.59	0.053
		8	8	3	32.6	0.37	0.042	35.2	0.35	0.040	21.4	0.53	0.053	23	0.53	0.049
		8	10	3	34.2	0.36	0.039	33.8	0.37	0.040	21	0.51	0.047	24.8	0.49	0.049
		8	12	3	31.6	0.36	0.042	34	0.35	0.038	19.6	0.47	0.049	23.2	0.47	0.048
		8	16	3	29.6	0.36	0.036	30.8	0.36	0.039	27.4	0.45	0.042	25	0.44	0.043

Table A1.27. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Horoirangi Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Spotty	3	6	1	85.6	0.10	0.017	92.6	0.10	0.014	19.8	0.31	0.047	17.8	0.32	0.049
		3	8	1	89.8	0.10	0.016	94.2	0.09	0.013	20.4	0.27	0.043	23	0.27	0.039
		3	10	1	93	0.10	0.015	96.2	0.09	0.014	25.6	0.24	0.034	27	0.25	0.034
		3	12	1	94.6	0.10	0.013	95.2	0.09	0.014	30.8	0.22	0.033	32.8	0.22	0.032
		3	16	1	94	0.09	0.013	96.6	0.09	0.012	36.2	0.20	0.030	41	0.19	0.028
		4	6	1	95.2	0.09	0.014	97.6	0.08	0.013	22	0.27	0.042	21	0.28	0.041
		4	8	1	97.6	0.09	0.013	98.6	0.08	0.012	28.8	0.24	0.034	26.8	0.24	0.035
		4	10	1	98	0.09	0.013	97.8	0.08	0.012	36.2	0.21	0.033	33.4	0.22	0.030
		4	12	1	98	0.08	0.012	98.8	0.08	0.012	39	0.19	0.029	38	0.20	0.027
		4	16	1	98	0.08	0.011	98.8	0.08	0.011	52.8	0.17	0.025	48.8	0.17	0.026
		5	6	1	98.6	0.08	0.013	99.8	0.07	0.012	26.4	0.25	0.037	24.4	0.25	0.036
		5	8	1	98.6	0.08	0.012	100	0.07	0.011	36.4	0.22	0.034	32.4	0.21	0.030
		5	10	1	98.4	0.08	0.011	99.8	0.07	0.011	37.8	0.19	0.027	41.4	0.19	0.026
		5	12	1	99.4	0.08	0.011	100	0.07	0.010	48.4	0.17	0.026	44	0.17	0.028
		5	16	1	100	0.07	0.011	99.8	0.07	0.010	53.8	0.15	0.022	59.4	0.15	0.024
		6	6	1	98.8	0.08	0.011	99.8	0.07	0.009	30.2	0.23	0.034	27.8	0.23	0.031
		6	8	1	99.6	0.07	0.011	100	0.07	0.010	38.4	0.19	0.030	39.4	0.20	0.027
		6	10	1	99.8	0.07	0.010	100	0.07	0.009	45	0.18	0.025	48.6	0.17	0.026
		6	12	1	100	0.07	0.010	99.8	0.06	0.009	55.8	0.16	0.024	54.6	0.16	0.022
		6	16	1	99.8	0.07	0.009	100	0.07	0.009	64.4	0.14	0.021	67.2	0.14	0.021
		8	6	1	100	0.07	0.009	100	0.06	0.009	37.4	0.20	0.031	40.4	0.20	0.028
		8	8	1	100	0.06	0.009	100	0.06	0.008	47.8	0.17	0.027	47	0.17	0.026
		8	10	1	100	0.06	0.009	100	0.06	0.009	60.4	0.15	0.022	59.4	0.15	0.024
		8	12	1	99.8	0.06	0.009	100	0.06	0.009	67.6	0.14	0.018	68.8	0.14	0.020
		8	16	1	100	0.06	0.008	100	0.06	0.008	78	0.12	0.018	79	0.12	0.017

Table A1.28. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Spotty	3	6	2	61.6	0.19	0.023	64.2	0.18	0.019	12.6	0.58	0.068	11	0.59	0.064
		3	8	2	62.8	0.19	0.022	69.2	0.17	0.022	17.2	0.50	0.061	15.4	0.49	0.059
		3	10	2	65	0.19	0.020	73.4	0.17	0.018	16.8	0.45	0.055	20.4	0.44	0.051
		3	12	2	65	0.18	0.021	70.6	0.17	0.019	18.2	0.42	0.046	17.8	0.43	0.044
		3	16	2	71	0.17	0.020	72	0.16	0.020	25.2	0.36	0.045	24	0.35	0.038
		4	6	2	68.6	0.17	0.020	78.4	0.16	0.019	12.6	0.52	0.057	13.6	0.52	0.058
		4	8	2	73.2	0.16	0.018	79.6	0.15	0.018	22	0.44	0.057	18.2	0.45	0.048
		4	10	2	73	0.16	0.018	79.2	0.15	0.017	20.8	0.40	0.046	21	0.41	0.044
		4	12	2	78.4	0.16	0.019	81.4	0.15	0.018	22	0.37	0.040	23.2	0.36	0.042
		4	16	2	81.6	0.15	0.017	84	0.15	0.017	26	0.32	0.036	26.2	0.32	0.036
		5	6	2	80.4	0.16	0.016	85.2	0.14	0.016	14.2	0.48	0.053	13.4	0.47	0.050
		5	8	2	84.4	0.15	0.018	87	0.14	0.017	18.8	0.40	0.045	19.4	0.41	0.043
		5	10	2	86	0.15	0.014	89	0.14	0.015	26.8	0.36	0.043	25	0.36	0.041
		5	12	2	83.4	0.14	0.016	89.6	0.14	0.014	26	0.34	0.036	30.6	0.33	0.044
		5	16	2	89.6	0.14	0.015	87.4	0.13	0.015	31.2	0.29	0.032	32.6	0.29	0.033
		6	6	2	86.2	0.15	0.015	92	0.13	0.014	13.4	0.43	0.046	17.2	0.43	0.046
		6	8	2	87.8	0.14	0.015	90.2	0.13	0.014	20.6	0.38	0.039	22	0.37	0.043
		6	10	2	89.8	0.13	0.015	93.6	0.12	0.013	25.2	0.34	0.037	26.8	0.33	0.037
		6	12	2	91.2	0.13	0.012	94.2	0.12	0.014	32.6	0.31	0.035	27.8	0.31	0.034
		6	16	2	90.8	0.13	0.014	93.6	0.12	0.014	39	0.27	0.028	40.4	0.26	0.029
		8	6	2	93.2	0.13	0.014	96.4	0.12	0.014	20	0.38	0.043	19.8	0.38	0.041
		8	8	2	96.6	0.12	0.013	97.6	0.11	0.012	28.4	0.33	0.039	22.8	0.33	0.033
		8	10	2	95.4	0.12	0.013	97.4	0.11	0.012	31.8	0.29	0.035	36.4	0.29	0.032
		8	12	2	96.6	0.11	0.012	97.6	0.11	0.012	38.2	0.27	0.031	40.6	0.27	0.028
		8	16	2	96.8	0.11	0.014	97	0.11	0.012	44.8	0.23	0.025	46.6	0.23	0.026

Table A1.29. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of spotty using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Spotty	3	6	3	62.8	0.24	0.020	70.4	0.22	0.022	14	0.74	0.059	14.2	0.72	0.063
		3	8	3	67.8	0.22	0.021	74.6	0.21	0.018	15.6	0.60	0.057	15.4	0.63	0.055
		3	10	3	70.2	0.22	0.020	70.4	0.21	0.019	22.2	0.54	0.053	20.6	0.53	0.046
		3	12	3	67.6	0.22	0.019	77.2	0.20	0.020	24	0.52	0.049	22	0.51	0.043
		3	16	3	74.6	0.21	0.018	76.8	0.21	0.017	26.2	0.44	0.042	27.8	0.44	0.041
		4	6	3	73.4	0.21	0.019	80.8	0.19	0.017	18.2	0.65	0.057	16	0.65	0.056
		4	8	3	75.8	0.20	0.019	82.6	0.19	0.016	16.2	0.56	0.048	20	0.55	0.050
		4	10	3	81.4	0.20	0.017	82.4	0.19	0.016	29.2	0.49	0.044	19.8	0.50	0.038
		4	12	3	83.6	0.20	0.017	88.4	0.18	0.015	25	0.47	0.039	25.8	0.46	0.038
		4	16	3	81.6	0.19	0.016	88.6	0.18	0.014	28.6	0.40	0.033	33.8	0.39	0.037
		5	6	3	81.2	0.20	0.017	88.6	0.18	0.015	14.4	0.61	0.047	18.2	0.58	0.048
		5	8	3	85.8	0.19	0.016	87.8	0.18	0.014	21	0.51	0.041	19.2	0.51	0.041
		5	10	3	88.4	0.18	0.015	90.2	0.17	0.015	27.4	0.45	0.038	25.6	0.45	0.037
		5	12	3	90	0.18	0.014	90.8	0.17	0.013	25.8	0.41	0.034	24.4	0.42	0.034
		5	16	3	89.6	0.17	0.014	93.6	0.16	0.013	36.2	0.36	0.032	38	0.35	0.032
		6	6	3	88	0.18	0.015	93.6	0.16	0.014	18.8	0.54	0.046	18.2	0.55	0.048
		6	8	3	92.2	0.17	0.014	94.8	0.16	0.013	23.4	0.47	0.040	22.6	0.47	0.037
		6	10	3	93	0.17	0.013	94.4	0.16	0.013	29.2	0.42	0.034	29.8	0.41	0.035
		6	12	3	93.4	0.16	0.014	95.4	0.16	0.013	31.4	0.38	0.030	32.2	0.38	0.032
		6	16	3	93.4	0.16	0.014	95	0.15	0.012	40.6	0.33	0.030	43.8	0.33	0.027
		8	6	3	94	0.16	0.012	96.8	0.15	0.012	20.2	0.48	0.041	25.6	0.48	0.040
		8	8	3	97	0.15	0.012	97.8	0.14	0.012	30.2	0.41	0.034	30.4	0.42	0.034
		8	10	3	96.8	0.15	0.012	98.4	0.14	0.011	35	0.37	0.033	34.4	0.37	0.030
		8	12	3	97.2	0.15	0.011	98.6	0.14	0.010	40.8	0.33	0.027	41	0.33	0.025
		8	16	3	97.6	0.14	0.013	98.8	0.13	0.011	49.2	0.29	0.024	53.6	0.29	0.023

Table A1.30. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Long Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Tarakihi	3	6	1	11.6	0.51	0.078	10	0.47	0.070	8.6	0.62	0.096	11.2	0.56	0.096
		3	8	1	13.2	0.50	0.077	12.8	0.45	0.074	11.6	0.56	0.108	13.2	0.54	0.081
		3	10	1	12.2	0.48	0.074	12.8	0.44	0.074	12.8	0.54	0.085	13.8	0.50	0.078
		3	12	1	12.4	0.46	0.077	11	0.45	0.069	9	0.52	0.080	9.8	0.50	0.078
		3	16	1	16	0.45	0.078	14.6	0.43	0.074	11.4	0.49	0.075	12	0.47	0.077
		4	6	1	12.6	0.46	0.073	15.4	0.41	0.069	12.2	0.55	0.088	12.6	0.51	0.090
		4	8	1	15	0.44	0.069	15.4	0.40	0.070	15.4	0.51	0.091	13	0.47	0.072
		4	10	1	17.6	0.41	0.074	16	0.40	0.065	11.8	0.49	0.071	14.6	0.45	0.080
		4	12	1	13	0.41	0.068	16	0.40	0.064	13.8	0.45	0.078	12	0.44	0.077
		4	16	1	15.2	0.40	0.065	17.4	0.39	0.066	14.6	0.43	0.072	13.8	0.41	0.062
		5	6	1	13.4	0.41	0.068	18.2	0.37	0.065	14.2	0.50	0.085	13.6	0.46	0.076
		5	8	1	14.6	0.39	0.063	21.6	0.36	0.067	15.4	0.46	0.079	14	0.43	0.071
		5	10	1	19.4	0.39	0.067	15	0.36	0.060	14.2	0.43	0.068	14.6	0.41	0.066
		5	12	1	16.8	0.38	0.058	15	0.36	0.064	13	0.41	0.066	15	0.40	0.063
		5	16	1	19.6	0.37	0.067	20	0.36	0.060	18.2	0.40	0.068	14.2	0.38	0.059
		6	6	1	17.2	0.38	0.066	18.6	0.36	0.064	13	0.45	0.075	18.4	0.41	0.079
		6	8	1	18.6	0.37	0.067	17.2	0.34	0.062	18.4	0.42	0.072	18	0.39	0.071
		6	10	1	18.4	0.36	0.068	18.8	0.34	0.061	16.2	0.39	0.069	15.6	0.38	0.064
		6	12	1	13.6	0.35	0.059	21.2	0.34	0.058	15.8	0.39	0.068	18.4	0.37	0.066
		6	16	1	17.8	0.35	0.062	20.4	0.33	0.057	18.4	0.37	0.070	18.8	0.36	0.065
		8	6	1	18.4	0.34	0.056	22.4	0.32	0.058	16	0.40	0.064	21.2	0.36	0.066
		8	8	1	19.6	0.33	0.054	19.8	0.31	0.056	15.4	0.37	0.062	22.4	0.35	0.063
		8	10	1	21	0.32	0.056	21.2	0.31	0.059	16.6	0.35	0.059	19.2	0.34	0.061
		8	12	1	21.2	0.31	0.059	21	0.32	0.056	24.4	0.34	0.066	20.4	0.33	0.058
		8	16	1	19	0.31	0.057	21	0.31	0.052	18.8	0.33	0.057	20.8	0.33	0.060

Table A1.31. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Long Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Tarakihi	3	6	2	10.6	0.96	0.116	13.2	0.89	0.116	11.6	1.16	0.149	10.2	1.06	0.126
		3	8	2	13.8	0.90	0.113	12	0.81	0.106	9.4	1.04	0.125	8.8	1.01	0.127
		3	10	2	14.2	0.88	0.109	14.2	0.81	0.102	11.6	0.99	0.122	11.6	0.92	0.119
		3	12	2	10.6	0.86	0.118	12	0.80	0.103	10.2	0.93	0.118	11.8	0.91	0.117
		3	16	2	14	0.82	0.108	12.8	0.80	0.105	11.2	0.88	0.112	13	0.85	0.109
		4	6	2	14.6	0.83	0.116	12.6	0.76	0.108	8	1.03	0.113	12.4	0.93	0.124
		4	8	2	12.4	0.80	0.107	12.6	0.76	0.100	12.8	0.93	0.111	11	0.85	0.107
		4	10	2	11.6	0.79	0.099	11	0.73	0.097	11.4	0.89	0.102	10	0.86	0.105
		4	12	2	13.6	0.77	0.099	12.2	0.72	0.089	12.2	0.84	0.106	10.2	0.82	0.107
		4	16	2	14	0.75	0.099	15	0.72	0.100	13.4	0.80	0.103	10.8	0.76	0.098
		5	6	2	15.2	0.77	0.096	14.8	0.70	0.095	11.8	0.92	0.113	13.2	0.84	0.117
		5	8	2	15.4	0.74	0.094	13.8	0.69	0.090	12.8	0.87	0.104	11.2	0.80	0.109
		5	10	2	12.2	0.72	0.090	14.4	0.66	0.091	11.2	0.80	0.093	10.6	0.76	0.098
		5	12	2	14.6	0.69	0.089	13.4	0.65	0.086	10	0.78	0.093	15.2	0.72	0.099
		5	16	2	14.8	0.66	0.091	14.6	0.67	0.085	9.4	0.75	0.095	10.4	0.70	0.086
		6	6	2	13.8	0.71	0.096	13.8	0.66	0.083	10.4	0.87	0.100	9.8	0.77	0.093
		6	8	2	13.8	0.67	0.089	12.2	0.61	0.080	16.2	0.78	0.107	11.4	0.74	0.098
		6	10	2	13.8	0.65	0.091	14.8	0.62	0.084	11.4	0.74	0.097	12	0.71	0.097
		6	12	2	15	0.65	0.073	15	0.60	0.083	13.8	0.71	0.093	13	0.70	0.087
		6	16	2	14.2	0.63	0.084	20	0.61	0.092	13.4	0.68	0.084	17.8	0.65	0.095
		8	6	2	17	0.62	0.091	17	0.58	0.083	13.6	0.75	0.099	16.4	0.70	0.086
		8	8	2	16.4	0.60	0.082	17.6	0.56	0.080	16.6	0.69	0.100	15	0.64	0.087
		8	10	2	14.8	0.58	0.081	18.4	0.54	0.077	13	0.64	0.085	16.8	0.62	0.090
		8	12	2	14.2	0.59	0.076	15.8	0.53	0.085	15.6	0.63	0.087	17.2	0.59	0.090
		8	16	2	14.6	0.56	0.079	16.4	0.53	0.070	16.6	0.59	0.081	16.4	0.57	0.078

Table A1.32. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Long Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
LIMR	Tarakihi	3	6	3	14.6	1.18	0.120	12.2	1.03	0.107	12.6	1.49	0.139	13.4	1.24	0.130
		3	8	3	13.6	1.10	0.120	14.8	1.02	0.097	9.4	1.27	0.126	11.2	1.20	0.119
		3	10	3	15.2	1.07	0.112	15.6	0.98	0.095	12.2	1.24	0.113	15.2	1.13	0.116
		3	12	3	13.4	1.06	0.098	13.4	0.98	0.093	12.6	1.17	0.110	11.8	1.09	0.113
		3	16	3	14.8	1.01	0.104	14.8	0.95	0.102	14.8	1.10	0.104	13.6	1.06	0.111
		4	6	3	15.4	1.00	0.105	13.8	0.92	0.103	11.2	1.26	0.115	13.8	1.15	0.108
		4	8	3	12.4	0.99	0.095	13.8	0.93	0.091	12.6	1.15	0.119	14	1.07	0.097
		4	10	3	13.8	0.92	0.087	13.2	0.90	0.096	15.2	1.07	0.113	14.8	1.03	0.104
		4	12	3	11.6	0.92	0.092	13.6	0.87	0.085	13.6	1.04	0.107	12.8	0.96	0.094
		4	16	3	14.6	0.90	0.093	12.4	0.87	0.085	12.8	1.01	0.098	13.2	0.96	0.094
		5	6	3	15.2	0.96	0.091	12.4	0.86	0.081	13.6	1.13	0.103	10.8	1.05	0.094
		5	8	3	13.4	0.90	0.086	14.2	0.83	0.093	10.8	1.06	0.097	13.2	0.99	0.101
		5	10	3	13.6	0.88	0.086	18.6	0.82	0.079	13	1.00	0.092	12.6	0.94	0.094
		5	12	3	14.6	0.87	0.092	15.2	0.81	0.086	15.8	0.95	0.090	15.6	0.89	0.084
		5	16	3	15.4	0.83	0.087	15	0.82	0.086	15	0.93	0.093	13.8	0.85	0.085
		6	6	3	15.8	0.88	0.091	15.2	0.79	0.079	11.6	1.10	0.101	15.6	0.93	0.097
		6	8	3	16.8	0.83	0.089	18.8	0.77	0.083	14.2	0.96	0.106	13	0.90	0.087
		6	10	3	13.8	0.81	0.077	19.2	0.73	0.079	15.4	0.92	0.093	12.2	0.84	0.083
		6	12	3	17.2	0.80	0.085	18	0.74	0.084	16.6	0.88	0.080	18	0.83	0.090
		6	16	3	18.6	0.77	0.083	16.2	0.73	0.079	14.4	0.85	0.085	15.2	0.80	0.081
		8	6	3	19	0.77	0.086	22.2	0.70	0.079	11	0.94	0.085	16.2	0.86	0.092
		8	8	3	18.8	0.74	0.084	16.4	0.70	0.075	13.6	0.88	0.078	16.8	0.83	0.083
		8	10	3	17.2	0.73	0.072	21.8	0.66	0.080	17.8	0.82	0.082	15.6	0.76	0.080
		8	12	3	16.6	0.71	0.072	20.6	0.66	0.072	17	0.78	0.084	17	0.74	0.075
		8	16	3	18.8	0.69	0.072	17.4	0.65	0.072	18.4	0.74	0.078	19.2	0.71	0.078

Table A1.33. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Tonga Island Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Tarakihi	3	6	1	10.4	0.58	0.099	12	0.57	0.092	10.2	0.65	0.112	12.6	0.61	0.110
		3	8	1	12.2	0.58	0.098	13.2	0.54	0.094	12	0.62	0.102	10.4	0.60	0.102
		3	10	1	13.4	0.57	0.093	15.2	0.56	0.095	15.6	0.61	0.104	11.2	0.59	0.107
		3	12	1	13.2	0.55	0.101	12.8	0.56	0.091	12.4	0.59	0.103	14.2	0.61	0.108
		3	16	1	13	0.54	0.096	11	0.55	0.095	12.4	0.58	0.090	11.8	0.56	0.093
		4	6	1	13.4	0.54	0.100	13.8	0.55	0.098	13.4	0.59	0.104	10.8	0.59	0.097
		4	8	1	13.6	0.54	0.093	13.8	0.53	0.088	11.6	0.59	0.105	10	0.57	0.092
		4	10	1	9.2	0.54	0.088	16	0.53	0.095	12.6	0.56	0.096	15	0.54	0.095
		4	12	1	12.4	0.55	0.098	12.8	0.54	0.087	15.2	0.55	0.097	15.8	0.55	0.100
		4	16	1	10.6	0.55	0.091	11.6	0.53	0.097	12.8	0.56	0.094	14.8	0.55	0.092
		5	6	1	13	0.52	0.089	14.2	0.53	0.085	13.6	0.57	0.100	17	0.53	0.098
		5	8	1	14.6	0.52	0.090	13.8	0.53	0.091	13.8	0.54	0.087	11	0.55	0.088
		5	10	1	11.4	0.53	0.085	12	0.51	0.091	12.4	0.53	0.089	9.2	0.55	0.088
		5	12	1	15.8	0.51	0.095	15.2	0.51	0.079	16.8	0.54	0.100	13.4	0.53	0.090
		5	16	1	12.2	0.52	0.093	13.2	0.50	0.082	10.8	0.53	0.091	13.8	0.53	0.084
		6	6	1	13.4	0.52	0.087	13.8	0.50	0.091	13.8	0.54	0.097	12.2	0.53	0.090
		6	8	1	13.6	0.51	0.087	13.8	0.52	0.091	15.2	0.53	0.089	14.2	0.53	0.091
		6	10	1	15.8	0.51	0.080	12.8	0.51	0.084	11.8	0.54	0.095	13	0.54	0.088
		6	12	1	12.8	0.52	0.083	14.6	0.51	0.089	12	0.52	0.089	15.4	0.53	0.095
		6	16	1	10.4	0.53	0.086	11.4	0.51	0.086	16.6	0.53	0.091	13	0.52	0.092
		8	6	1	14.8	0.50	0.088	14.2	0.50	0.093	12.4	0.52	0.096	12.2	0.52	0.091
		8	8	1	15	0.49	0.091	12.4	0.50	0.082	12	0.52	0.091	15.4	0.51	0.087
		8	10	1	13.8	0.50	0.093	11.8	0.50	0.082	15.4	0.50	0.097	14.4	0.52	0.089
		8	12	1	13.8	0.50	0.083	15.6	0.49	0.085	15.4	0.51	0.092	11.6	0.51	0.090
		8	16	1	13	0.48	0.080	15.2	0.49	0.085	12.2	0.51	0.085	15	0.52	0.095

Table A1.34. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Tarakihi	3	6	2	15.6	0.97	0.137	15.4	0.94	0.155	10.8	1.18	0.159	14.6	1.04	0.147
		3	8	2	12.8	0.96	0.129	14.6	0.92	0.136	14	1.06	0.154	13.8	1.05	0.151
		3	10	2	15.8	0.93	0.147	15	0.91	0.134	14.6	1.04	0.144	12.6	1.01	0.147
		3	12	2	16	0.94	0.156	15.2	0.89	0.134	13.6	0.99	0.140	14.8	1.01	0.143
		3	16	2	17.4	0.91	0.138	15.6	0.89	0.141	14.4	0.96	0.147	16.2	0.95	0.149
		4	6	2	16.4	0.91	0.132	15.2	0.89	0.134	14	1.05	0.139	13.4	0.99	0.156
		4	8	2	16.6	0.87	0.145	15.4	0.86	0.135	13	1.03	0.130	16	0.94	0.141
		4	10	2	17.2	0.89	0.143	15.4	0.85	0.128	15	0.93	0.144	14.4	0.92	0.142
		4	12	2	17.6	0.88	0.143	14.4	0.86	0.133	16.2	0.93	0.146	18.8	0.91	0.136
		4	16	2	18.6	0.85	0.134	16.6	0.85	0.119	15.2	0.92	0.150	14.4	0.87	0.127
		5	6	2	16.2	0.88	0.143	16.6	0.83	0.135	16.4	0.95	0.150	14	0.92	0.137
		5	8	2	18	0.83	0.132	17.2	0.82	0.125	16	0.94	0.158	14.6	0.90	0.133
		5	10	2	15.6	0.86	0.127	16.2	0.85	0.127	17.8	0.88	0.135	17.4	0.86	0.138
		5	12	2	14.6	0.89	0.130	16.4	0.84	0.140	16.4	0.90	0.141	16.8	0.87	0.136
		5	16	2	17.2	0.82	0.134	18.8	0.81	0.125	18.8	0.86	0.137	17.2	0.85	0.125
		6	6	2	16.6	0.84	0.139	19.4	0.82	0.132	16.8	0.93	0.133	14.8	0.88	0.125
		6	8	2	16.6	0.84	0.126	18.8	0.84	0.132	15	0.87	0.137	17.6	0.89	0.136
		6	10	2	17.8	0.83	0.129	20.6	0.78	0.134	17.2	0.85	0.126	17	0.85	0.134
		6	12	2	19.8	0.84	0.127	18.4	0.81	0.124	17.6	0.88	0.131	18	0.82	0.130
		6	16	2	18	0.82	0.137	15	0.83	0.122	15.4	0.86	0.122	14.8	0.84	0.123
		8	6	2	20.2	0.80	0.134	15.4	0.75	0.120	16.8	0.86	0.130	14.8	0.84	0.136
		8	8	2	20.2	0.79	0.120	16.8	0.81	0.124	15.6	0.80	0.128	16.8	0.83	0.129
		8	10	2	17.6	0.81	0.129	15.2	0.80	0.112	19.4	0.80	0.135	19.6	0.80	0.123
		8	12	2	20.4	0.81	0.130	17.4	0.78	0.123	18.4	0.81	0.122	18.6	0.83	0.125
		8	16	2	21	0.81	0.129	18.6	0.77	0.128	16.2	0.82	0.123	20.8	0.76	0.133

Table A1.35. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Tonga Island Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
TIMR	Tarakihi	3	6	3	18.2	1.13	0.147	14	1.14	0.125	15.8	1.35	0.144	16	1.27	0.142
		3	8	3	20	1.13	0.150	18.2	1.08	0.141	15.8	1.29	0.141	14.2	1.27	0.140
		3	10	3	18.8	1.09	0.131	18.4	1.12	0.133	17.4	1.22	0.150	17.6	1.25	0.147
		3	12	3	16.6	1.10	0.130	18.6	1.01	0.127	17	1.19	0.139	14.6	1.15	0.133
		3	16	3	18.8	1.06	0.126	21.2	1.02	0.138	16.2	1.18	0.131	20.8	1.09	0.127
		4	6	3	17.2	1.02	0.111	23.8	1.01	0.127	18.2	1.24	0.140	16.8	1.17	0.132
		4	8	3	19	1.02	0.138	17.4	1.04	0.117	15.2	1.15	0.144	19.2	1.10	0.137
		4	10	3	18.8	1.05	0.130	22	0.93	0.136	18.4	1.12	0.141	17	1.06	0.135
		4	12	3	20	0.98	0.123	20.6	0.95	0.126	19.4	1.08	0.134	19.8	1.03	0.135
		4	16	3	19.6	1.01	0.125	19	1.00	0.120	21.6	1.03	0.137	21.8	1.04	0.145
		5	6	3	17.8	0.96	0.127	21.2	0.95	0.115	17.6	1.17	0.136	18.8	1.08	0.129
		5	8	3	18.8	0.93	0.111	22.2	0.96	0.118	18.6	1.04	0.128	20	1.01	0.127
		5	10	3	21.6	0.97	0.124	18.2	0.97	0.120	19.6	1.04	0.134	17	0.98	0.124
		5	12	3	19.4	0.98	0.121	21.2	0.91	0.121	18.8	1.02	0.125	19	1.01	0.125
		5	16	3	20.4	0.96	0.117	21	0.89	0.116	17.6	1.00	0.117	19	0.91	0.112
		6	6	3	18.2	0.96	0.127	21.2	0.96	0.114	17.8	1.05	0.127	18.6	1.05	0.129
		6	8	3	20	0.89	0.121	25.6	0.88	0.130	21.2	1.02	0.122	20.2	0.99	0.134
		6	10	3	20.8	0.90	0.121	18.6	0.93	0.116	20.4	0.97	0.126	18.4	0.97	0.140
		6	12	3	22.4	0.91	0.114	20.2	0.92	0.118	19.2	1.00	0.121	23.2	0.95	0.131
		6	16	3	23.4	0.91	0.123	18.2	0.91	0.104	20	0.92	0.113	20.8	0.92	0.131
		8	6	3	25.4	0.89	0.126	23.2	0.87	0.119	18	0.97	0.132	22.6	0.95	0.124
		8	8	3	22.2	0.88	0.114	22.4	0.88	0.113	21.4	0.94	0.114	20.8	0.91	0.121
		8	10	3	21.2	0.84	0.116	21.8	0.83	0.112	19.4	0.91	0.111	23	0.93	0.114
		8	12	3	24.2	0.86	0.119	20.4	0.86	0.108	23.2	0.90	0.126	21.2	0.85	0.119
		8	16	3	21.6	0.84	0.123	23.4	0.83	0.113	20.8	0.90	0.124	22.2	0.86	0.114

Table A1.36. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Horoirangi Marine Reserve dataset. This is for an annual monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Tarakihi	3	6	1	10.2	0.51	0.074	9	0.47	0.071	10.8	0.62	0.095	9.2	0.57	0.088
		3	8	1	13.2	0.49	0.078	12.8	0.46	0.073	10.6	0.58	0.083	11.8	0.53	0.084
		3	10	1	12	0.48	0.077	13	0.44	0.070	12.2	0.53	0.085	11.6	0.50	0.080
		3	12	1	13.2	0.46	0.077	12	0.45	0.072	11.2	0.52	0.085	11.6	0.49	0.082
		3	16	1	11.2	0.45	0.068	13	0.43	0.069	10.2	0.49	0.083	11.8	0.47	0.077
		4	6	1	16.8	0.45	0.076	16.8	0.42	0.073	11.2	0.53	0.087	12	0.50	0.079
		4	8	1	16.8	0.43	0.071	14.6	0.41	0.065	12.6	0.50	0.080	11.6	0.47	0.074
		4	10	1	14.6	0.42	0.071	15.8	0.40	0.066	12	0.47	0.082	12.6	0.46	0.066
		4	12	1	14.2	0.41	0.067	15.8	0.40	0.060	13	0.46	0.079	14.2	0.44	0.075
		4	16	1	15.2	0.41	0.071	14.6	0.39	0.062	13	0.44	0.075	15.4	0.42	0.067
		5	6	1	14.4	0.41	0.069	18.4	0.38	0.065	11.4	0.49	0.079	13	0.46	0.071
		5	8	1	16.4	0.40	0.070	15.2	0.36	0.058	12.2	0.46	0.065	16.2	0.43	0.063
		5	10	1	15.2	0.38	0.063	19.6	0.36	0.064	13.8	0.43	0.069	14.4	0.41	0.066
		5	12	1	18	0.38	0.057	18.8	0.36	0.063	14.6	0.41	0.070	15.4	0.39	0.058
		5	16	1	15.6	0.37	0.063	17.2	0.36	0.060	16.6	0.39	0.066	15	0.38	0.063
		6	6	1	15.2	0.38	0.061	19	0.36	0.062	13.6	0.45	0.083	13.2	0.42	0.077
		6	8	1	15.6	0.37	0.063	20.8	0.35	0.062	16.6	0.43	0.074	17.2	0.39	0.065
		6	10	1	19.8	0.36	0.065	21.4	0.34	0.061	13.6	0.39	0.058	16	0.37	0.061
		6	12	1	19.6	0.35	0.061	20.4	0.34	0.062	17.2	0.38	0.065	18.2	0.38	0.066
		6	16	1	16.2	0.34	0.062	17.6	0.33	0.055	16	0.37	0.065	17.2	0.36	0.056
		8	6	1	18.6	0.34	0.058	19	0.31	0.053	15	0.40	0.065	19.8	0.37	0.064
		8	8	1	19.8	0.32	0.054	21.8	0.32	0.057	18.2	0.36	0.062	19.8	0.34	0.057
		8	10	1	18.4	0.32	0.055	24.2	0.31	0.055	20.6	0.35	0.062	19.6	0.33	0.060
		8	12	1	18.8	0.32	0.057	23.8	0.30	0.052	19	0.33	0.059	18	0.33	0.061
		8	16	1	20	0.31	0.053	22.2	0.30	0.057	19.6	0.32	0.054	23.6	0.32	0.055

Table A1.37. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a biennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Tarakihi	3	6	2	12	0.93	0.128	11.8	0.85	0.101	8.8	1.14	0.146	11	1.05	0.146
		3	8	2	11	0.92	0.118	11.2	0.83	0.114	11	1.04	0.138	10	1.01	0.131
		3	10	2	13.4	0.87	0.118	11.6	0.80	0.109	8.6	1.01	0.125	10.6	0.94	0.121
		3	12	2	13.4	0.85	0.110	10.6	0.83	0.101	11	0.94	0.112	13.8	0.87	0.112
		3	16	2	10	0.80	0.098	11	0.78	0.101	12.6	0.89	0.114	11.2	0.87	0.113
		4	6	2	10	0.84	0.108	15	0.78	0.102	7.8	1.02	0.121	8.8	0.96	0.121
		4	8	2	11.2	0.80	0.101	13	0.74	0.089	9.6	0.92	0.129	11	0.89	0.116
		4	10	2	14.6	0.78	0.104	13	0.73	0.102	11	0.89	0.113	9.8	0.83	0.110
		4	12	2	11	0.75	0.093	12.6	0.73	0.103	13.6	0.84	0.114	11.6	0.82	0.104
		4	16	2	13.8	0.72	0.086	13	0.71	0.087	10.4	0.82	0.103	15.4	0.77	0.107
		5	6	2	13.6	0.74	0.100	12.6	0.72	0.098	10.6	0.92	0.117	12.4	0.89	0.113
		5	8	2	12.8	0.73	0.093	12.4	0.69	0.088	13	0.86	0.114	10.8	0.80	0.095
		5	10	2	11.6	0.72	0.094	12.8	0.68	0.084	12.4	0.81	0.102	13.2	0.77	0.099
		5	12	2	13	0.68	0.099	15	0.65	0.088	12.4	0.76	0.101	11.4	0.74	0.089
		5	16	2	12.2	0.68	0.088	17	0.64	0.082	11.4	0.72	0.100	12.6	0.68	0.094
		6	6	2	15.6	0.71	0.099	13.8	0.66	0.091	11	0.87	0.103	11.4	0.76	0.098
		6	8	2	18.4	0.68	0.097	13.8	0.62	0.076	14	0.78	0.103	15	0.73	0.100
		6	10	2	13.2	0.66	0.080	15	0.62	0.081	11.4	0.75	0.089	14.6	0.71	0.086
		6	12	2	12.8	0.64	0.080	12.6	0.61	0.088	17.6	0.71	0.098	15	0.67	0.088
		6	16	2	16.8	0.63	0.093	14.6	0.61	0.081	15	0.67	0.091	13.8	0.65	0.085
		8	6	2	17.4	0.63	0.083	17.6	0.58	0.082	12.4	0.78	0.096	14.2	0.69	0.093
		8	8	2	15.6	0.59	0.081	17.8	0.55	0.083	13.6	0.69	0.097	14.4	0.64	0.091
		8	10	2	13.4	0.58	0.082	17.8	0.54	0.079	16	0.65	0.086	16.4	0.61	0.090
		8	12	2	15	0.56	0.075	14.6	0.55	0.076	16.8	0.62	0.078	16	0.60	0.078
		8	16	2	19.4	0.55	0.082	20.4	0.53	0.078	17.6	0.60	0.093	16.2	0.57	0.080

Table A1.38. Power ($\alpha=0.05$), median 95% confidence interval width and median absolute bias for all combinations of monitoring choices for monitoring of tarakihi using parameters estimated from the Horoirangi Marine Reserve dataset. This is for a triennial monitoring frequency for negative and positive trends corresponding to a doubling/halving of abundance for both dispersion parameters.

Reserve	Species	Sampling Design			Poisson dispersed						Overdispersed					
					Trend - Negative			Trend - Positive			Trend - Negative			Trend - Positive		
		Sites	Transects	Frequency	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias	Power	CI width	Bias
HMR	Tarakihi	3	6	3	13.6	1.17	0.114	11.6	1.06	0.104	8.8	1.44	0.132	11.2	1.32	0.131
		3	8	3	13.4	1.13	0.109	12.4	0.99	0.095	14.2	1.27	0.148	13.2	1.19	0.114
		3	10	3	13	1.08	0.112	13	0.97	0.105	10.6	1.22	0.119	12.6	1.16	0.104
		3	12	3	13	1.05	0.104	14.6	1.00	0.102	11.8	1.17	0.112	16.6	1.11	0.108
		3	16	3	14.4	1.01	0.091	14.4	0.95	0.099	15.8	1.12	0.115	14.6	1.05	0.108
		4	6	3	12.2	1.07	0.100	12	0.96	0.092	12.8	1.23	0.122	11.2	1.17	0.105
		4	8	3	12.6	1.01	0.100	15.2	0.93	0.087	11.8	1.14	0.108	13.4	1.05	0.099
		4	10	3	12.8	0.97	0.101	15	0.92	0.095	16.4	1.10	0.103	12.6	1.05	0.116
		4	12	3	11	0.97	0.095	14	0.90	0.084	14.6	1.05	0.100	13.8	0.97	0.092
		4	16	3	15	0.88	0.093	14.6	0.86	0.082	12.6	0.98	0.104	16.4	0.93	0.092
		5	6	3	14.2	0.95	0.095	12	0.85	0.088	11.8	1.13	0.103	11.8	1.07	0.101
		5	8	3	11.8	0.91	0.084	16	0.85	0.086	10.8	1.05	0.104	10.8	0.99	0.093
		5	10	3	13.8	0.91	0.093	20	0.82	0.098	10.4	0.96	0.098	13.2	0.89	0.091
		5	12	3	14.6	0.85	0.083	17.4	0.80	0.091	12.8	0.96	0.097	15.2	0.88	0.090
		5	16	3	14.8	0.83	0.078	16.6	0.80	0.073	14.4	0.92	0.088	14.8	0.88	0.089
		6	6	3	15.2	0.89	0.089	15	0.80	0.077	15.2	1.07	0.112	13.4	0.97	0.098
		6	8	3	17.2	0.82	0.084	16	0.77	0.075	12	0.96	0.096	11.4	0.90	0.085
		6	10	3	16.4	0.84	0.092	17.4	0.76	0.087	14.4	0.92	0.092	15	0.88	0.085
		6	12	3	17.8	0.78	0.082	17.4	0.75	0.076	12.6	0.88	0.085	15.8	0.85	0.086
		6	16	3	16.8	0.79	0.085	15	0.73	0.081	16.4	0.85	0.086	15.8	0.77	0.083
		8	6	3	17.2	0.77	0.080	17.8	0.70	0.075	14	0.93	0.091	15.8	0.86	0.089
		8	8	3	16.8	0.76	0.077	16.8	0.69	0.072	14.2	0.88	0.080	18.8	0.80	0.083
		8	10	3	22.4	0.72	0.079	18.4	0.67	0.080	17.2	0.81	0.084	16	0.76	0.079
		8	12	3	17.4	0.71	0.071	19.4	0.66	0.074	15.4	0.82	0.085	18.2	0.73	0.074
		8	16	3	16.6	0.70	0.070	18.2	0.67	0.068	18.6	0.74	0.074	18	0.70	0.076

Appendix 2A – Bathymetry data for SWAN wave model development

2A.1 – Acquisition of bathymetry data

Base bathymetry data were obtained from the National Institute of Water and Atmospheric Research (NIWA) in New Zealand. The bathymetry data were collected using multibeam soundings using NIWA's deepwater research vessel *Tangaroa* and was gridded at 2 m resolution. Due to the constraints of ship-based bathymetry acquisition (inability to access nearshore areas) there were considerable gaps in the data (Chapter 4, Figure 4.1) that needed to be filled in before the SWAN model could be run. In order to fill in these gaps two methods were utilised. For very nearshore bathymetry (coastal areas 0-200 m offshore) aerial imagery was used to predict the bathymetry based on ocean colour (process illustrated in Figure A2.1), whereas for offshore areas, or surrounding areas where only a coarse representation of bathymetry are required (edges of the computational domain), an interpolated bathymetry layer derived from bathymetry charts was used.

2A.2 – Nearshore bathymetry estimation - image acquisition

The nearshore bathymetry was estimated based on a multi-stage process involving several different pieces of software. The bathymetry map provided by NIWA was first loaded into ArcMap10 (ESRI 2011), fully georeferenced (projection WGS 1984 UTM-60S) and visualised as a raster image. Subsequently, colour images of the coast and surrounding ocean were obtained from Google Earth. The imagery obtained on 30/12/2010 was used throughout all analyses as there was minimal swell visible on this day, and there was consistent coverage across the entire coastline ensuring that predicting inshore bathymetry was consistent across the entire coastline. Approximately 400 m by 400 m areas were visualised in Google Earth and control points (points with known coordinates for later georeferencing) added at each of the four corners using a small red marker. These images were then exported (Figure A2.1-panel a). Each image was then loaded into imageJ (Abramoff *et al.* 2004), cropped to the extent of the four control point corners and then split into the three RGB colour channels, which were expressed as greyscale images representing the colour depth in each of these channels. The brightness and contrast of the blue channel was subsequently adjusted such that the minimum and maximum colour depths were adjusted to 53 and 86, respectively (Figure A2.1 – panel b). These limits were defined to maximise the colour range of the nearshore

ocean colour in order to obtain the largest differences in colour between areas of different depths. The image was despeckled and outliers removed using image processing in imageJ to remove as much surface glare as possible. A Gaussian blur was applied with a radius of 4 pixels (each pixel represented ~ 0.3 by 0.3 m square) to remove much of the noise in the image in order to maximise the signal to noise ratio, but without blurring so much of the image that the signal was lost (Figure A2.1 – panel c). This was performed for an array of images covering the entire coastline from Breaker Bay to Sinclair Head, excluding sandy bay areas. Missing bathymetry for sandy bay area's was interpolated based on information regarding the general slope of the bathymetry leading up to the edge of the bathymetry layer and the position of the shoreline. These images were then loaded into the same geodatabase as the NIWA bathymetry layer and georeferenced according to the locations of the control points defined in Google Earth. These images were then interpolated onto a 2 m by 2 m resolution grid to match the NIWA bathymetry grid. Overlaying the images onto the NIWA bathymetry revealed that submerged obstacles represented in the NIWA bathymetry file were visible in the ocean colour images and that the extent and positioning of the representations closely matched (Figure A2.1 panels c and d).

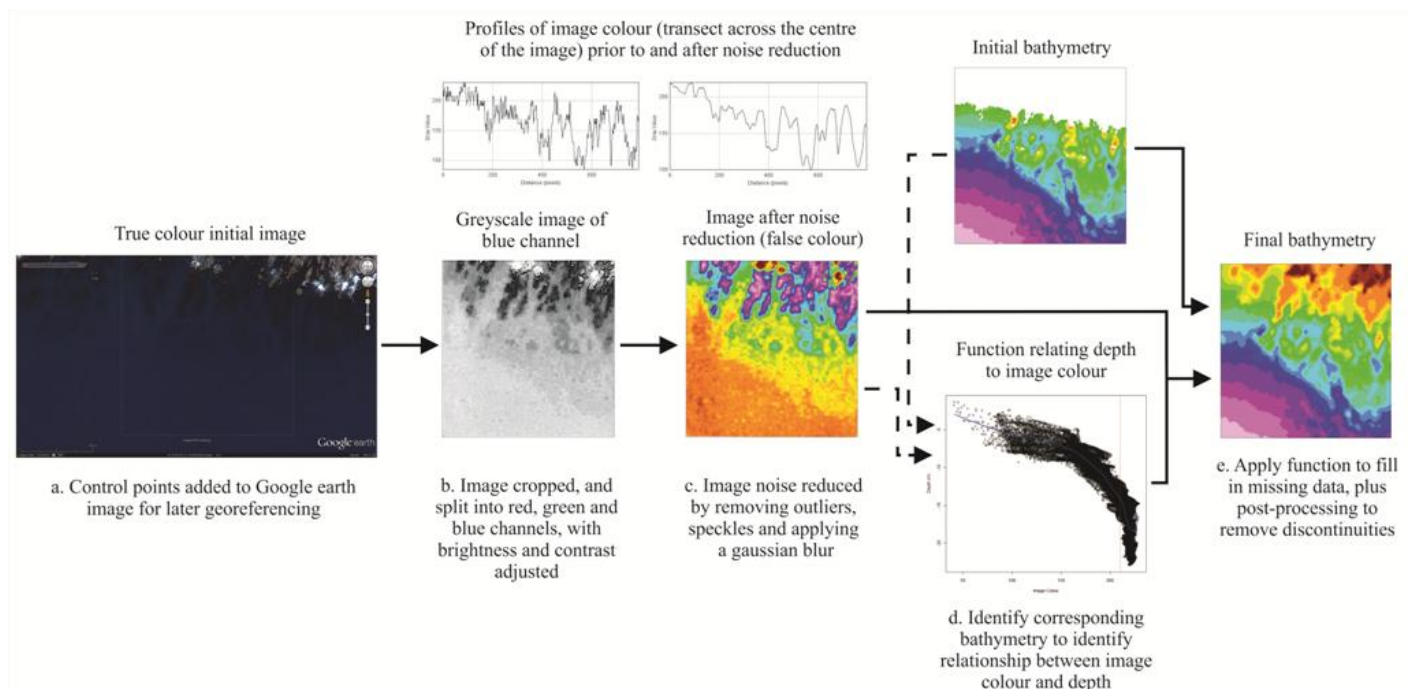


Figure A2.1. Illustration of the steps used to apply aerial photography to estimate nearshore bathymetry

2A.3 – Nearshore bathymetry estimation - colour depth relationship

To identify the relationship between image colour and depth sections of overlapping bathymetry (NIWA) and images were cropped and exported from ArcMap as ascii text files (Figure A2.1 – panel d). These training data were then loaded into R v14 (R development core team 2011) and the corresponding depth values were plotted against the corresponding image colour (Figure A2.1 – panel d and Figure A2.2) (all image-depth correspondence functions are included in Appendix 2B, Figures B2.1-B2.7). The relationships were non-linear, and so a loess smoothing function (function `loess` in R) was applied to the data to estimate the smooth relationship between image colour and depth (Figure A2.2). As this relationship may vary between locations along the south coast, this was applied at several locations, allowing the estimation of several different functions that could be applied to each section of coastline separately. These functions, although not exact, provide a means to predict water depths in the range 15 to 2 m, with an accuracy of ± 2 m (Figure A2.2). However, the relationship became less clear and less precise for depths greater than 15 m and due to the few NIWA bathymetry data points that had depths less than 2 m, the identified relationships were unable to predict to depths less than 2 m.

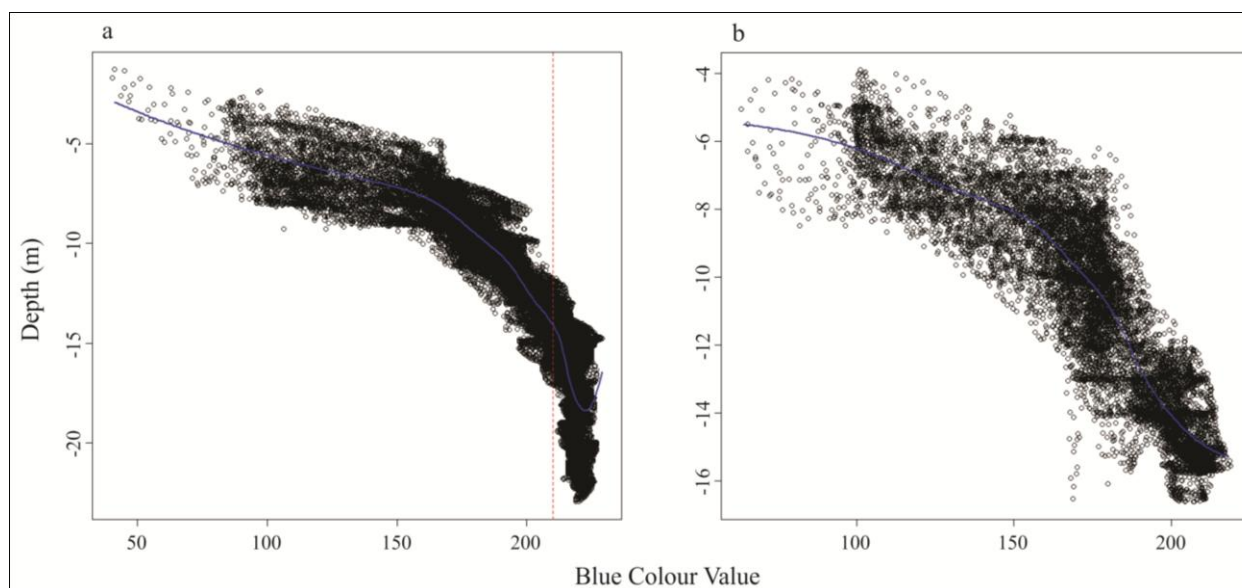


Figure A2.2. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery in (a) several locations located between Island Bay ($41^{\circ} 20.9267' \text{ S}$, $174^{\circ} 46.1638' \text{ E}$) and the western side of Owhiro Bay ($41^{\circ} 20.984' \text{ S}$, $174^{\circ} 44.8776' \text{ E}$) and (b) Princess Bay ($41^{\circ} 20.9113' \text{ S}$, $174^{\circ} 47.5031' \text{ E}$). The blue line illustrates the loess fit to the data, while the red dotted line in (a) indicates the cut-off implemented as above this colour is no longer a good indicator of depth.

2A.4 – Nearshore bathymetry estimation - bathymetry prediction

Each interpolated 2 m by 2 m resolution raster layer derived from the Google Earth images were exported as ascii text files from ArcMap. The colour values were then loaded into R and depths corresponding to these colour values were predicted according to the relationship defined by the loess function applied to the training data. This depth information was then exported from R and reloaded into ArcMap as a series of raster layers, which were subsequently combined into a continuous nearshore bathymetry layer.

2A.5 – Offshore and surrounding bathymetry estimation

To obtain a representation of the bathymetry offshore and in surrounding areas, as well as for nearshore areas where depth was greater than 15 m, electronic versions of the Land Information New Zealand (LINZ) bathymetry charts NZ 463 (showing the greater Wellington region, and Cook Strait) and NZ 4633 (showing Wellington Harbour entrance and bathymetry to Island Bay) were downloaded from the LINZ website as tif files. These files illustrate the bathymetry using a combination of depth contour lines and point depth soundings. These images were loaded into ArcMap and georeferenced accordingly. A polyline shape file (file consisting of lines/polygons to which specific information can be attribute to different lines) was then created and the bathymetry contours represented in the LINZ bathymetry charts were traced with each line being attributed a depth, generating an electronic low resolution contour map of the bathymetry. This layer was created so that it encompassed the entire computational domain. A 2 m by 2 m resolution grid was then created in ArcMap using the topo to Raster function. This function interpolates a topographically correct representation of the information provided in a contour map, and thus enabled the generation of a low resolution representation of the surrounding bathymetry and the bathymetry for areas further offshore than given in the NIWA bathymetry data.

2A.6 – Combining bathymetry layers

The three bathymetry layers, based on NIWA's bathymetry data, the image derived bathymetry data and the low resolution chart derived data were combined into a single layer in ArcMap. They were combined such that information in the NIWA bathymetry chart took precedence over the image derived data, with the remaining gaps filled in with the chart derived data. To ensure that the bathymetry data did not have any discontinuities at the boundaries of these layers, the resulting bathymetry map was converted to a contour map, which was then examined and adjusted by deleting or moving contour lines (no adjustments

were made in the areas given by the NIWA bathymetry maps) so that discontinuities were removed from the map. Furthermore, contour lines for the shoreline (depth = 0 m) and areas where depth information was obscured by *Durvillaea antarctica* fronds visible in the aerial imagery (set to a depth of -0.5 m as these areas are submerged at high tide, but exposed at low tide) was added to this contour layer. The final contour map was then interpolated using the topo to Raster function in ArcMap to obtain the final bathymetry map in raster format (Chapter 4, Figure 4.2). The final image was then exported as a 2 m by 2 m resolution gridded map, and as a 30 m by 30 m resolution map for initial testing and coarse scale model runs.

Appendix 2B - Colour-depth correspondence plots

Here the ocean-colour to depth data for numerous locations along the Wellington South Coast are presented (in addition to Appendix 2A, Figure A2.3).

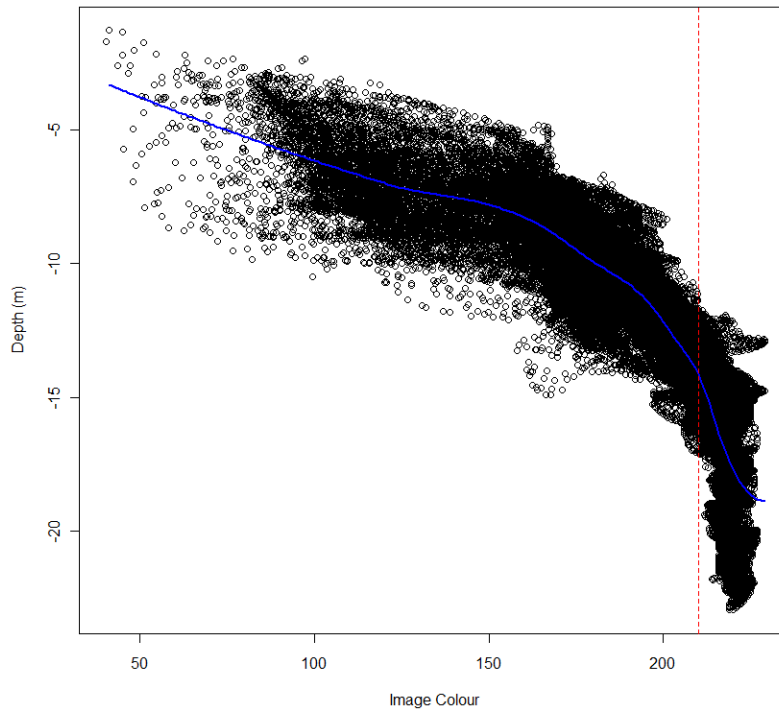


Figure B2.1. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery between Island Bay and Owhiro Bay. The blue line illustrates the loess fit to the data, while the red dotted line indicates the cut-off implemented as above this colour is no longer a good indicator of depth.

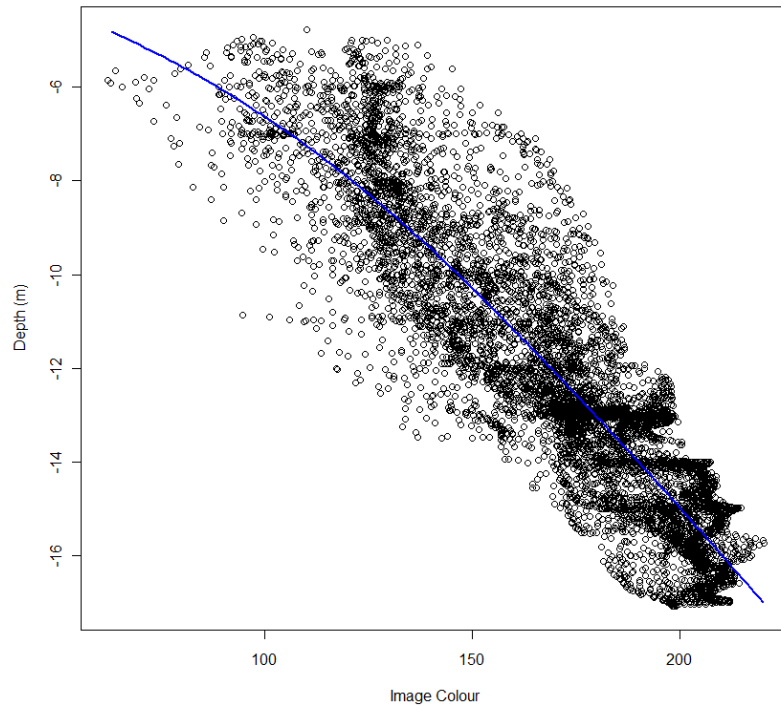


Figure B2.2. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery between Houghton Bay and Island Bay. The blue line illustrates the loess fit to the data.

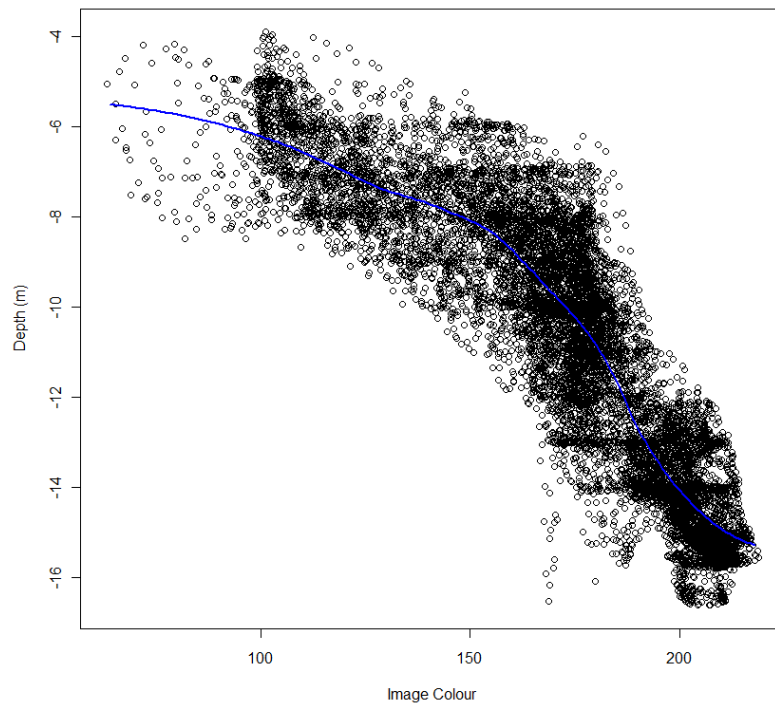


Figure B2.3. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery from the reef south of Princess Bay. The blue line illustrates the loess fit to the data.

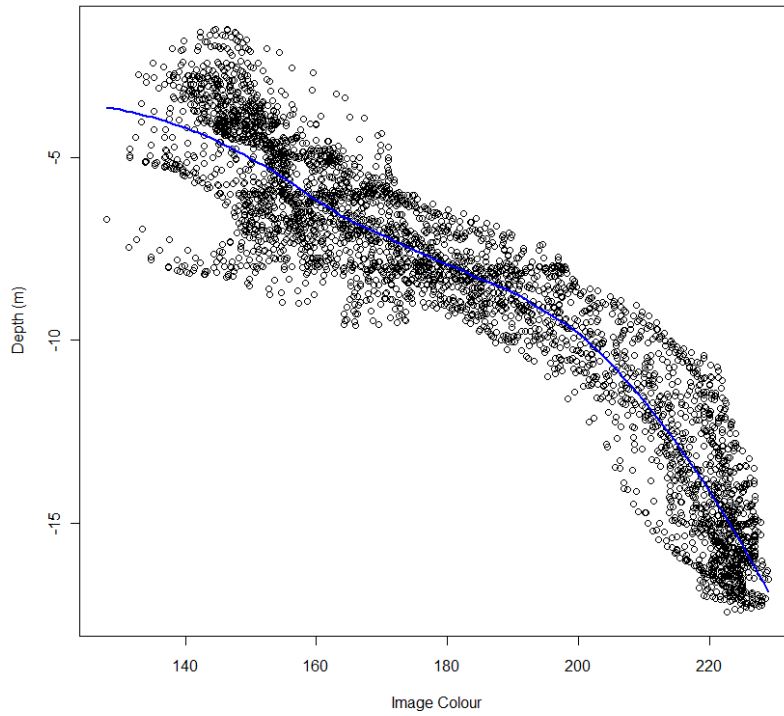


Figure B2.4. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery from the reef East of Princess Bay at the entrance to Lyall Bay. The blue line illustrates the loess fit to the data.

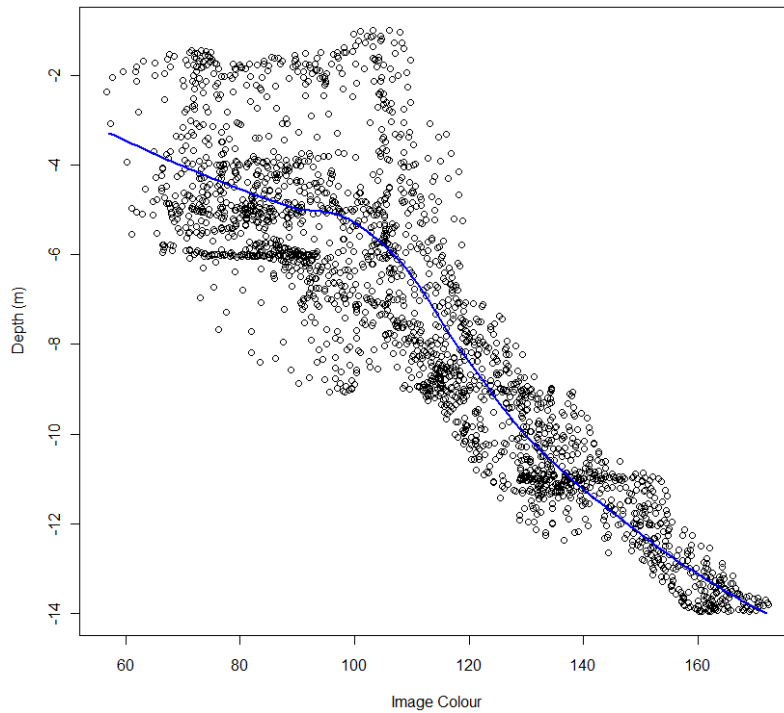


Figure B2.5. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery from the reef at the tip of the Moa Point peninsula. The blue line illustrates the loess fit to the data.

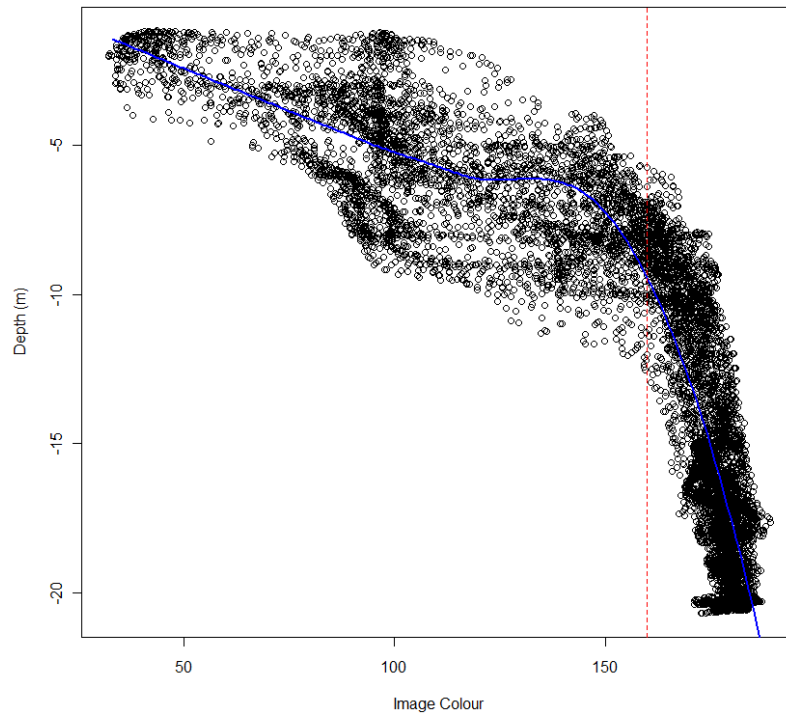


Figure B2.6. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery from the West side of the reef south of Palmer Head. The blue line illustrates the loess fit to the data, while the red dotted line indicates the cut-off implemented as above this colour is no longer a good indicator of depth.

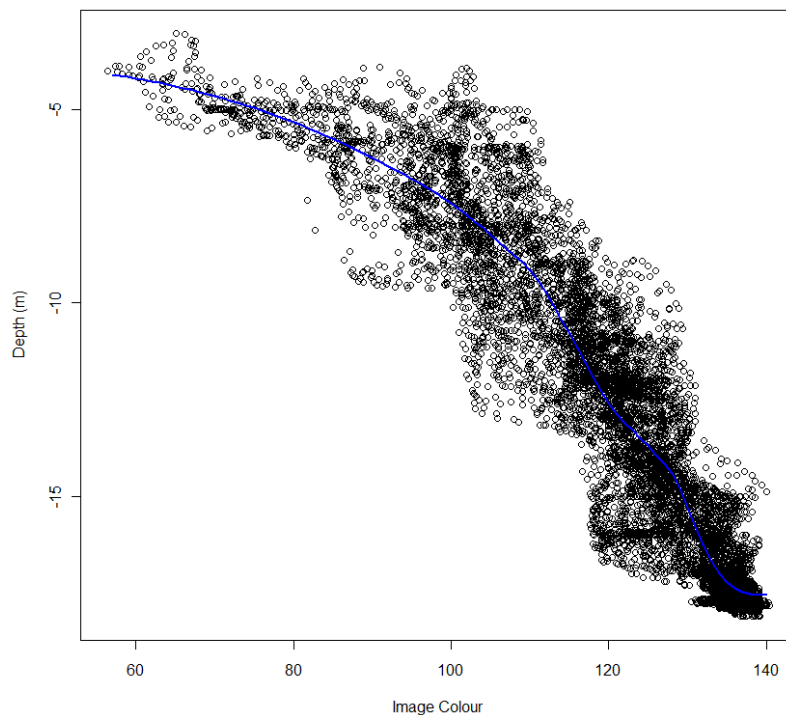


Figure B2.7. Plots of depth as a function of image colour for data obtained from overlapping bathymetry and aerial imagery from the East side of the reef south of Palmer Head. The blue line illustrates the loess fit to the data.

Appendix 2C – SWAN wave model sensitivity analyses

2C.1 – Potential alternative formulations of physical processes

Within the SWAN model there are several options available regarding the formulation of physical processes. The formulation of bottom friction processes governs how energy is dissipated as the waves interact with the seabed and eventually how they break once they reach shallow water. The formulation of wind-wave interactions is also important as it governs how wave energy is created through transference of wind energy to wave energy, and also as wind-based dissipation of wave energy (white-capping). Additional formulations of processes such as triad wave-wave interactions can also be investigated (Booij et al. 1999; Ris et al. 1999). In the scenario investigated in Chapters 4 and 5 much of the wave energy derives from incoming swell in addition to strong local wind speeds which can modify the wave energy through wind-wave interactions. Variations in the formulation of these physical processes are therefore likely to influence model predictions (Booij et al. 1999; Ris et al. 1999).

The sensitivity of SWAN model predictions were evaluated by trialling two different formulations of bottom friction and wind-wave interactions. For bottom friction, the formulation identified by Madsen (1988), which includes variable bottom friction strength as defined through a seabed roughness scale length (see Chapter 4), was trialled against the JONSWAP formulation of bottom friction, which assumes a constant bottom-friction coefficient. For wind-wave interactions (wind growth and whitecapping), the formulation according to WAM cycle 3 was trialled against the formulation of these processes given by WAM cycle 4 (i.e. Ris et al. 1999), which is the formulation utilised in all analyses in Chapter 4. Relevant differences between WAM cycle 3 and 4 include:

- The calculation of wind friction velocity, which is used to calculate the energy imparted to waves. Cycle 3 calculates the friction velocity as a constant proportion of the wind speed 10 m above the water surface (Komen et al. 1984; SWAN Team 2006a), whereas Cycle 4 calculates friction velocity by considering atmospheric boundary layer effects and the roughness length of the sea (Janssen 1991, SWAN Team 2006a). As the roughness scale length is spatially variable (depends on local wave height and wavelength) this effectively acts to create a spatially variable wind

field. The functional forms of the equations describing how energy is imparted to waves also differ between cycle 3 and cycle 4.

- Alternative parameters for the equations governing whitecapping and wave steepening. Cycle 3 utilises the parameters given in Komen et al. (1984), whereas cycle 4 utilises the parameters given by Janssen (1991) (SWAN Team 2006a).

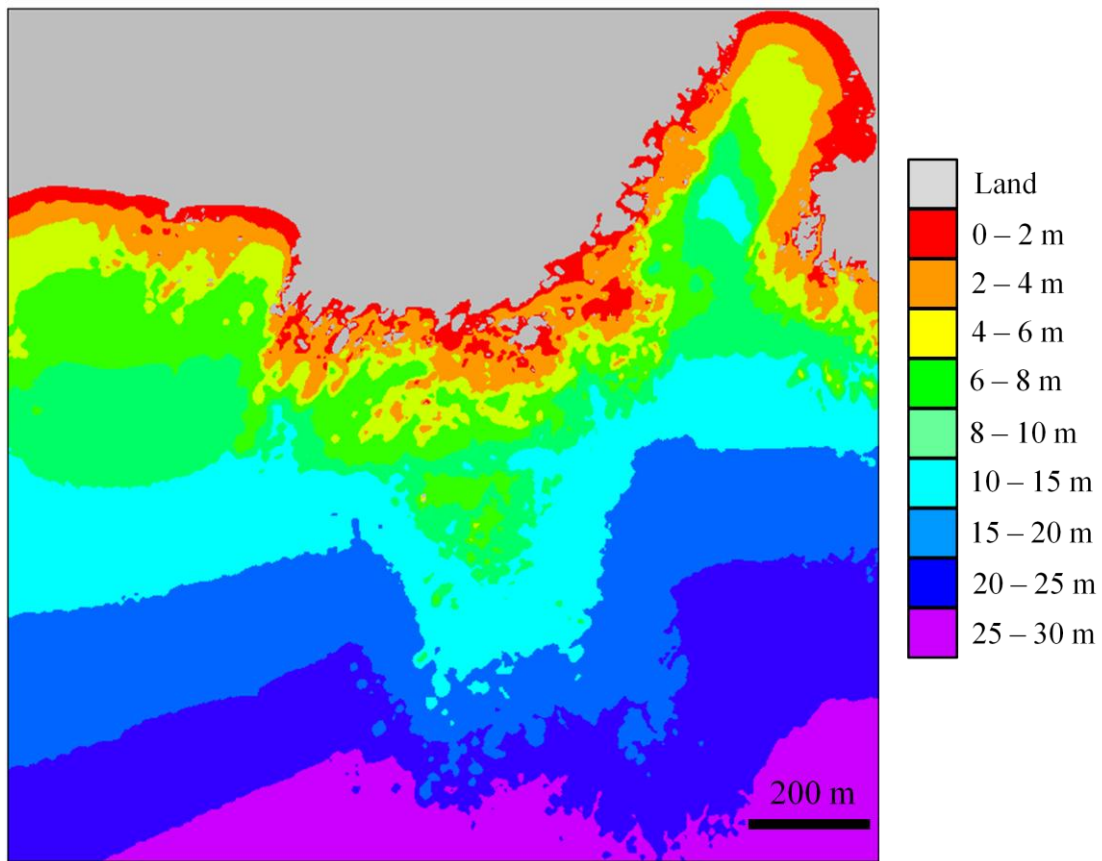
2C.2 – Sensitivity Analyses

2C.2.1 - SWAN Model

Each of the parameter sets were trialled under two wind-wave regimes and for three locations (Table C2.1). Grid locations were chosen to represent a range of bathymetry and bottom types in order to try and identify the maximum possible discrepancy among formulations. Nested location #4 is predominantly open to incoming swell, but consists of a range of substrate types and complex bathymetry (Figure C2.1). Nested location #5 covers Island Bay and the surrounding rocky coastline, which consists of a mix of bottom types (sand in the bay, versus gravel and bedrock on the surrounding open coastline) and bathymetry (flat sandy areas that contrast with complex bathymetry around the sirens rocks to the west of island bay) as well as containing a large obstacle in the form of the Taputeranga Island (Figure C2.2). Finally nested location #12 has extensive areas of submerged and emergent reef to the south of Palmer Head (Figure C2.3), and thus will be a good test of how much of a difference the wave breaking formulation has on model results. The two parameter sets for wind and waves were chosen to represent the most frequent swell (class 18), and also the most extreme events, which are used throughout Chapter 4 to examine the influence of wave forces on macroalgal species (class 21). For each of the formulations and wind-wave boundary conditions the same routine as detailed in Chapter 4 was performed whereby a 30 m resolution model was run, providing input values for each of the three nested locations to minimise the influence of edge effects (see Chapter 4). Based on these inputs a 2 m resolution model for each of the test locations was then performed and the subtidal orbital velocity and wave energy was extracted from the model outputs.

Table C2.1. Location of trial grids as well as sea conditions that were examined.

Location of trials						
Nest No	Coordinates				Size (m)	
	Bottom left		Top Right		N-S	E-W
	Lat	Long	Lat	Long		
	(° ' S)	(° ' E)	(° ' S)	(° ' E)		
4	41 21.4307	174 44.5691	41 20.6908	174 45.6287	1400	1436
5	41 21.3621	174 45.5924	41 20.6186	174 46.6235	1410	1400
12	41 21.2804	174 48.6997	41 20.5449	174 49.7299	1400	1400
Conditions						
Class #	Averaged parameters used as boundary conditions					Frequency
	Wind		Waves			
	Speed	Direction	Height	Direction	Period	
	(ms ⁻¹)	(° from N)	(m)	(° from N)	(s)	
18	12.2	181.88	2.41	178.69	8.57	471
21	17	198.68	4.32	178.07	10.22	32

**Figure C2.1.** Bathymetry of test location nest #4.

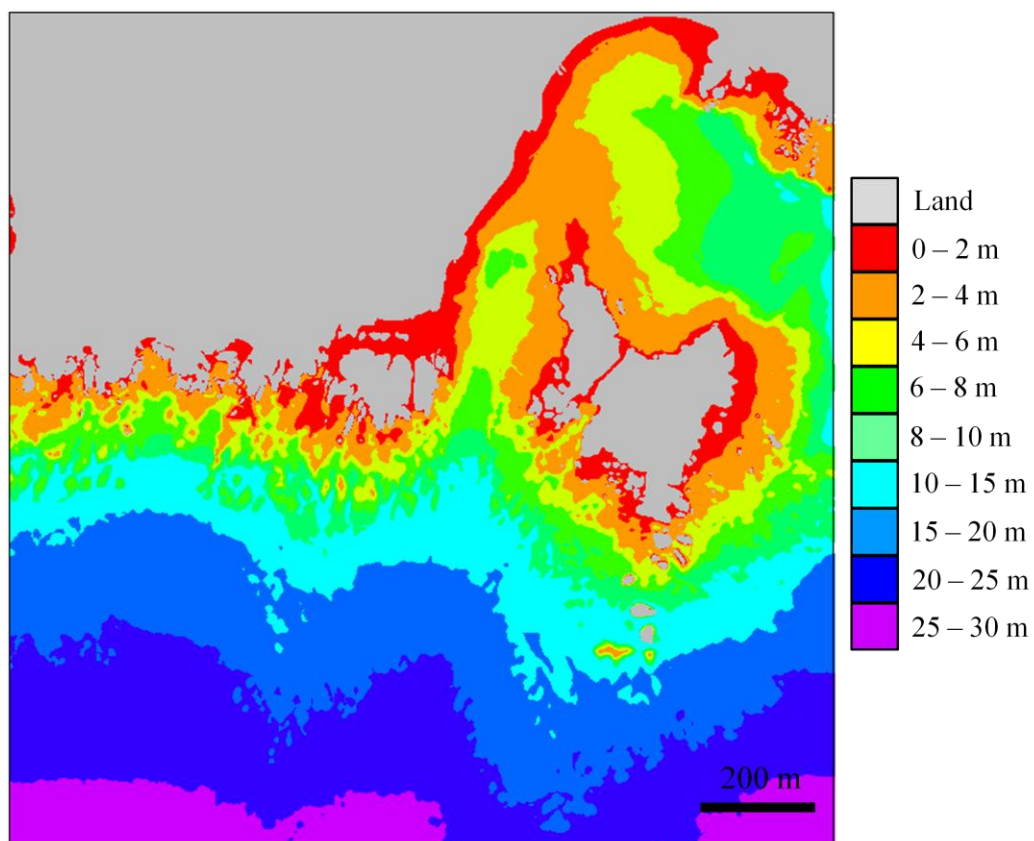


Figure C2.2. Bathymetry of test location nest #5.

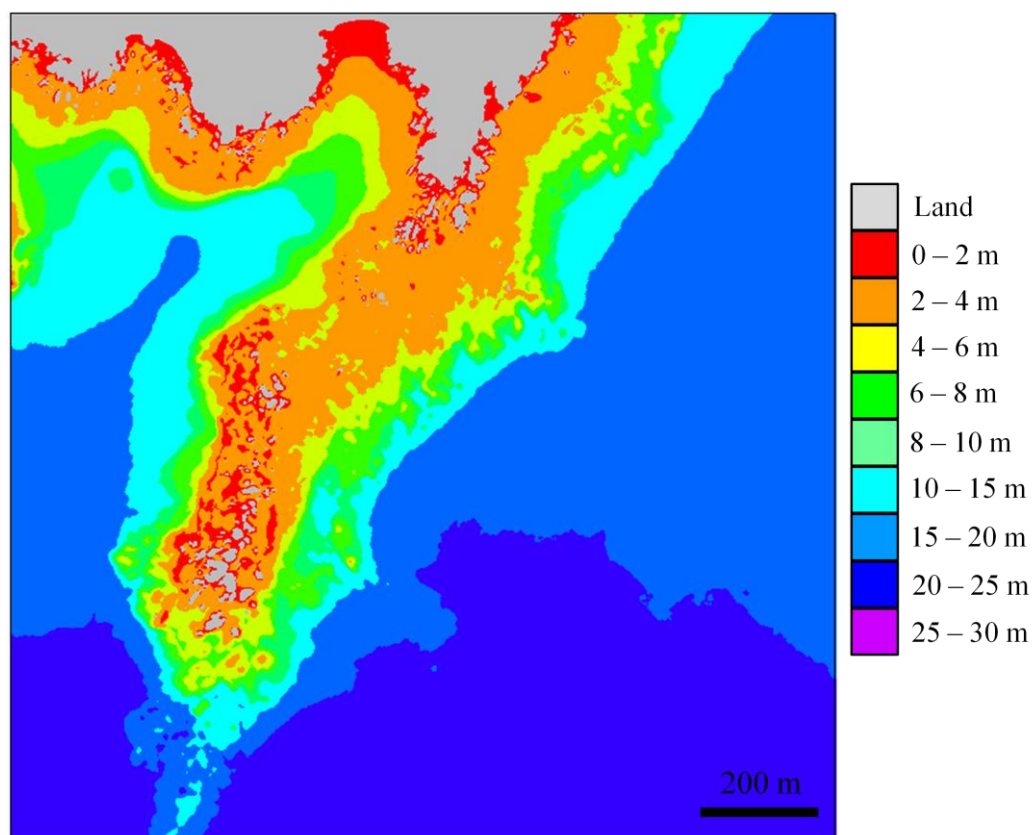


Figure C2.3. Bathymetry of test location nest #12.

2C.2.2 – Comparisons and statistics

For each of the test locations the model results for subtidal orbital velocity and wave energy were compared between alternative parameterisations of bottom friction (evaluated with the WAM cycle 4 formulation of wind-wave interactions) and wind-wave interactions (evaluated with the Madsen formulation of bottom friction). For each set the following was carried out:

1. The difference $\Delta_i = v1_i - v2_i$ between the two predicted values $v1_i$ and $v2_i$ for the formulations being examined was evaluated on a cell by cell basis (hence the subscript i which denotes cell id). A relative measure, $\Delta^\circ_i = \Delta_i / \bar{v}_i$, was also

calculated as the difference between the two predicted values divided by the mean predicted value for that cell, \bar{v}_i . For each set the range of Δ and Δ° which encapsulates 95% and 99% of the cell by cell differences was obtained, and density profiles (continuous histograms) of Δ and Δ° were plotted.

2. Root mean squared error (RMSE) was calculated as

$$RMSE = \sqrt{\frac{\sum_i^n \Delta_i^2}{n}}$$

○ where n is the number of cells.

3. To standardise this so that the RMSE can be expressed as a percentage of the mean, the coefficient of variation of the RMSE (CV(RMSE)) was calculated as

$$CV(RMSE) = 2 \frac{RMSE}{(\bar{v1} + \bar{v2})}$$

○ where $\bar{v1}$ and $\bar{v2}$ are the mean predicted values for orbital velocity or wave energy for each of the alternate formulations in that comparison.

4. To examine whether differences were more extreme in shallow, intermediate or deep water, each of the above was evaluated for (1) all water depths, (2) 20-10 m, (3) 10-5 m and (4) < 5 m.
5. For the most extreme wave class the breaking probability of *Macrocystis pyrifera* was calculated for each location according to the equations detailed in Chapter 4. The probabilities were then binned into classes corresponding to stipe breakage probabilities of 0 - 0.1%, 0.1 - 0.25%, 0.25 - 0.5%, 0.5 - 1%, 1 - 2.5%, 2.5 - 5%, 5 - 10%, 10 - 20%, 20 - 50%, 50 - 75% and 75 - 100% and the percent area of each

location falling into each class was compared across formulations. The agreement between the different formulations was also examined by quantifying the proportion of cells where the predictions were in agreement (i.e. the same probability bin), and when they didn't agree (i.e. predictions were in different probability bins). This was performed for each probability bin.

2C.3 Results and discussion

2C.3.1 - Bottom friction – orbital velocity

Comparing model results revealed that the models which utilised the JONSWAP representation of bottom friction produced slightly higher orbital velocities than the equivalent model using the Madsen formulation of bottom friction (figures C2.4 – C2.9). However both formulations produce model results that are very similar to each other in terms of the absolute values predicted and the distribution of these data with relatively low % differences between formulations (Table C2.2). Model comparison statistics confirm this as the CV(RMSE) values were less than 0.05, which is equivalent to an RMSE corresponding to ~ 5 % of the overall mean value, and the median % difference between models was less than 4% of the mean predicted value for all depth ranges, wave classes and locations examined (Table C2.2). Comparison statistics also reveal that the largest discrepancies among models is found in shallow water (0-5m) where the median % difference between models was ~ 2-4 %, compared to ~1-2 % for locations at depths of 5 - 10m and 0.2 – 1 % for locations at depths of 10 – 20 m (Table C2.2). Qualitatively this is in agreement with the general principle that bottom friction influences waves predominantly in shallow water, and so differences in the formulation of these processes are likely to be less important in deep water. However, even in the 0-5 m depth range, 95% of the cells had differences that were less than 13.7% of the mean value across formulations (Table C2.2), indicating that despite these differences the models produce very similar model predictions overall. There were also very few differences among locations with nested location #5 having marginally higher differences between model formulations than either #4 or #12 (Table C2.2). However, at most the differences exhibited in nested location #5 were only higher by 2.3 % compared to either #4 or #12 (Table C2.2). Differences between wave classes were also fairly minimal, except for the differences found in nested location #12 in shallow water (< 5 m) where the median % difference was 2% higher for wave class 18 than wave class 21 (Table C2.2).

Table C2.2. Statistics for orbital velocity predictions of model runs with the Madsen formulation, versus the JONSWAP formulation of bottom friction processes. All metrics are calculated based on: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

Class	Nest #	Depth range (m)	RMSE (ms^{-1})	CV	$\Delta (\times 10^{-3} \text{ ms}^{-1})$			$\Delta^\circ (\%)$		
					median	95%	99%	median	95%	99%
18	4	All	0.010	0.021	2.5	(0.4, 27.8)	(0.3, 38.8)	0.60	(0.2, 4.4)	(0.1, 7.6)
		20-10	0.003	0.008	2.0	(0.5, 8.1)	(0.5, 12.1)	0.54	(0.2, 1.5)	(0.2, 2.1)
		10-5	0.012	0.017	9.1	(2.5, 25)	(2, 27.9)	1.37	(0.4, 3)	(0.3, 3.3)
		< 5	0.022	0.030	19.7	(0.6, 41.8)	(0, 55.2)	2.62	(0.2, 8.6)	(0, 14.7)
21	4	All	0.013	0.016	8.4	(1.9, 30.1)	(0.6, 40.8)	0.88	(0.4, 3.7)	(0.1, 6.7)
		20-10	0.009	0.011	7.6	(2.9, 19.1)	(2.7, 23.7)	0.93	(0.4, 1.9)	(0.4, 2.2)
		10-5	0.017	0.015	14.5	(8.6, 28.4)	(7.2, 32.4)	1.45	(0.8, 2.4)	(0.7, 2.7)
		< 5	0.024	0.026	21.1	(0.3, 43.9)	(0, 57.2)	2.28	(0, 8)	(0, 14.2)
18	5	All	0.013	0.030	4.5	(0.5, 34.2)	(0.4, 49.4)	0.95	(0.2, 7.9)	(0.2, 15.7)
		20-10	0.004	0.009	2.7	(1.2, 8)	(0.9, 9.7)	0.72	(0.4, 1.5)	(0.3, 2)
		10-5	0.012	0.021	10.4	(5.5, 19)	(4, 20.9)	2.06	(1, 4.6)	(0.8, 5.6)
		< 5	0.024	0.041	21.0	(0.7, 47.8)	(0, 63.8)	3.79	(1.4, 13.7)	(0, 35.1)
21	5	All	0.017	0.022	11.8	(2.4, 36.1)	(0.2, 51.5)	1.39	(0.5, 6.8)	(0, 13.9)
		20-10	0.011	0.013	8.8	(4.8, 18.4)	(4.3, 20.2)	1.12	(0.7, 1.8)	(0.7, 2.7)
		10-5	0.020	0.022	19.4	(9.3, 26.8)	(7.5, 29.6)	1.99	(1.4, 4.1)	(1.2, 4.8)
		< 5	0.027	0.035	25.0	(0.3, 49.5)	(0, 66.3)	3.62	(0.1, 12)	(0, 31.2)
18	12	All	0.011	0.028	2.0	(0.1, 31.1)	(0, 38.3)	0.63	(0, 6.1)	(0, 8)
		20-10	0.002	0.008	1.9	(0.5, 5.6)	(0.3, 8.2)	0.17	(0.2, 2.6)	(0.1, 4.1)
		10-5	0.009	0.018	7.8	(2.9, 17.3)	(2.4, 22.3)	1.52	(0.6, 6.1)	(0.6, 6.8)
		< 5	0.023	0.036	21.4	(4.1, 38.7)	(0, 47.3)	3.32	(1.3, 8.1)	(0, 13.9)
21	12	All	0.013	0.019	1.6	(1.6, 30.6)	(1.2, 37.4)	1.13	(0.3, 4.4)	(0.2, 6.2)
		20-10	0.008	0.012	6.8	(3.3, 12.6)	(2.7, 14.4)	0.55	(0.5, 2)	(0.5, 2.5)
		10-5	0.016	0.018	15.8	(7.9, 24.3)	(6.4, 26.3)	1.08	(1.1, 3.4)	(0.9, 4.4)
		< 5	0.024	0.028	23.6	(3.5, 37.7)	(0, 47.7)	1.36	(1.1, 6.3)	(0, 13.1)

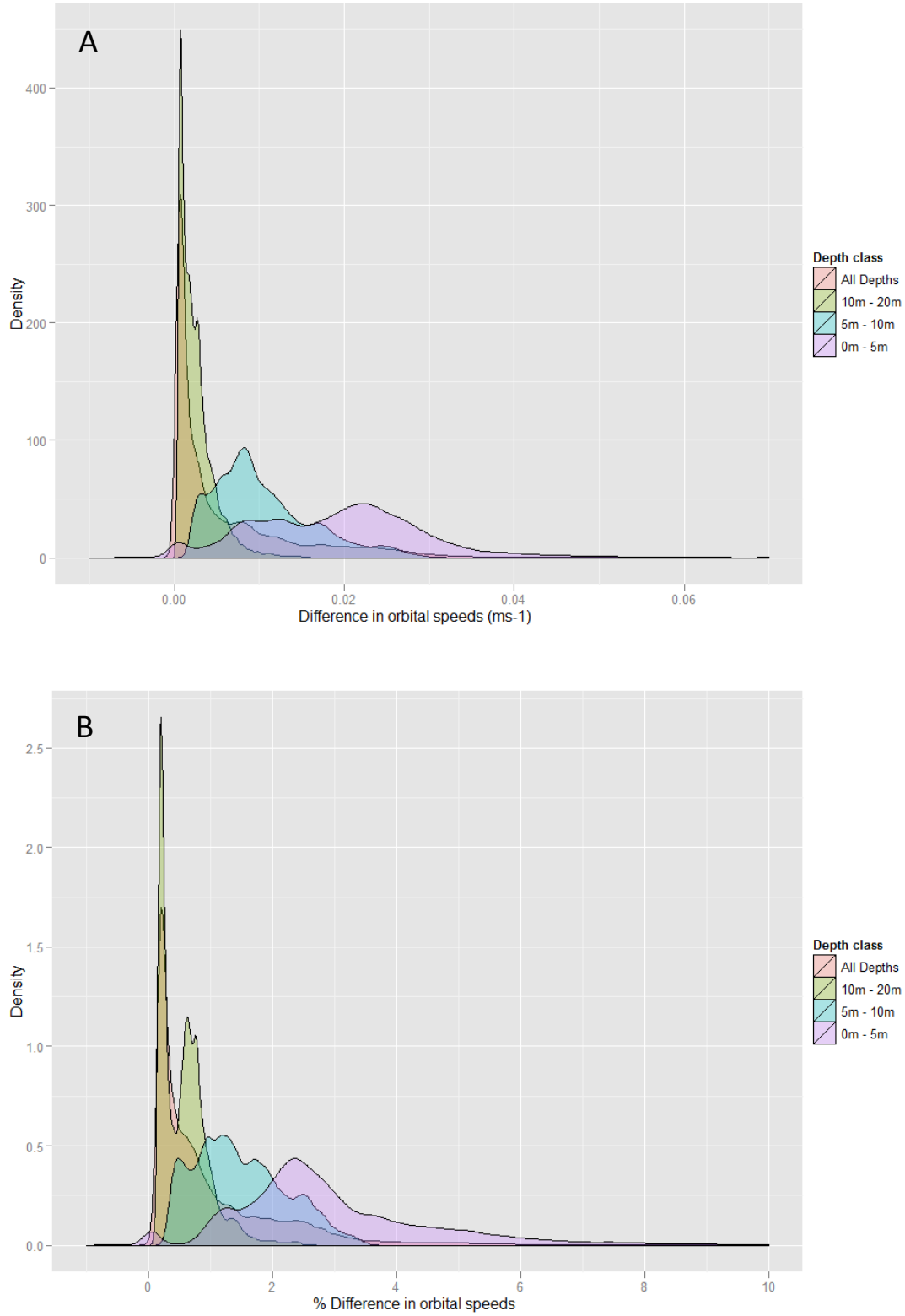


Figure C2.4. Density profiles of the differences in predicted orbital speeds for wave class 18 in nested grid #4 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in orbital speeds (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

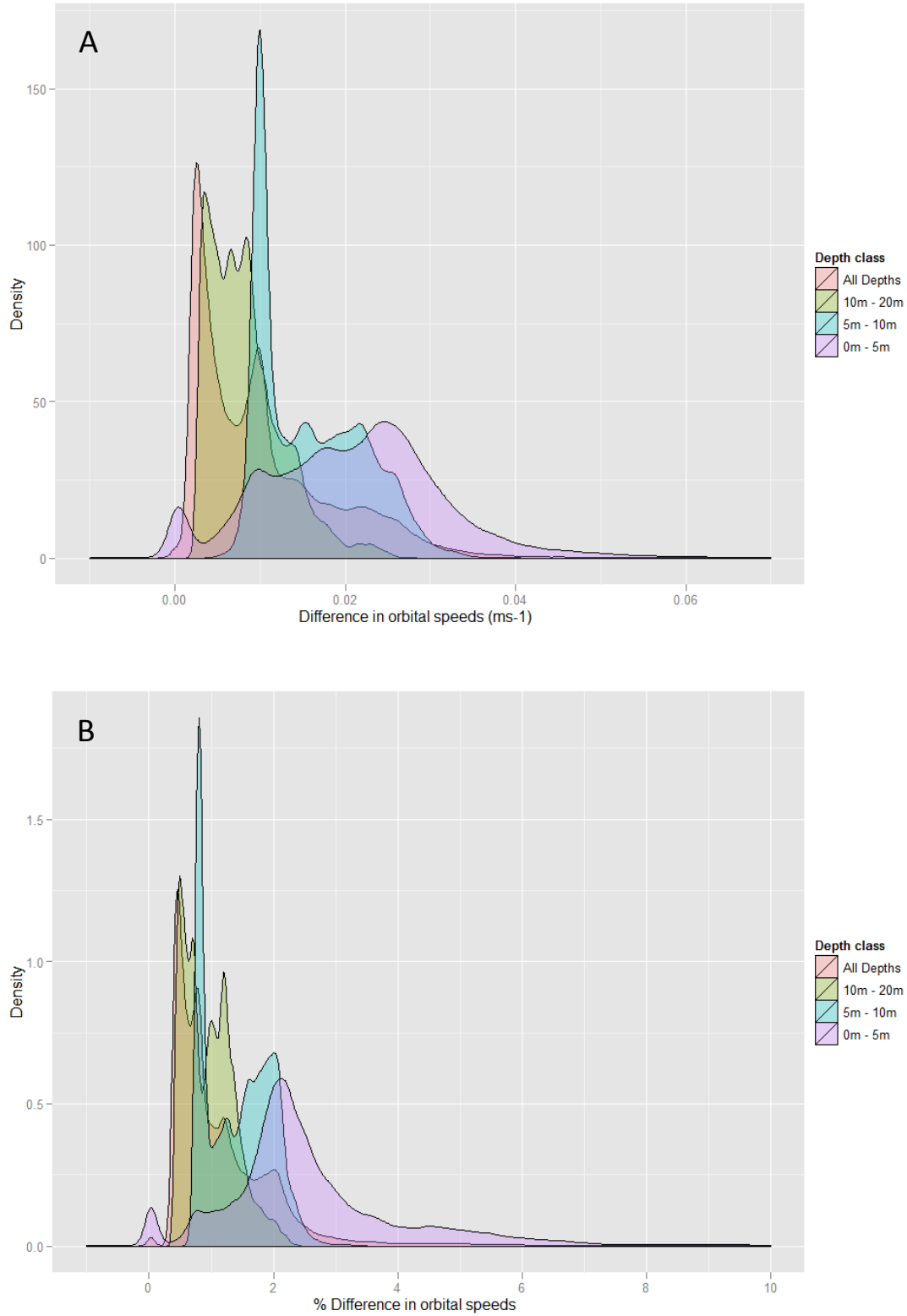


Figure C2.5. Density profiles of the differences in predicted orbital speeds for wave class 21 in nested grid #4 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in orbital speeds (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

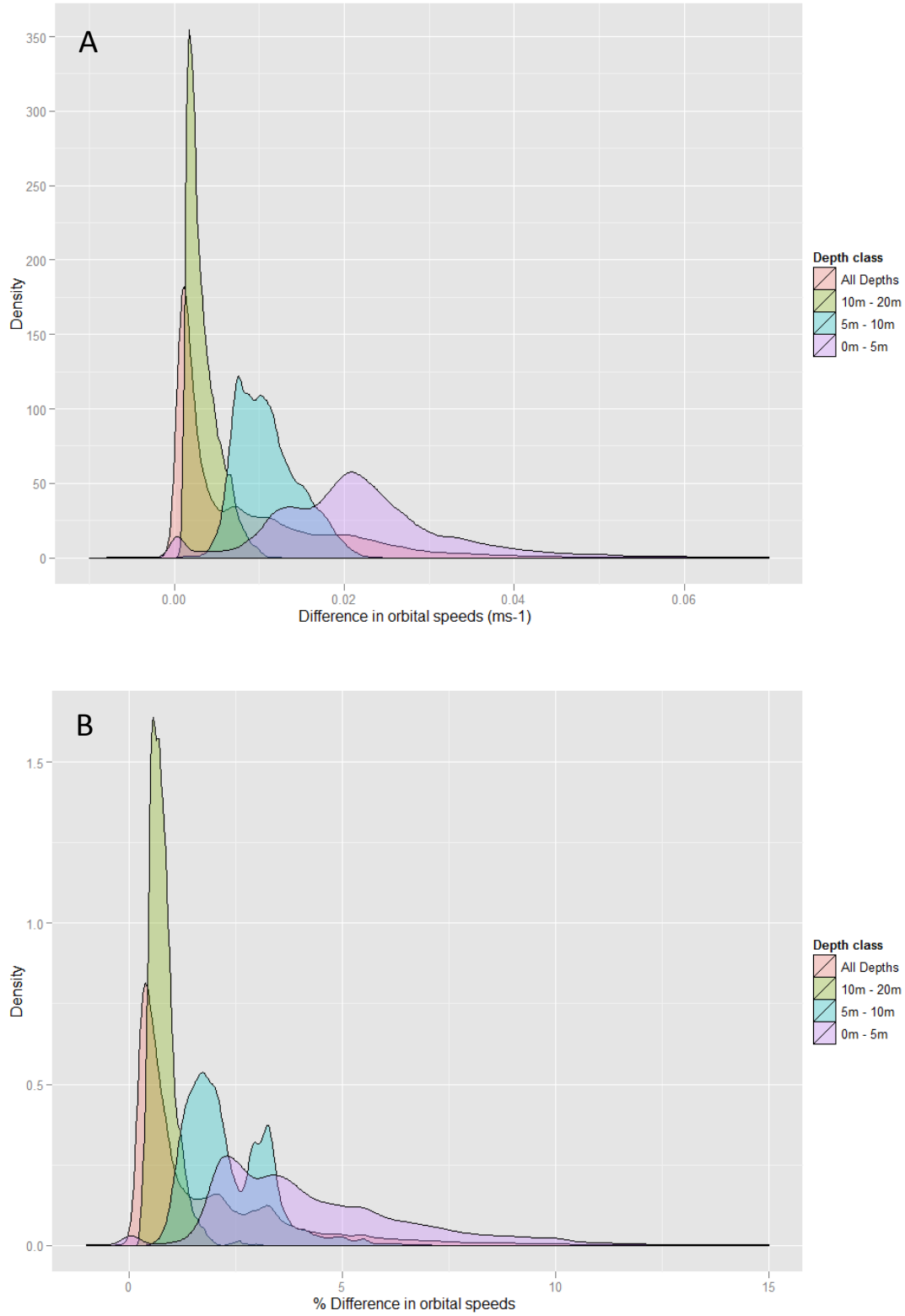


Figure C2.6. Density profiles of the differences in predicted orbital speeds for wave class 18 in nested grid #5 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in orbital speeds (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

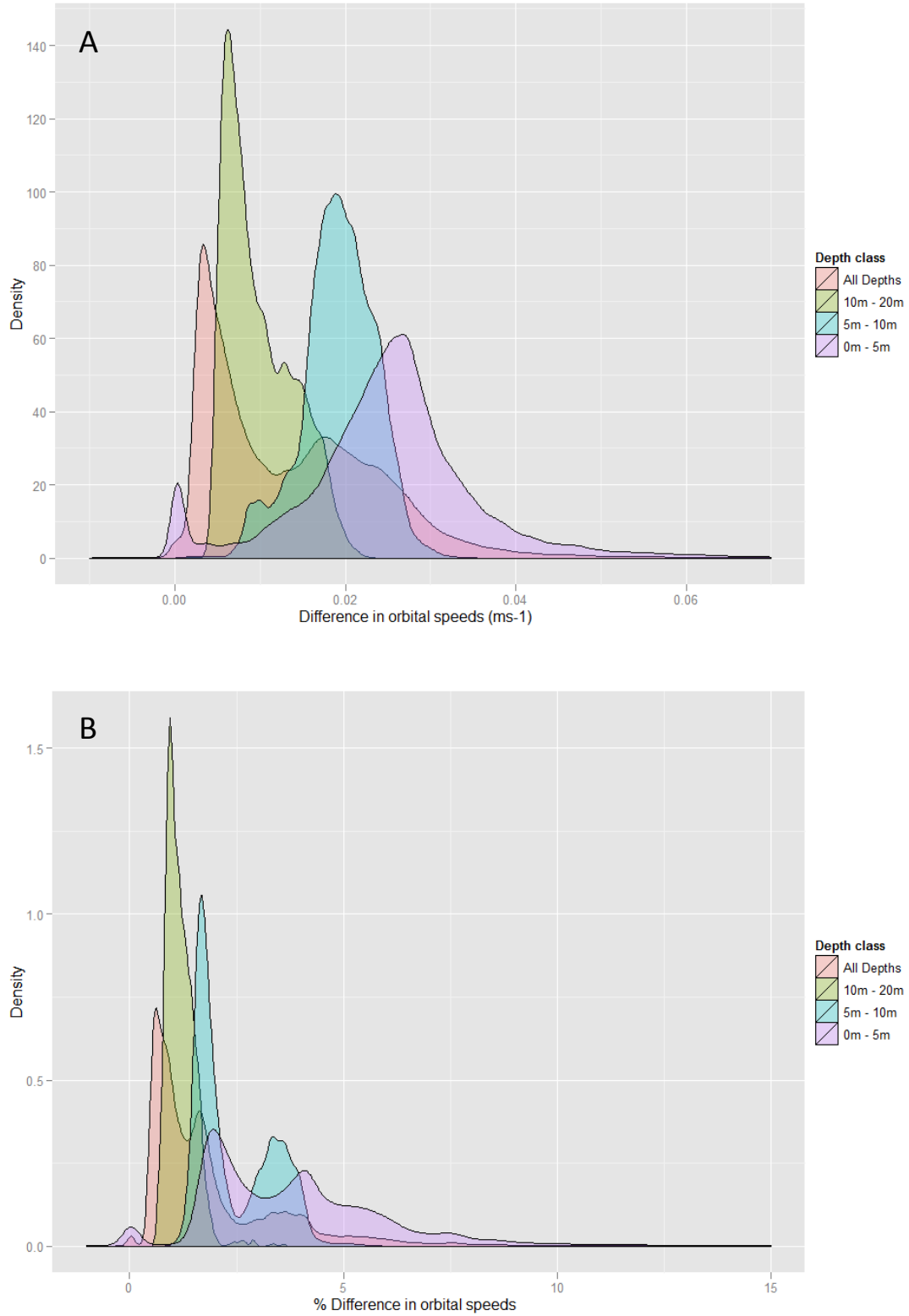


Figure C2.7. Density profiles of the differences in predicted orbital speeds for wave class 21 in nested grid #5 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in orbital speeds (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

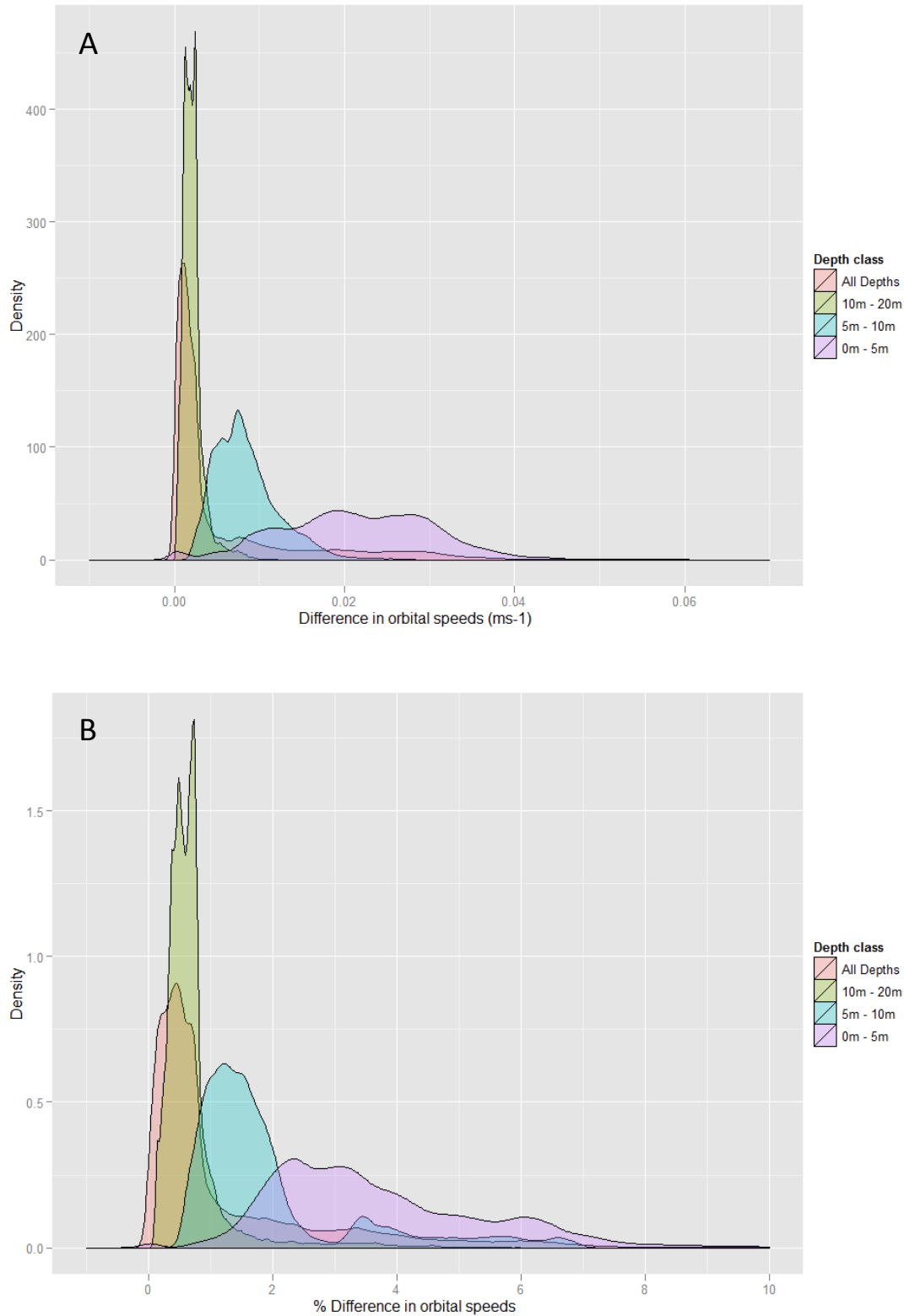


Figure C2.8. Density profiles of the differences in predicted orbital speeds for wave class 18 in nested grid #12 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in orbital speeds (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

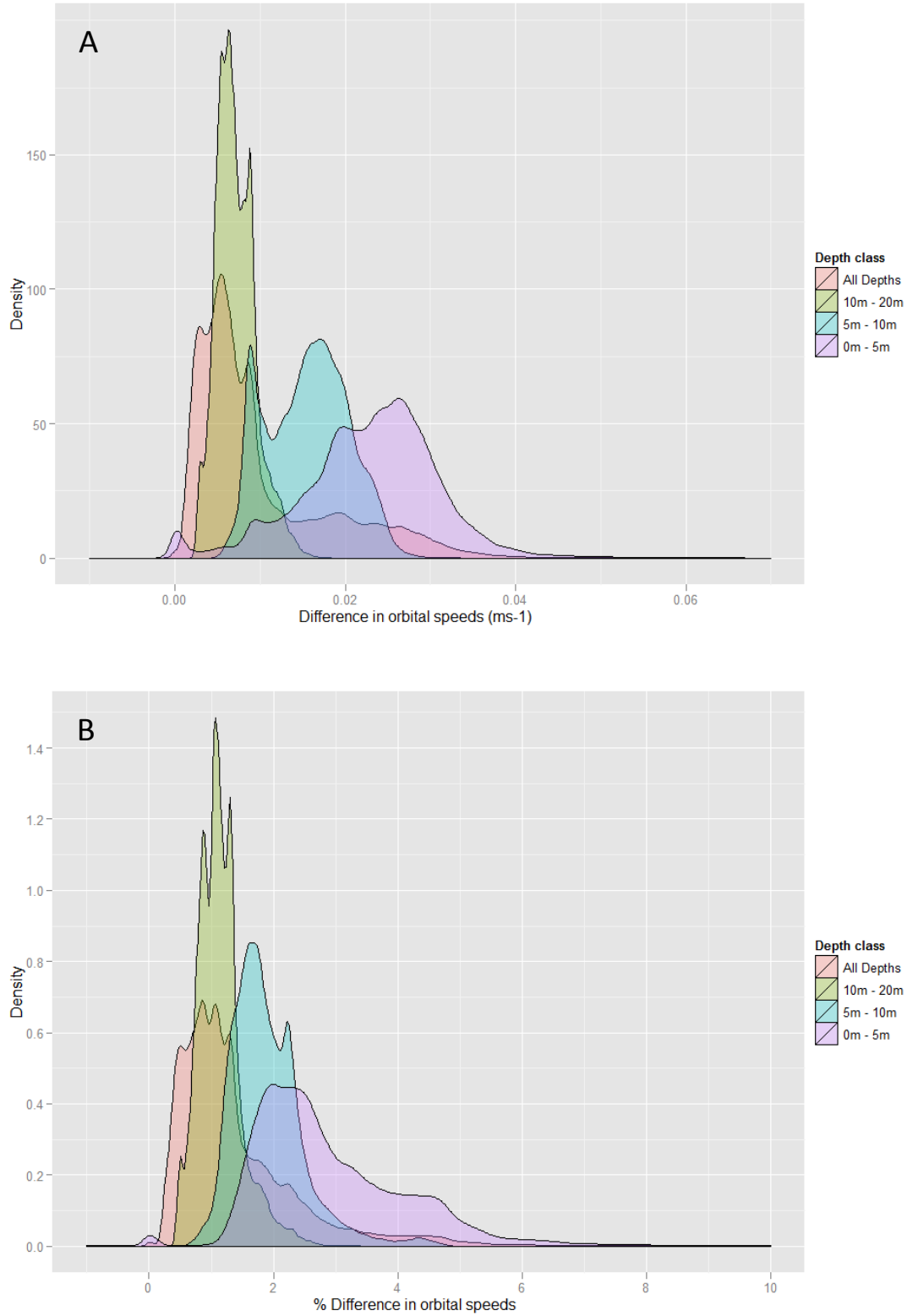


Figure C2.9. Density profiles of the differences in predicted orbital speeds for wave class 21 in nested grid #12 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in orbital speeds (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

2C.3.2 - Bottom friction – wave energy

Similarly to the results for bottom friction, models which utilised the JONSWAP representation of bottom friction produced slightly higher wave energies than the equivalent model using the Madsen formulation of bottom friction (figures C2.10 – C2.15), but again these results are indicative of a change in the magnitude of values (i.e. each value is proportionally larger in one formulation over another) predicted rather than a wholesale change in the spatial distribution of wave energy. Model comparison statistics reveal that the differences in wave energy are proportionally larger than the differences in orbital velocity for the same model runs (Table C2.3). For example, whereas the CV(RMSE) for orbital velocity were all less than 0.05, the CV(RMSE) for wave energy varies between 0.01-0.02 for locations at depths of 10 - 20 m, 0.03 – 0.04 for locations at 5 – 10 m and 0.054 – 0.07 for locations at depths of 0 – 5 m (Table C2.3). This coincides with an increase in the median % difference (Δ°) by a factor of ~ 2 across all model runs, with much of this discrepancy arising from the 0 – 5 m depth range (Table C2.3). Examining the density profiles reveals that the absolute differences (Δ) in shallow water are similar to, if not smaller than, the differences in deeper water, but because of the lower mean wave energy in shallow water these differences when expressed as a percentage are much higher (Figures C2.10-C2.15). However, even in the 0-5 m depth range, the CV(RMSE) corresponds to a RMSE of $\sim 7\%$ of the overall mean predicted value, and 95% of the cells had differences that were less than 25% of the mean (Table C2.3) value across formulations. Similar patterns were also observed in relation to the differences among locations, with nested location #5 having higher differences between model formulations than both #4 or #12 (Table C2.3), and there were no noticeable differences between the wave classes examined (Table C2.3).

Table C2.3. Statistics for wave energy predictions of model runs with the Madsen formulation, versus the JONSWAP formulation of bottom friction processes. All metrics are calculated based on: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

Class	Nest	Depth range (m)	RMSE (Wm^{-1})	CV	$\Delta (\times 10^{-2} \text{ Wm}^{-1})$			$\Delta^\circ (\%)$		
					median	95%	99%	median	95%	99%
18	4	All	0.034	0.017	1.7	(0.3, 9.4)	(0, 11.8)	0.97	(0.2, 8.2)	(0.2, 14.4)
		20-10	0.027	0.011	1.9	(0.6, 5.7)	(0.5, 9.1)	0.84	(0.2, 2.6)	(0.2, 3.7)
		10-5	0.056	0.029	4.4	(1.2, 11.7)	(0.7, 13)	2.46	(0.7, 5.6)	(0.6, 6.2)
		< 5	0.034	0.060	1.8	(0, 7.8)	(-0.1, 9.9)	4.95	(0.7, 16.5)	(-1.7, 29.3)
21	4	All	0.122	0.019	9.3	(0.4, 24.8)	(0, 30.5)	1.59	(0.6, 7)	(0.5, 13)
		20-10	0.150	0.019	12.3	(6.2, 26.9)	(5.9, 32.2)	1.62	(0.7, 3.5)	(0.7, 4)
		10-5	0.139	0.028	11.2	(2.3, 26.6)	(1.3, 31.4)	2.73	(1.4, 4.5)	(1.4, 5.2)
		< 5	0.050	0.054	2.5	(0, 12.5)	(-0.3, 16)	4.40	(0, 15)	(-3.1, 26.1)
18	5	All	0.031	0.018	1.9	(0.1, 7)	(0, 8.2)	1.55	(0.3, 14.8)	(0.2, 28.4)
		20-10	0.031	0.013	2.6	(1.2, 6)	(1, 6.9)	1.12	(0.5, 2.7)	(0.4, 3.4)
		10-5	0.046	0.036	4.2	(0.6, 8.2)	(0.4, 9.2)	3.75	(1.8, 7.5)	(1.4, 9.5)
		< 5	0.028	0.070	1.3	(0, 6.5)	(-0.1, 7.5)	6.63	(2.4, 25.2)	(-0.7, 67.5)
21	5	All	0.127	0.023	9.9	(0.1, 25)	(0, 28.9)	2.53	(0.8, 12.7)	(0, 25.3)
		20-10	0.173	0.021	15.9	(9.6, 27.6)	(8.5, 31)	1.98	(1.3, 3.4)	(1.1, 5)
		10-5	0.139	0.040	11.7	(1.1, 24.7)	(0.7, 28.1)	3.79	(2.6, 7.6)	(2.3, 8)
		< 5	0.048	0.065	2.5	(0, 12.2)	(-0.2, 16.4)	6.61	(0.2, 22.6)	(-1.4, 62.6)
18	12	All	0.020	0.013	1.4	(0, 4.7)	(-0.1, 6)	0.95	(0, 11.6)	(0, 17)
		20-10	0.017	0.010	1.5	(0.4, 2.9)	(0.2, 3.4)	0.90	(0.2, 2.7)	(0.1, 6.3)
		10-5	0.030	0.029	2.2	(0.4, 6)	(-0.2, 7.1)	2.60	(1, 12.2)	(-0.8, 16.2)
		< 5	0.026	0.061	2.0	(0, 5.3)	(0, 6.4)	5.88	(2, 16.8)	(0, 26.6)
21	12	All	0.096	0.019	8.5	(0.6, 16.2)	(0, 18.2)	1.97	(0.5, 8.5)	(0.4, 13)
		20-10	0.117	0.020	11.7	(3, 16.6)	(2, 18.4)	1.93	(0.9, 3.4)	(0.8, 3.8)
		10-5	0.102	0.035	9.4	(1.4, 17.7)	(0.1, 19.8)	3.32	(1.8, 5.5)	(0.2, 9.5)
		< 5	0.043	0.054	2.5	(0, 10.3)	(-0.1, 13.7)	4.73	(2.5, 13.2)	(-1.6, 24.1)

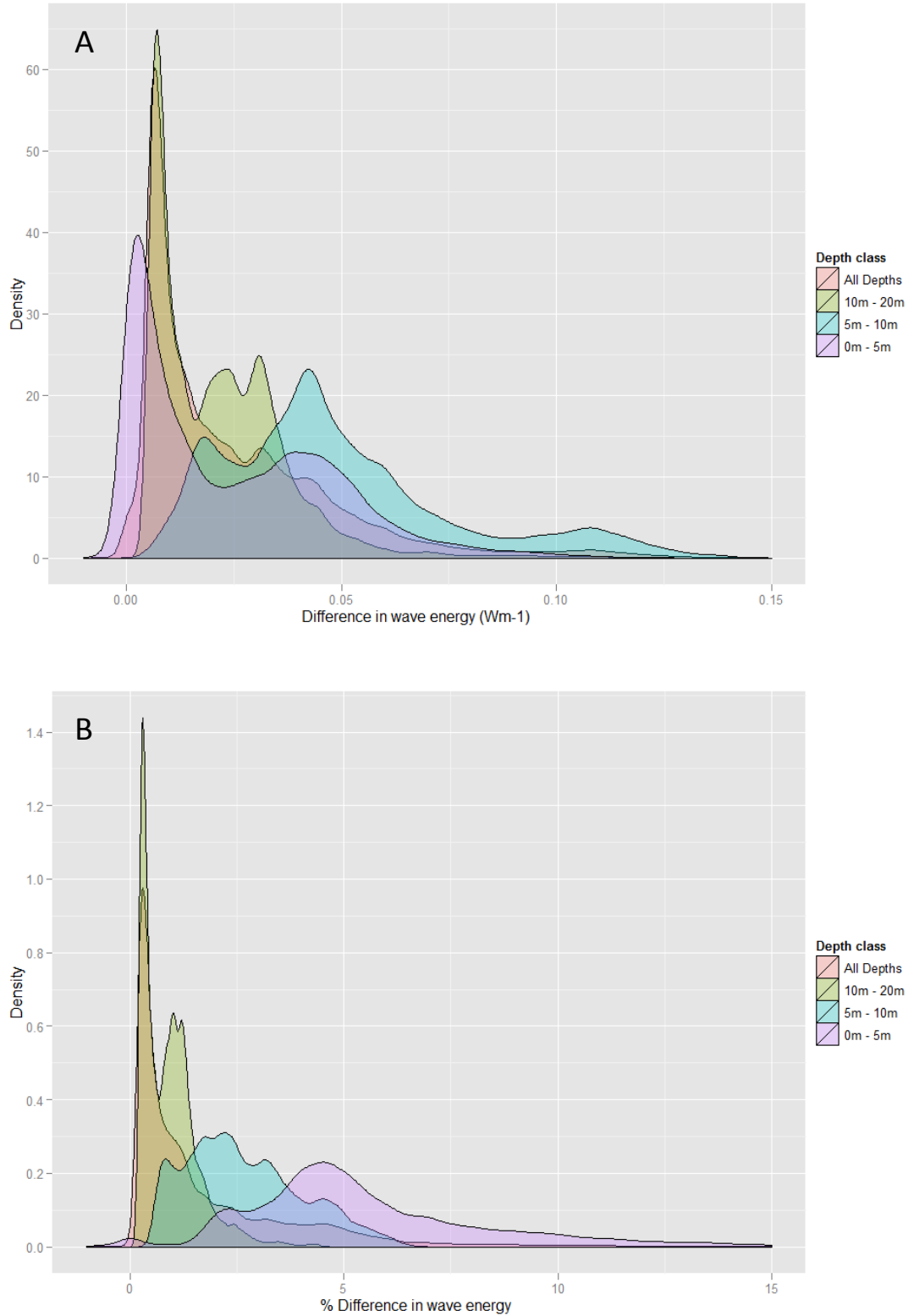


Figure C2.10. Density profiles of the differences in predicted wave energy for wave class 18 in nested grid #4 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

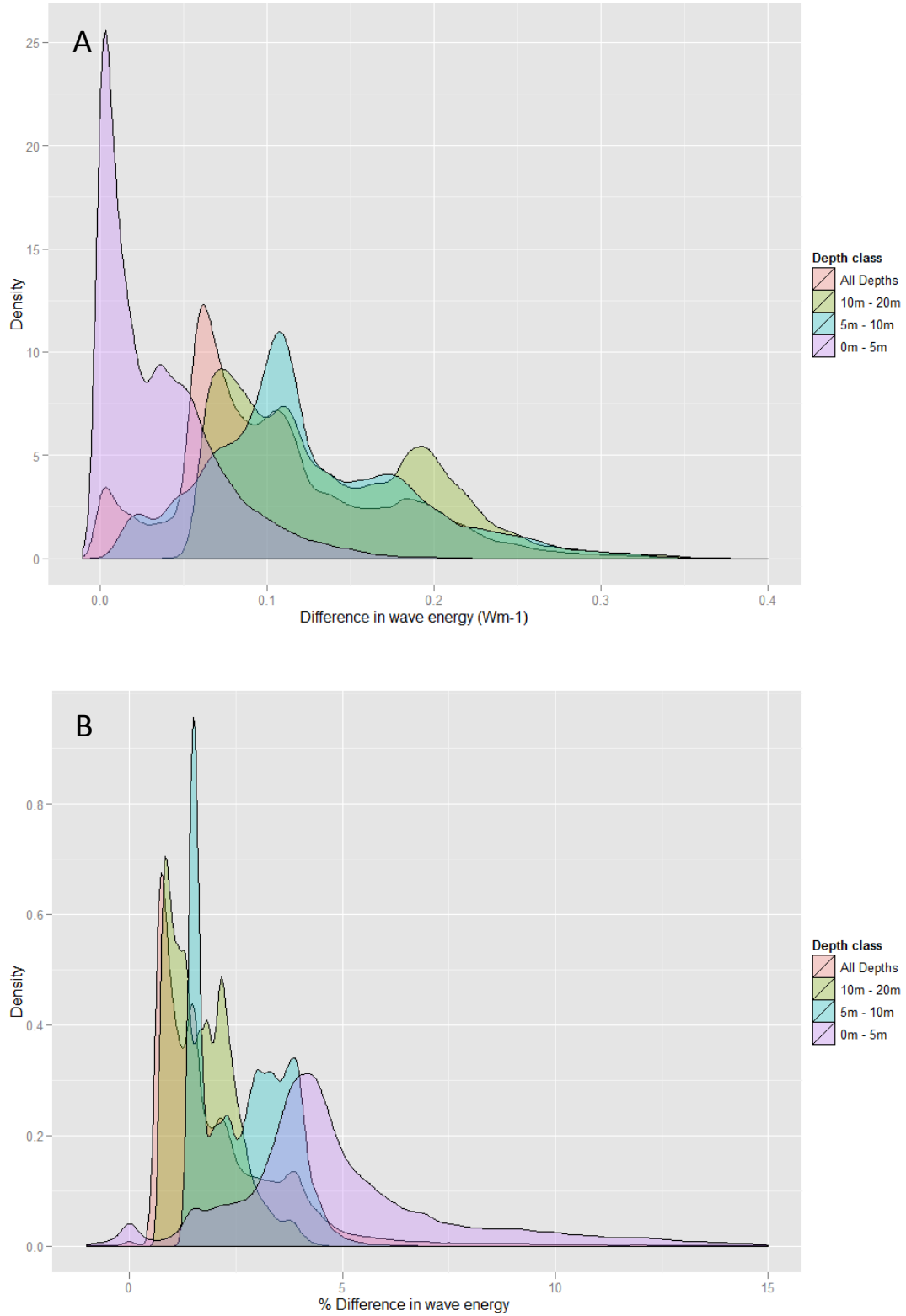


Figure C2.11. Density profiles of the differences in predicted wave energy for wave class 21 in nested grid #4 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{\text{JONSWAP}i} - v_{\text{Madsen}i}$.

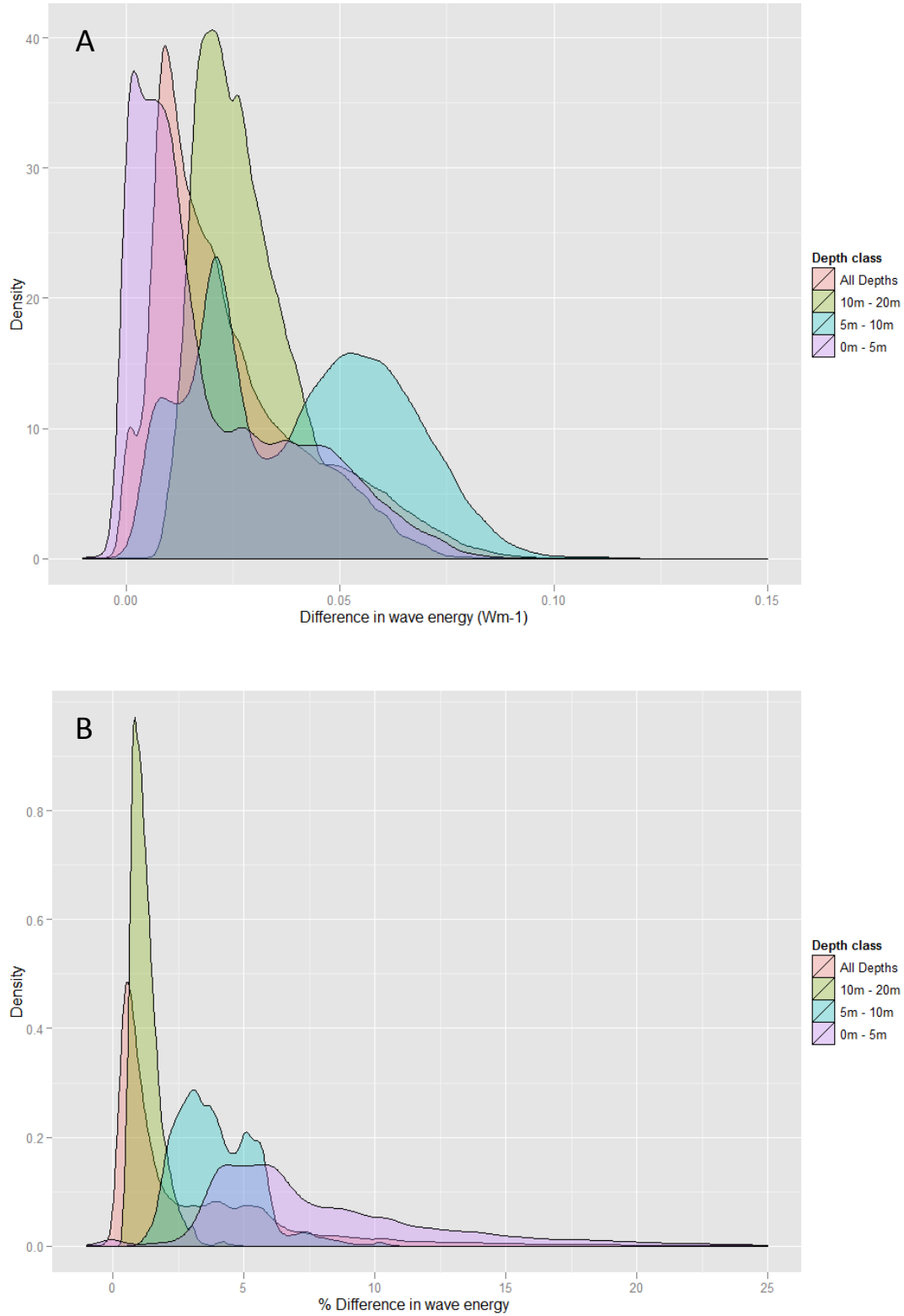


Figure C2.12. Density profiles of the differences in predicted wave energy for wave class 18 in nested grid #5 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(JONSWAP)i} - v_{(Madsen)i}$.

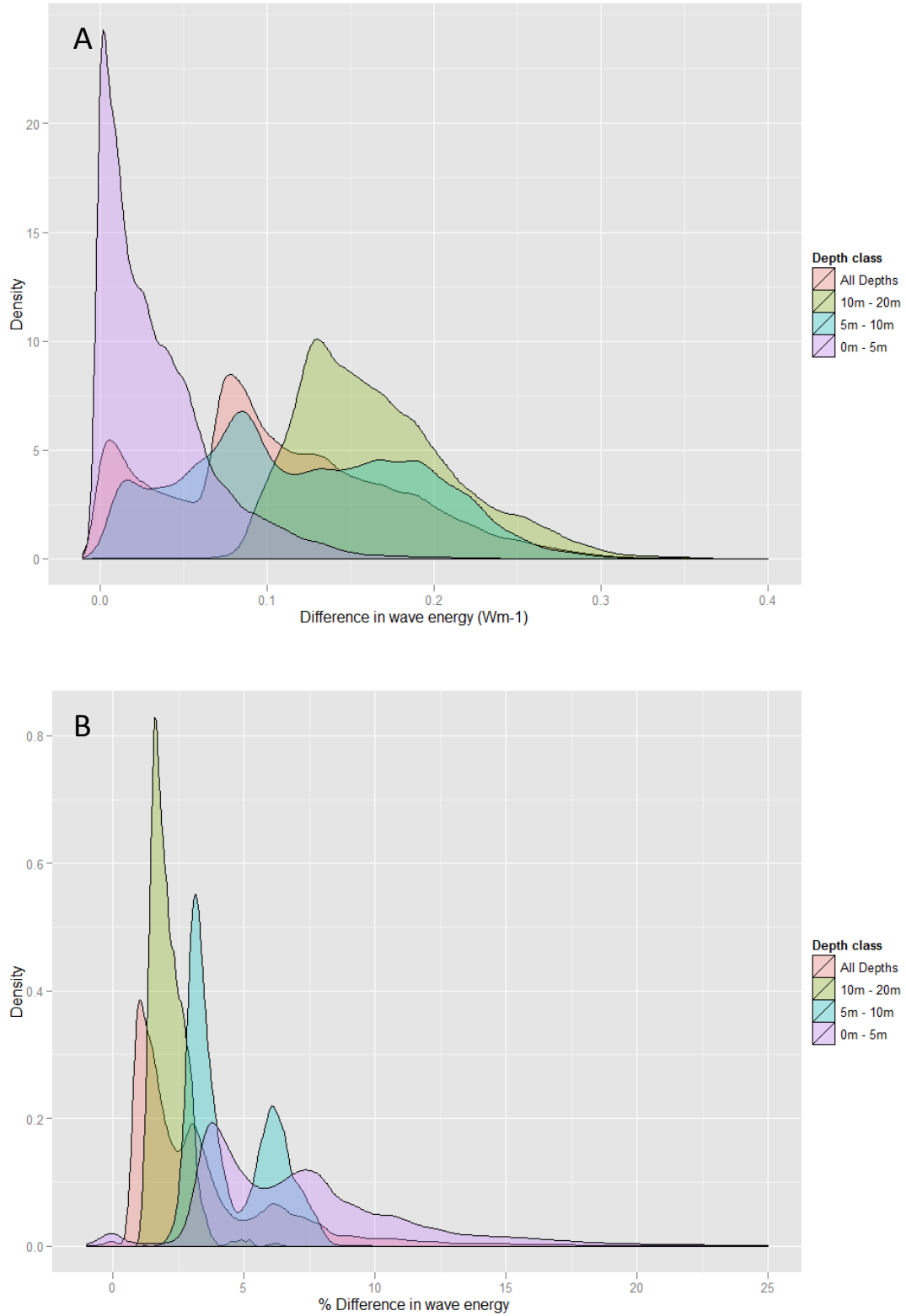


Figure C2.13. Density profiles of the differences in predicted wave energy for wave class 21 in nested grid #5 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

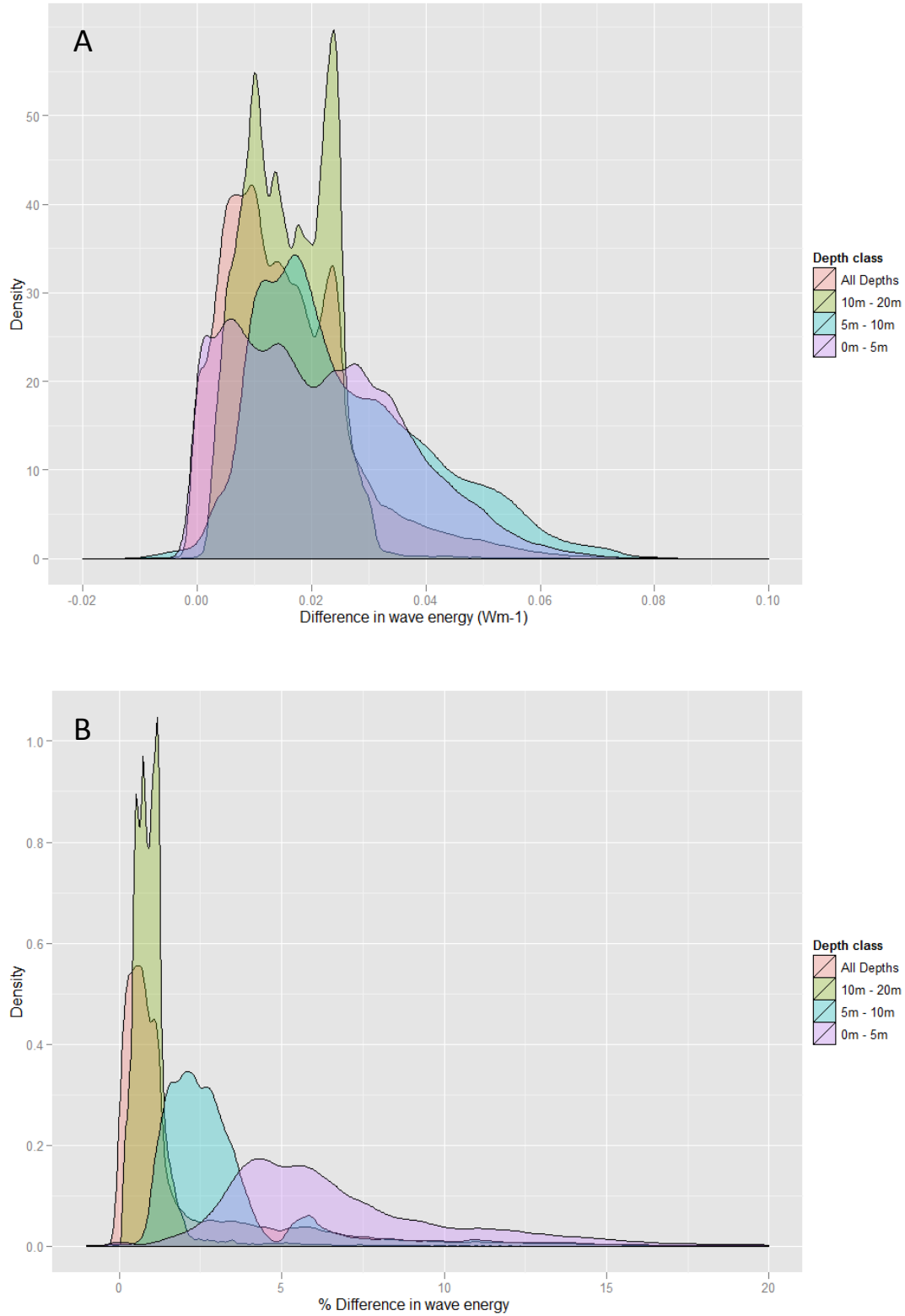


Figure C2.14. Density profiles of the differences in predicted wave energy for wave class 18 in nested grid #12 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

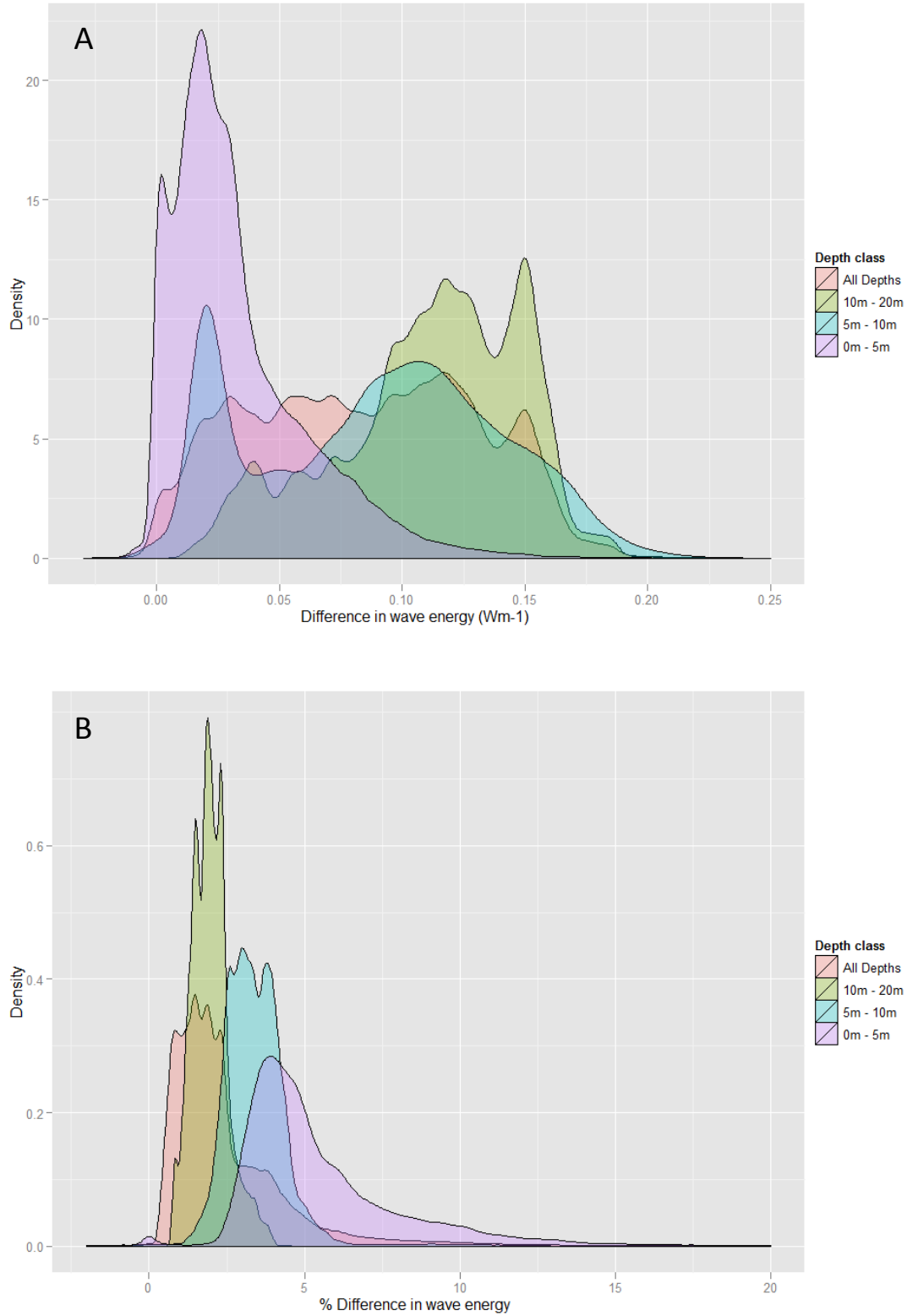


Figure C2.15. Density profiles of the differences in predicted wave energy for wave class 21 in nested grid #12 for model runs with the JONSWAP versus the Madsen formulation of bottom friction. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(\text{JONSWAP})i} - v_{(\text{Madsen})i}$.

2C.3.3 – Wind growth and whitecapping – orbital velocity

Differences between model results using the WAM cycle-4 and the WAM cycle-3 formulations of wind growth and whitecapping tended to differ between parameter sets, locations and depths (Table C2.4). For the less extreme wave conditions (class 18) the predictions produced by WAM cycle 4 models tended to be marginally lower than models using WAM cycle 3, with a median % difference between models of -0.2 to -1% depending on location and depth range (Table C2.4). For this wave class, cells in the 10 – 20 m depth range tended to have a more negative difference between results from WAM cycle 4 and cycle 3, indicating that differences between formulations were larger in deeper water than in the shallower depth. However, for this wave class overall, the difference between formulations was marginal with 95% and 99% of the cells having differences in the ranges of -1.5% to 3% and -2.5% to 4.4% (Figures C2.16 - C2.21), respectively, and low CV of between 0.003 and 0.009, indicating a RMSE that is less than 1% of the overall mean orbital velocity (Table C2.4).

For the more extreme wave class investigated, predictions produced by models using WAM cycle 4 tended to be higher than predictions from models using WAM cycle 3 in deeper water (10-20 m median % difference: 1 to 1.63%), but lower or approximately equal in shallow water (0-5 m median % difference: -0.27 to 0.06%). The range of Δ° however, was higher in shallow water (95% range for 0-5 m depth class: 3.5 to 5.7% depending on location) than in deep water (95% range for 20-10 m depth class: 1 to 2.1 %). This along with the median % differences indicates that in deeper water the discrepancy between formulations acts to introduce a consistent bias in the predictions (i.e. differences between cells are consistent but non-zero), whereas in shallow water these discrepancies are mostly noise (i.e. greater differences among cells, but overall centred on zero- also illustrated in Figures C2.16 - C2.21). These differences would be expected given that in deeper water the physical factors affecting waves are predominantly due to wind forcing, and so a larger discrepancy might be expected between alternative formulations. However, once these waves reach shallow water they begin to interact with the seabed and bottom friction and wave breaking processes are likely to be more important.

There were also noticeable differences among locations with differences between formulations that were higher in nested location # 12 than # 5 (median Δ° was between 0.1 - 0.7% higher and the 95% range of was 0.5 - 1.4% wider in #12 than in #5 evaluated across

depth classes for wave class 21), which were subsequently higher than # 4 (median Δ° was between 0.1 – 1.1% higher and the 95% range of was 0.4 – 0.8% wider in #5 than in #4 evaluated across depth classes). However, overall the difference between formulations was marginal with 95% and 99% of the cells having differences in the ranges of -1.8% to 4.6% and -4.8% to 5.9% (Figures C2.13 - C2.18), respectively, and CV of between 0.007 and 0.018, indicating a RMSE that is less than 2% of the overall mean orbital velocity (Table C2.4).

Table C2.4. Statistics for orbital velocity predictions of model runs with the WAM 4, versus the WAM3 formulations of wind growth and whitecapping processes. All metrics are calculated based on: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

Class	Nest #	Depth range (m)	RMSE (ms^{-1})	CV	$\Delta (\times 10^{-3} \text{ ms}^{-1})$			$\Delta^\circ (\%)$		
					median	95%	99%	median	95%	99%
18	4	All	0.003	0.006	-2.5	(-6.4, 3.1)	(-9.3, 6.5)	-0.71	(-1, 0.6)	(-1, 1.5)
		20-10m	0.003	0.007	-2.9	(-3.4, -1.2)	(-3.6, -0.1)	-0.74	(-0.9, -0.2)	(-1, 0)
		10-5m	0.002	0.003	-1.6	(-5, 3.3)	(-6.6, 5.9)	-0.21	(-0.6, 0.6)	(-0.8, 1.4)
		< 5m	0.005	0.007	-1.6	(-9.9, 7.5)	(-12.2, 16.4)	-0.28	(-1.1, 1.7)	(-1.8, 3.8)
21	4	All	0.007	0.009	3.8	(-9.7, 14.9)	(-13, 19)	0.56	(-0.9, 1.6)	(-1.3, 2.3)
		20-10m	0.009	0.011	8.3	(3.8, 15.1)	(-1.9, 16.8)	1.02	(0.5, 1.6)	(-0.2, 1.8)
		10-5m	0.008	0.007	-0.1	(-10.6, 16.9)	(-12.4, 21.5)	-0.01	(-0.9, 1.7)	(-1, 2.6)
		< 5m	0.007	0.008	-1.9	(-13.5, 15)	(-16.8, 25.9)	-0.27	(-1.4, 2.1)	(-2.9, 4)
18	5	All	0.003	0.007	-2.4	(-7.1, 4.8)	(-10.7, 8.2)	-0.67	(-1, 1.3)	(-1.3, 1.8)
		20-10m	0.003	0.007	-2.8	(-3.7, -0.8)	(-4.2, 0.3)	-0.76	(-0.9, -0.2)	(-1, 0.1)
		10-5m	0.002	0.004	-0.1	(-3.7, 3.5)	(-6.2, 5.4)	-0.02	(-0.5, 1.1)	(-0.8, 1.6)
		< 5m	0.005	0.008	-0.3	(-10.4, 7.8)	(-13.9, 11.4)	-0.09	(-1.2, 1.7)	(-2.5, 2.2)
21	5	All	0.008	0.011	5.2	(-9.2, 17.9)	(-13.6, 21.7)	0.77	(-0.9, 2.3)	(-2, 2.7)
		20-10m	0.010	0.013	8.7	(3.5, 18.5)	(0.2, 21)	1.07	(0.5, 2.1)	(0, 2.3)
		10-5m	0.010	0.011	8.1	(-6.5, 20.4)	(-9.7, 25.8)	1.08	(-0.5, 2.5)	(-0.7, 3)
		< 5m	0.008	0.010	-0.2	(-13.2, 16.5)	(-17, 20.9)	-0.06	(-1.8, 2.5)	(-1.9, 2.8)
18	12	All	0.003	0.009	-2.9	(-4.9, 6.1)	(-6.7, 12.9)	-0.96	(-1.1, 1.7)	(-1.1, 3)
		20-10m	0.003	0.009	-3.2	(-3.8, 0.3)	(-4, 1.2)	-1.04	(-1.1, 0.1)	(-1.1, 0.6)
		10-5m	0.003	0.005	-1.2	(-5.2, 4.7)	(-7.3, 7.1)	-0.23	(-0.8, 1.7)	(-0.9, 2.3)
		< 5m	0.005	0.008	-1.3	(-6.6, 13.1)	(-9.6, 17.2)	-0.25	(-0.8, 3.1)	(-2.1, 4.4)
21	12	All	0.011	0.016	8.7	(-5.1, 23.1)	(-8.2, 32.8)	1.46	(-0.6, 3.7)	(-1.1, 4.8)
		20-10m	0.010	0.017	10.1	(4.7, 16.7)	(4.1, 20.5)	1.63	(0.7, 2.8)	(0.6, 3.7)
		10-5m	0.016	0.018	14	(0.7, 28.8)	(-5.7, 34.6)	1.77	(0.1, 4.4)	(-0.5, 5.3)
		< 5m	0.011	0.013	0.4	(-8.3, 31.6)	(-11.7, 39.5)	0.06	(-1.1, 4.6)	(-4.8, 5.9)

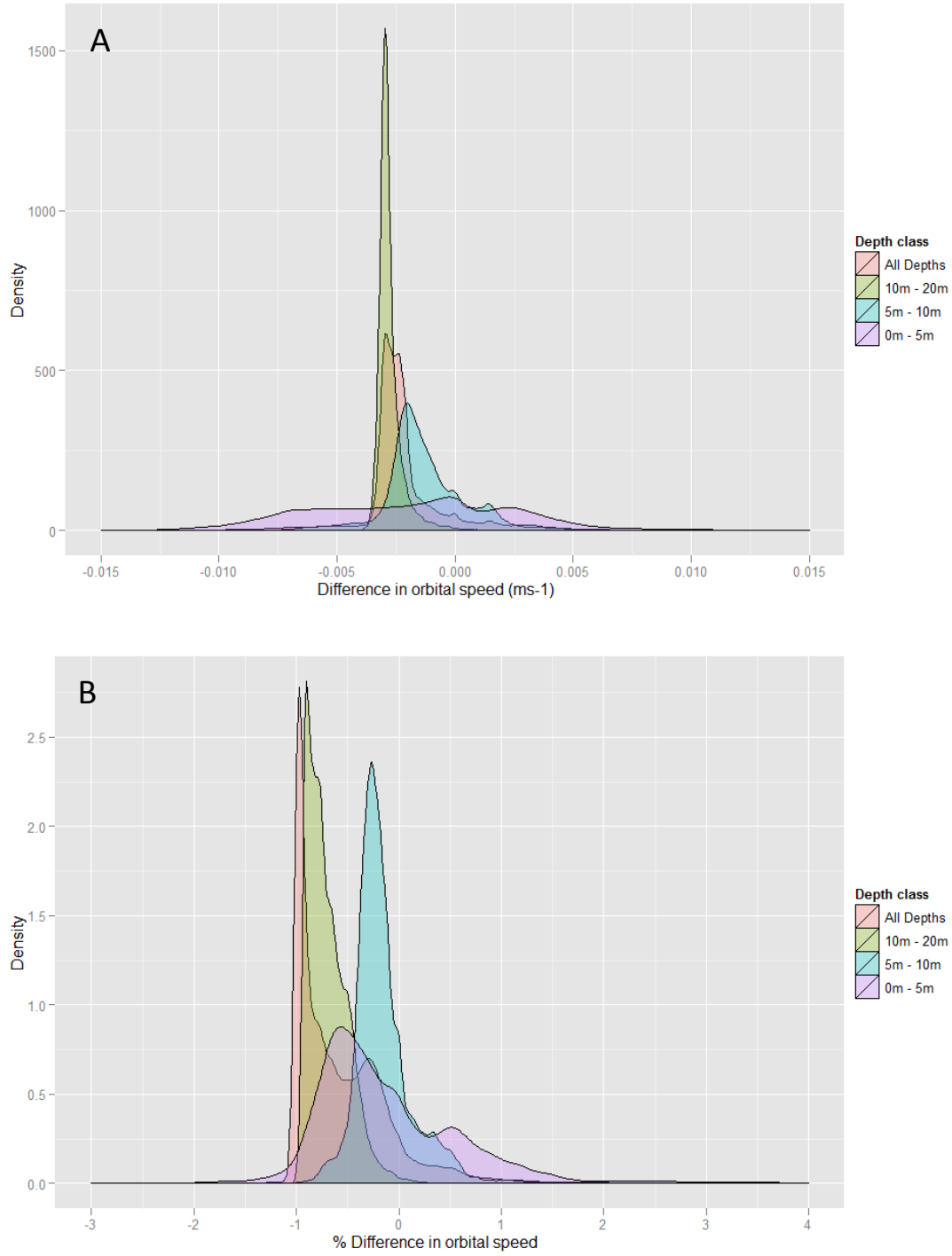


Figure C2.16. Density profiles of the differences in predicted orbital velocity for wave class 18 in nested grid #4 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in orbital speed (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

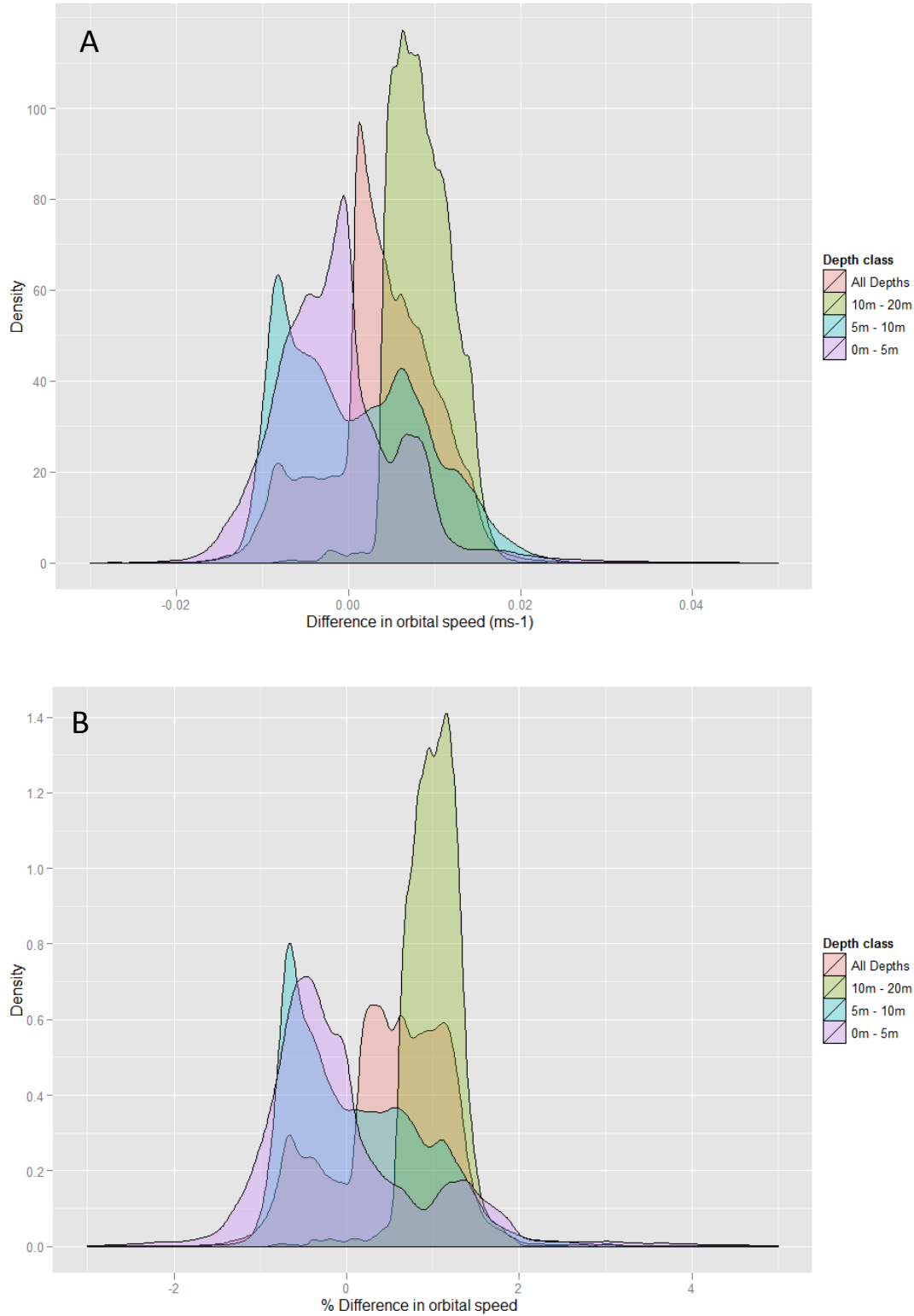


Figure C2.17. Density profiles of the differences in predicted orbital velocity for wave class 21 in nested grid #4 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in orbital speed (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

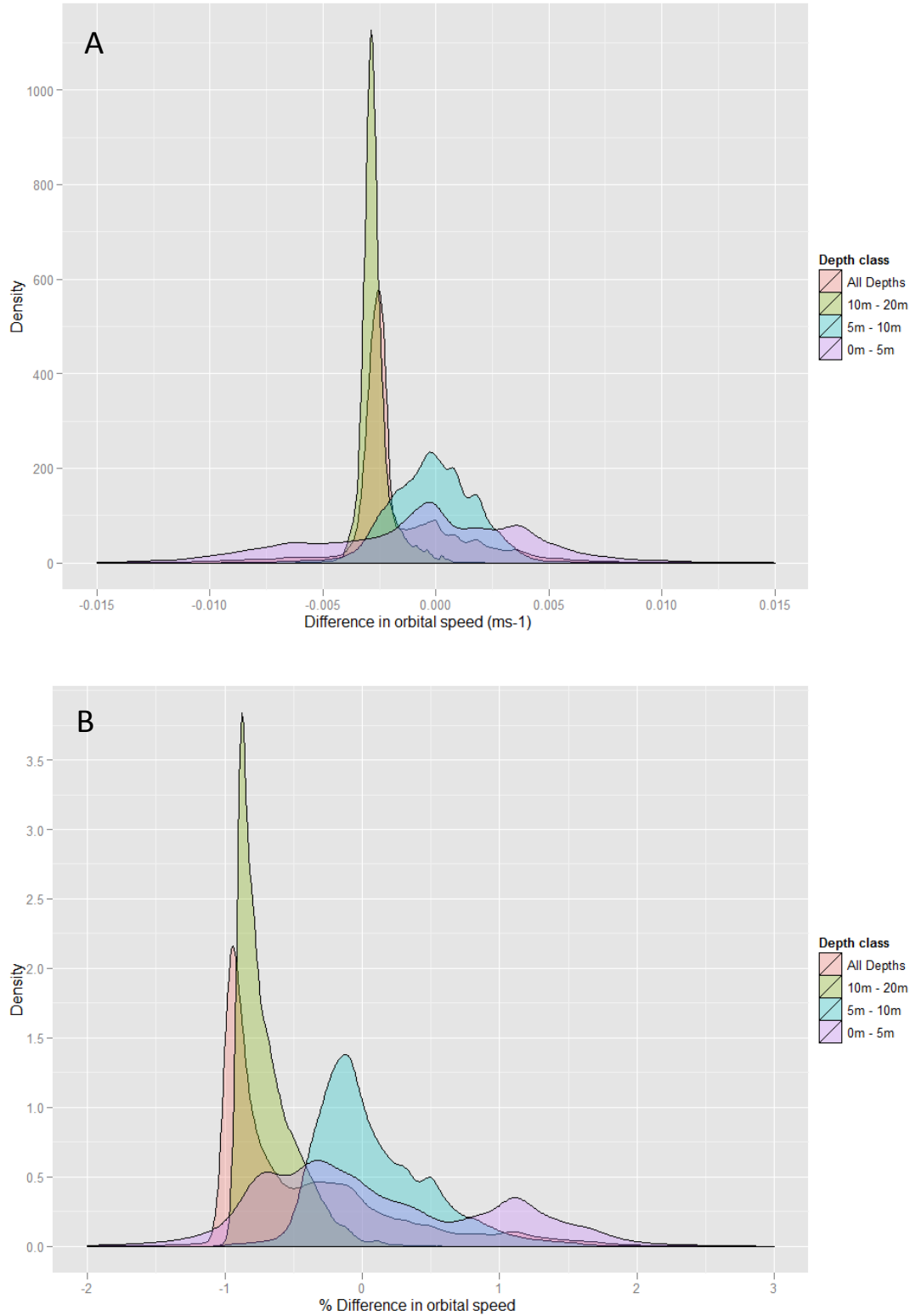


Figure C2.18. Density profiles of the differences in predicted orbital velocity for wave class 18 in nested grid #5 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in orbital speed (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

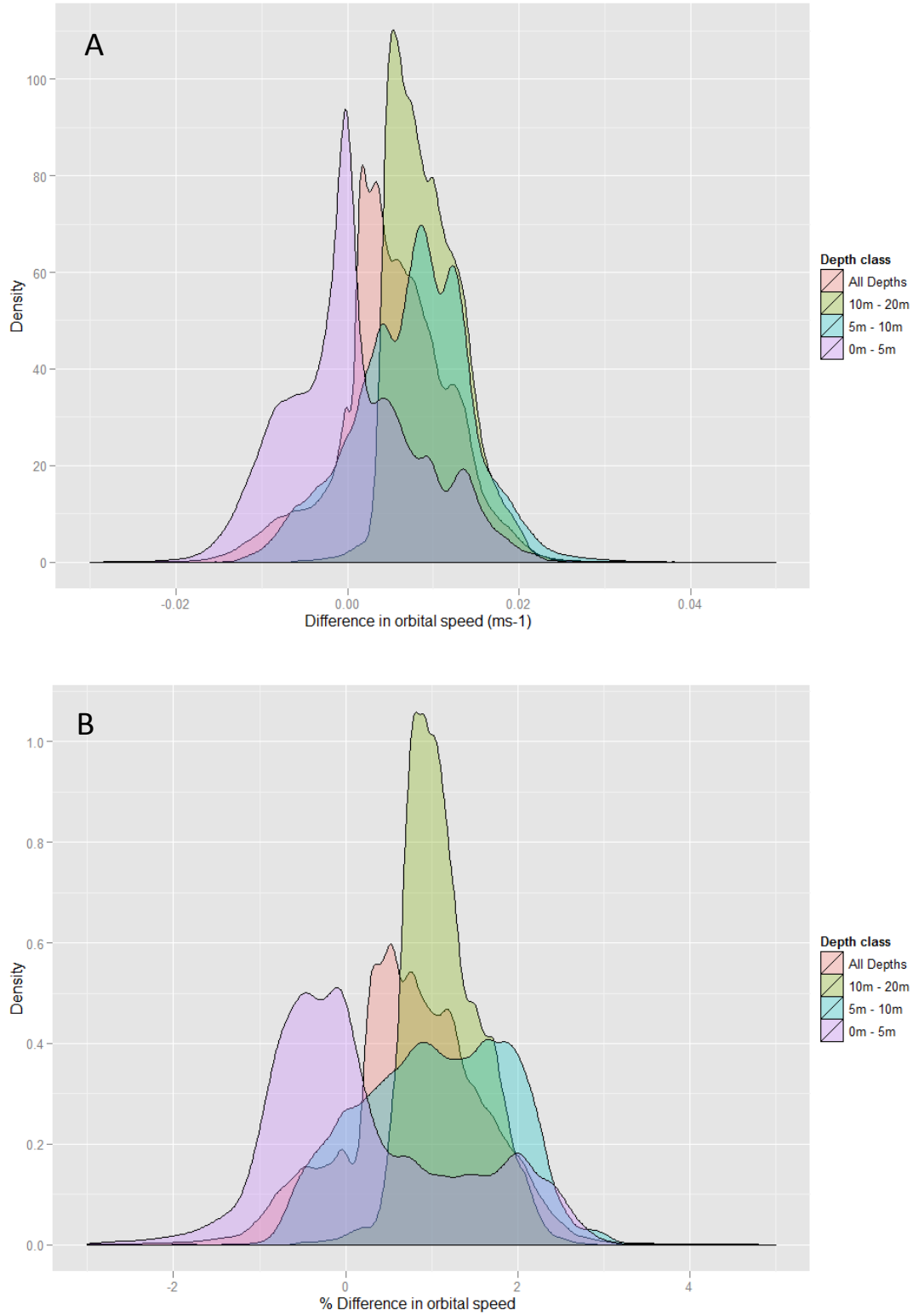


Figure C2.19. Density profiles of the differences in predicted orbital velocity for wave class 21 in nested grid #5 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in orbital speed (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

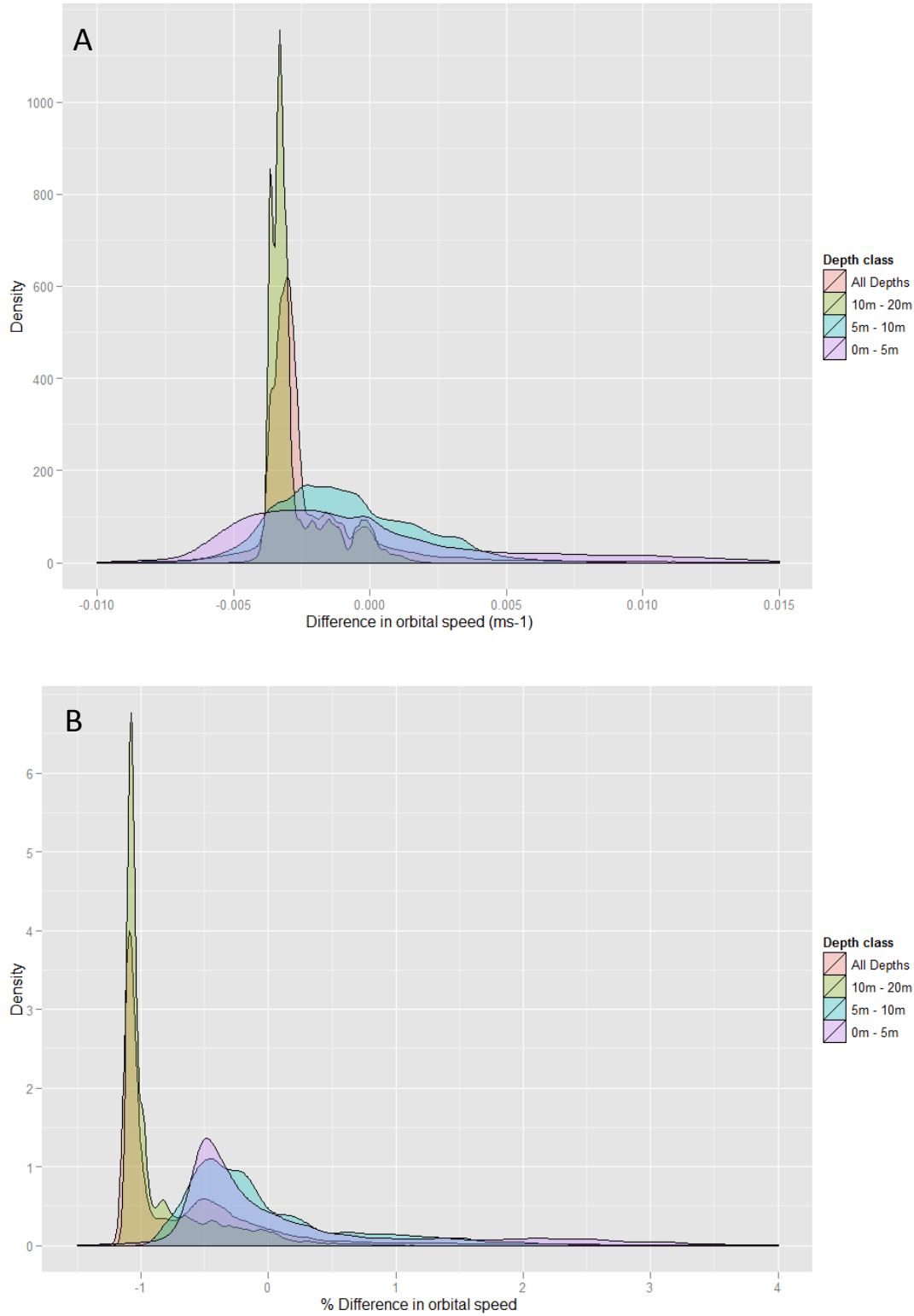


Figure C2.20. Density profiles of the differences in predicted orbital velocity for wave class 18 in nested grid #12 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in orbital speed (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

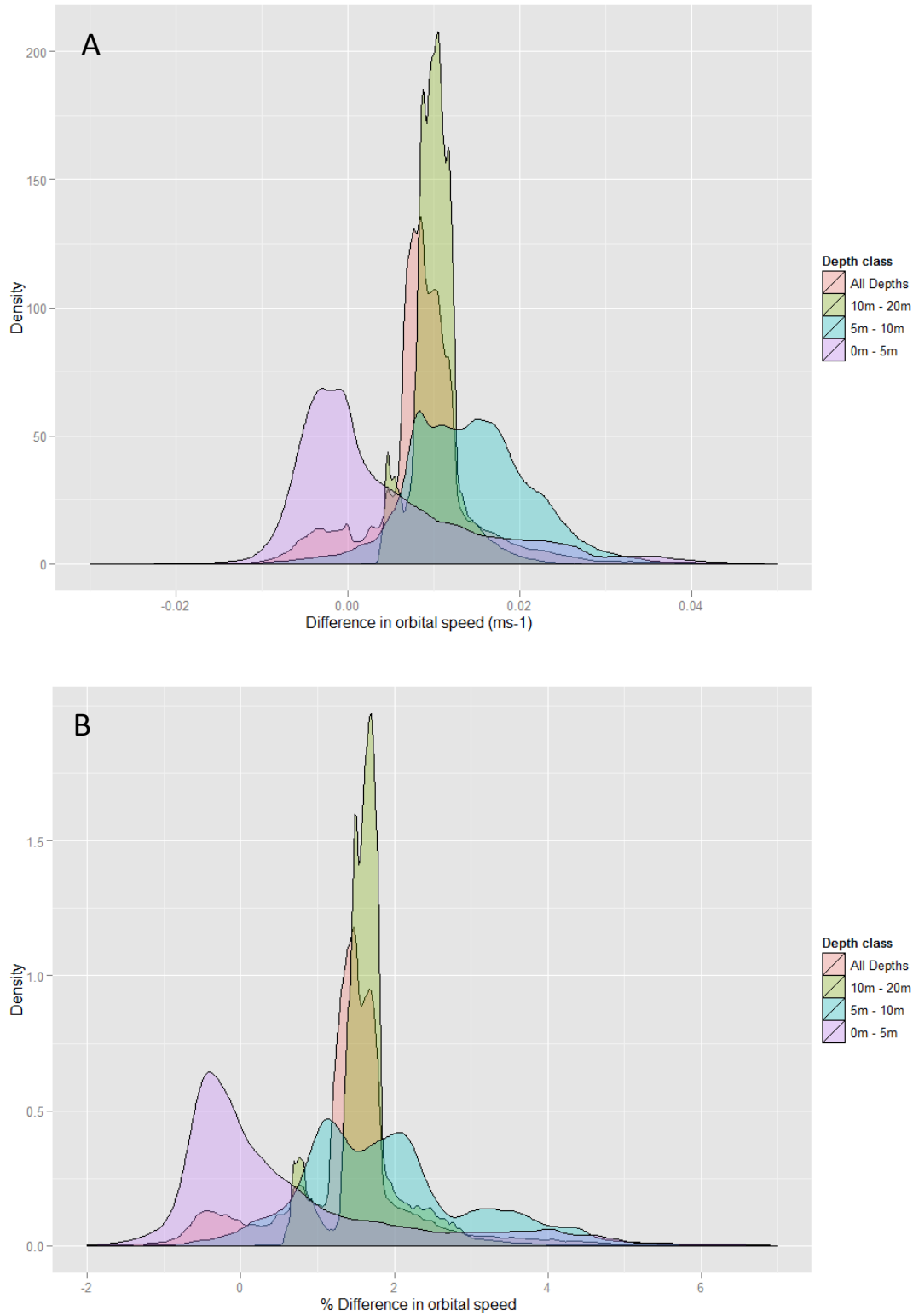


Figure C2.21. Density profiles of the differences in predicted orbital velocity for wave class 21 in nested grid #12 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in orbital speed (A) and as a % of the mean orbital speed (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

2C.3.4 – Wind growth and whitecapping – wave energy

Differences in wave energy between the WAM cycle-4 and the WAM cycle-3 formulations of wind growth and whitecapping were larger overall than those exhibited for orbital velocity and also displayed patterns among parameter sets, locations and depths that were different from those produced for orbital velocity (Table C2.5). For the less extreme wave conditions (class 18) the predictions produced by models using WAM cycle 4 tended to be marginally higher than models using WAM cycle 3, with a median % difference between models of -0.09 to 1.83% depending on location and depth range (Table C2.5). For this wave class, cells in the 10 – 20 m and 10 – 5 m depth ranges tended to have median Δ° values that were ~ 0.5 to 1.5% higher than cells in the shallowest depth range (Table C2.5), indicating that differences between formulations were larger in deeper water than in the shallower depth. However, for this wave class overall, the difference between formulations was marginal with 95% and 99% of the cells having differences in the ranges of -2.4% to 9.5% and -8.7% to 12.9% (Figures C2.19 - C2.24), respectively, and CV between 0.007 and 0.017, indicating a RMSE that is less than 2% of the overall mean orbital velocity (Table C2.5).

Predictions for the more extreme wave class produced by models using WAM cycle 4 tended to be higher than predictions from models using WAM cycle 3 in deeper water (10-20 m median Δ° : 4.4 to 5.5%), but lower or approximately equal in shallow water (0-5 m median Δ° : -0.25 to 0.24%). The range of Δ° however, was higher in shallow water (95% range for 0-5 m depth class: 7.9 to 13% depending on location) than in deep water (95% range for 20-10 m depth class: 2.9 to 6.3 %). This closely matches the patterns found when examining Δ° for orbital velocity with the discrepancy between formulations acting to introduce a consistent bias in the predictions (i.e. differences between cells are consistent but non-zero) in deeper water, whereas in shallow water these discrepancies are mostly noise (i.e. greater differences among cells, but overall centred on zero - also illustrated in Figures C2.22 - C2.27).

There were also noticeable differences among locations with differences between formulations that were higher in nested location # 12 than # 5 (median Δ° was between 0.2 – 1.2% higher and the 95% range of was 2 – 5.2% wider in #12 than in #5 evaluated across depth classes for wave class 21), which were subsequently higher than # 4 (median Δ° was between 0.3 – 2.6% higher and the 95% range of was 0.9 – 1.7% wider in #5 than in #4 evaluated across depth classes). The overall difference between formulations for this wave class was within -3.2% to 13.2% (95% range) and -8.6% to 21% (99% range) with a

CV(RMSE) between 0.018 and 0.061 indicating a RMSE that is at most 6.1% of the overall mean wave energy (Table C2.5).

Table C2.5. Statistics for wave energy predictions of model runs with the WAM 4, versus the WAM3 formulations of wind growth and whitecapping processes. All metrics are calculated based on: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

Class	Nest	Depth range (m)	RMSE (Wm^{-1})	CV	$\Delta (\times 10^{-2} \text{ Wm}^{-1})$			$\Delta^\circ (\%)$		
					median	95%	99%	median	95%	99%
18	4	All	0.021	0.011	2	(-0.8, 3.6)	(-1.7, 4.2)	0.90	(-1.1, 2.8)	(-1.8, 4.5)
		20-10m	0.025	0.011	2.4	(1.4, 3.7)	(0.7, 4.3)	1.00	(0.5, 2)	(0.3, 2.6)
		10-5m	0.022	0.012	2	(-0.6, 4)	(-1.5, 4.5)	0.96	(-0.3, 3.2)	(-0.8, 5.1)
		< 5m	0.008	0.014	0	(-1.8, 1.7)	(-2.4, 2.6)	-0.09	(-2.1, 4.2)	(-3.4, 9.7)
21	4	All	0.288	0.045	34.6	(-4.4, 41.8)	(-6.3, 44.3)	4.09	(-1.4, 5.5)	(-2.6, 6.4)
		20-10m	0.352	0.045	35.4	(19.9, 42.8)	(1.4, 44.8)	4.41	(2.9, 5.8)	(0.4, 6.4)
		10-5m	0.111	0.023	2.6	(-6.1, 27.6)	(-7.1, 31.1)	0.81	(-1.3, 5.1)	(-1.9, 6.6)
		< 5m	0.017	0.018	0	(-3.7, 3.6)	(-5.4, 6.7)	-0.25	(-2.9, 4.9)	(-5.4, 8.9)
18	5	All	0.022	0.013	2	(-0.7, 3.9)	(-1.6, 4.6)	1.04	(-1.3, 4.7)	(-2.5, 6.6)
		20-10m	0.028	0.012	2.7	(1.3, 4.1)	(0.6, 4.7)	1.17	(0.5, 2.3)	(0.2, 3.2)
		10-5m	0.021	0.017	1.6	(0.1, 4.2)	(-0.9, 5)	1.83	(0.1, 5.5)	(-0.6, 6.8)
		< 5m	0.007	0.017	0.1	(-1.4, 1.5)	(-2.2, 2.4)	0.37	(-2.4, 5.8)	(-4.3, 8.3)
21	5	All	0.295	0.055	35.1	(-1.6, 49.2)	(-3.5, 51.2)	4.34	(-1.6, 6.9)	(-3.5, 7.6)
		20-10m	0.383	0.049	38	(13.8, 50.4)	(5.9, 52.4)	4.81	(2.8, 7.2)	(1.4, 7.6)
		10-5m	0.125	0.037	6.3	(-1.7, 31.3)	(-4.3, 35.3)	3.37	(-0.5, 6.9)	(-1.1, 8)
		< 5m	0.017	0.024	0	(-2.9, 3.9)	(-4.7, 7)	0.08	(-3.2, 6.4)	(-6.7, 7.8)
18	12	All	0.012	0.008	0.7	(-0.6, 2.9)	(-1.2, 3.4)	0.39	(-1.1, 6.9)	(-1.9, 10.3)
		20-10m	0.013	0.007	0.8	(0, 3)	(-0.2, 3.4)	0.39	(0, 6.4)	(-0.1, 8.3)
		10-5m	0.014	0.013	0.7	(-1.1, 3.1)	(-2, 3.8)	0.77	(-0.8, 9.5)	(-2.2, 12.9)
		< 5m	0.007	0.016	0	(-1.1, 1.8)	(-1.7, 2.4)	-0.09	(-1.8, 8.9)	(-8.7, 12.8)
21	12	All	0.300	0.061	32.7	(-0.7, 44.2)	(-1.3, 48.3)	5.40	(-1.4, 10.1)	(-2.9, 13.7)
		20-10m	0.324	0.056	33.6	(10.3, 43.7)	(7, 48)	5.48	(3.9, 10.2)	(3.2, 12.7)
		10-5m	0.140	0.050	10.1	(0.9, 30.8)	(-2.2, 37.9)	4.56	(0.5, 13.2)	(-0.9, 16.8)
		< 5m	0.027	0.034	0.1	(-1.3, 8.3)	(-1.8, 12.1)	0.24	(-3, 10.2)	(-6.8, 21)

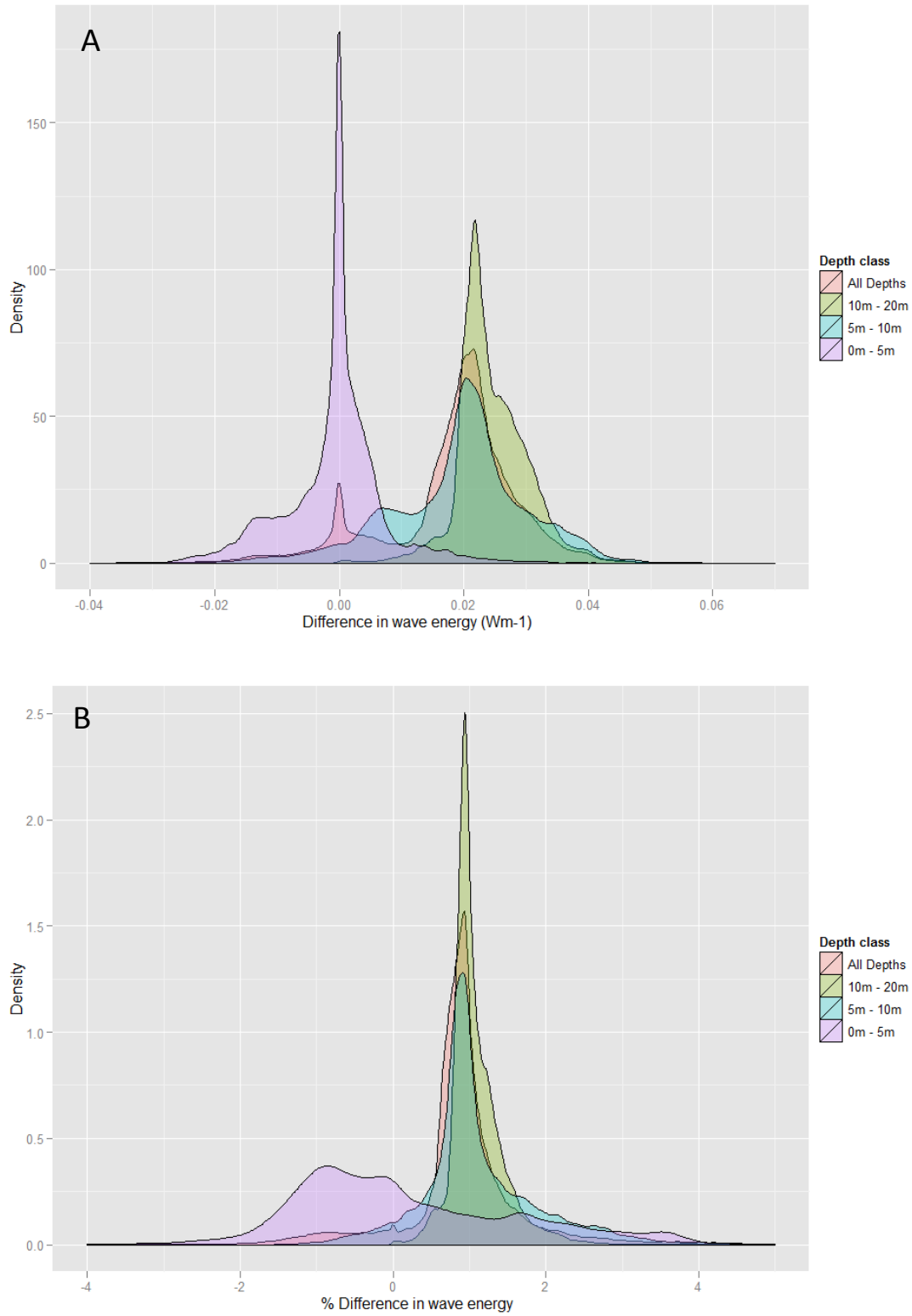


Figure C2.22. Density profiles of the differences in predicted wave energy for wave class 18 in nested grid #4 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

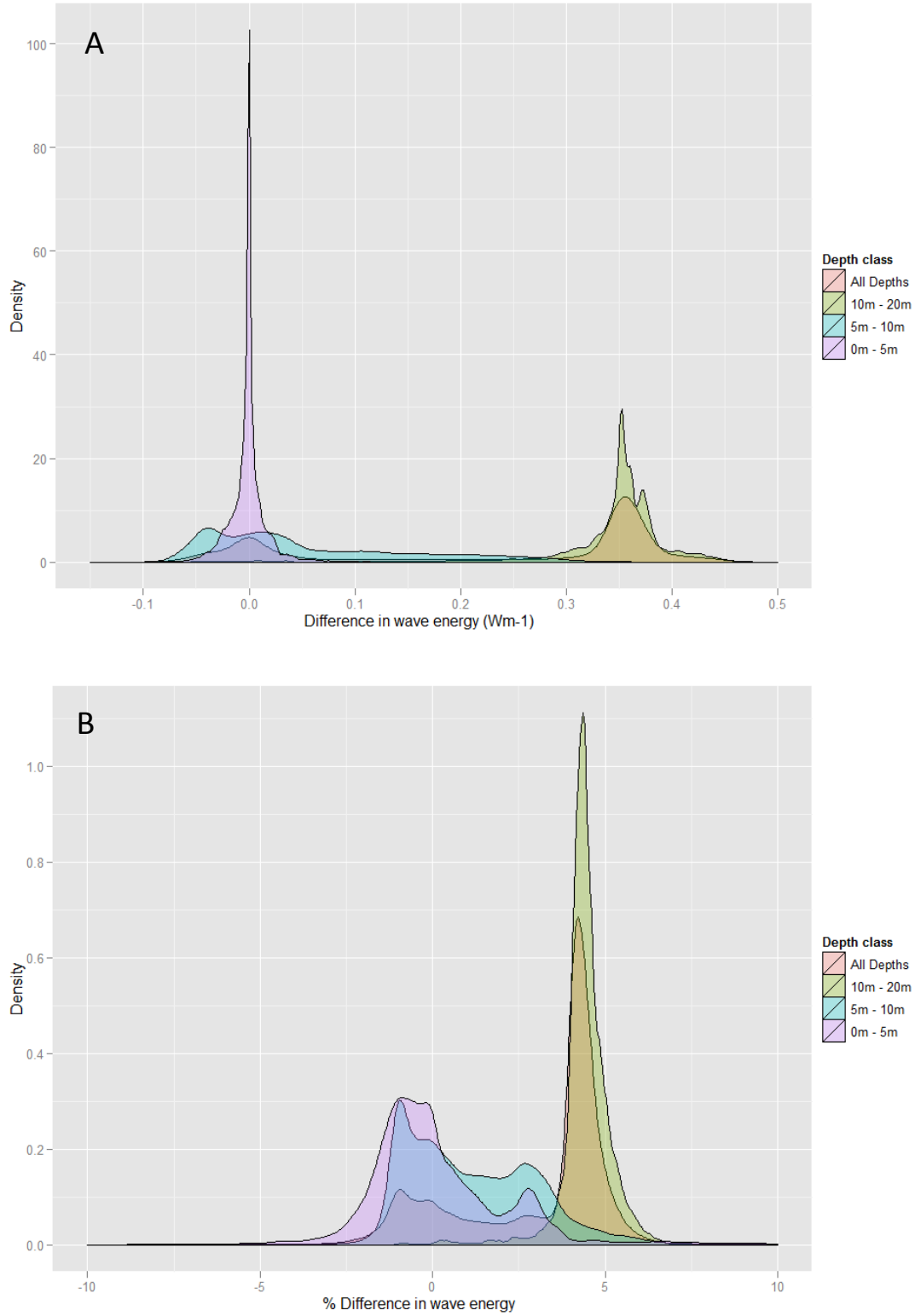


Figure C2.23. Density profiles of the differences in predicted wave energy for wave class 21 in nested grid #4 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$

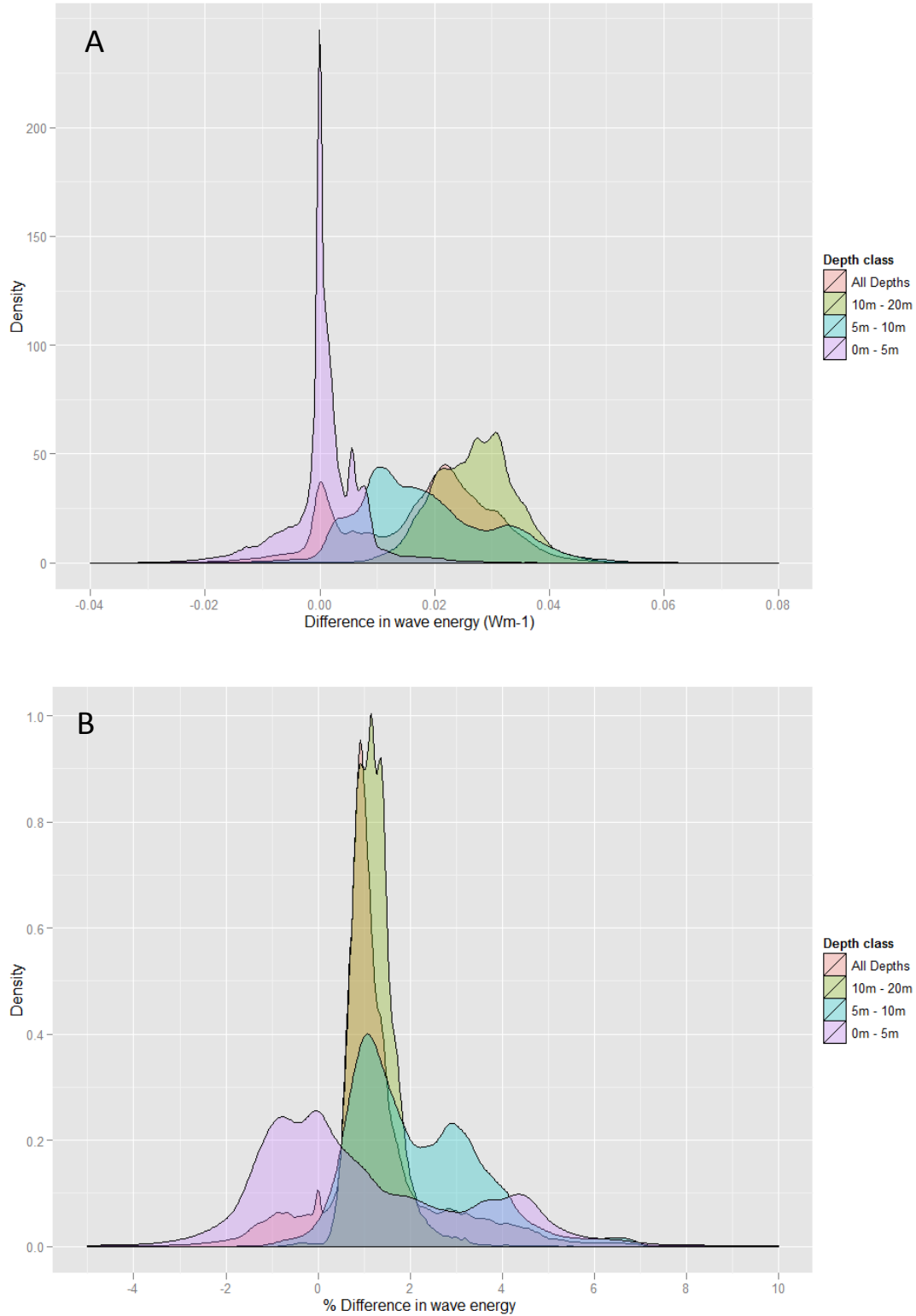


Figure C2.24. Density profiles of the differences in predicted wave energy for wave class 18 in nested grid #5 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(\text{WAM4})i} - v_{(\text{WAM3})i}$.

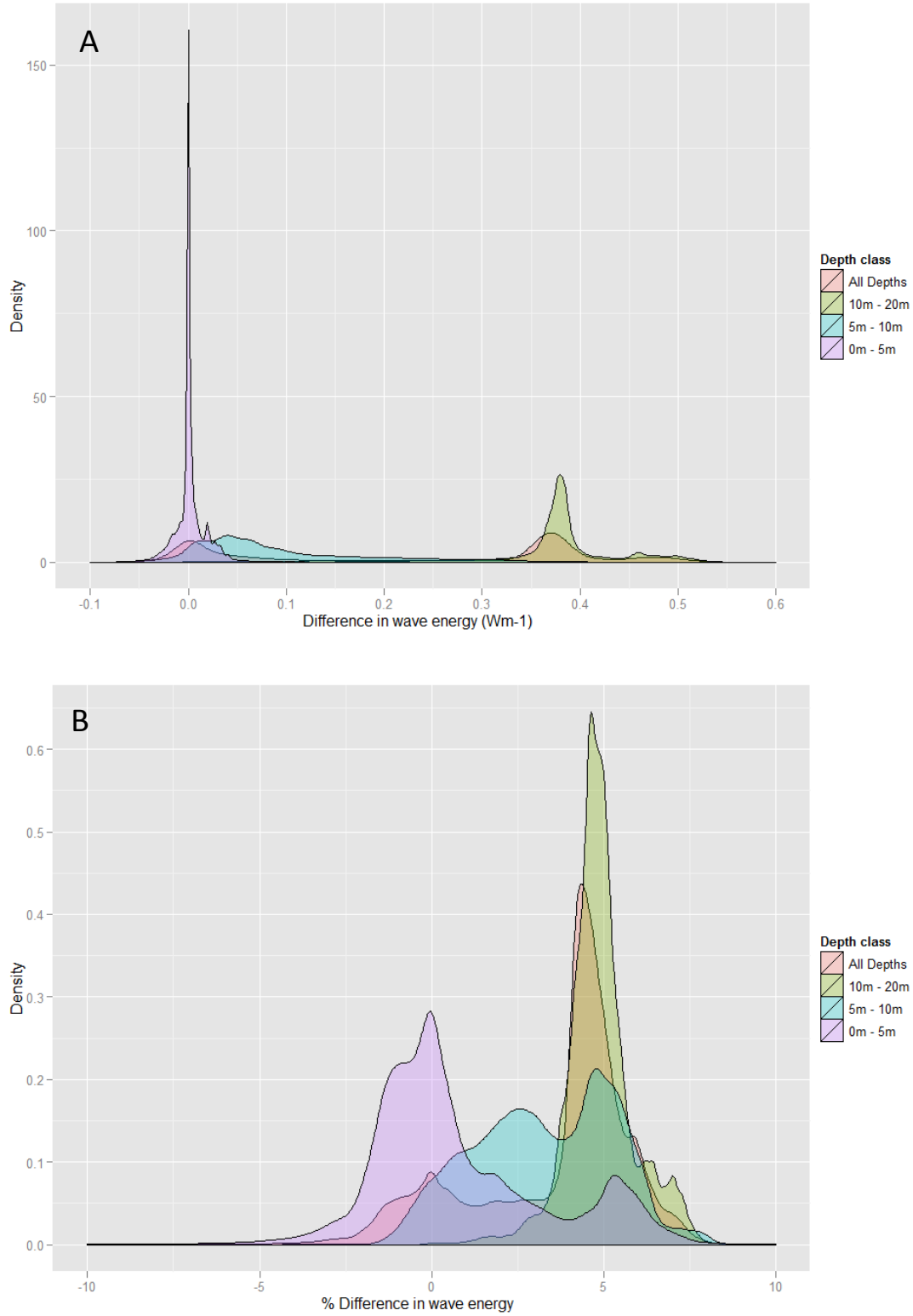


Figure C2.25. Density profiles of the differences in predicted wave energy for wave class 21 in nested grid #5 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$

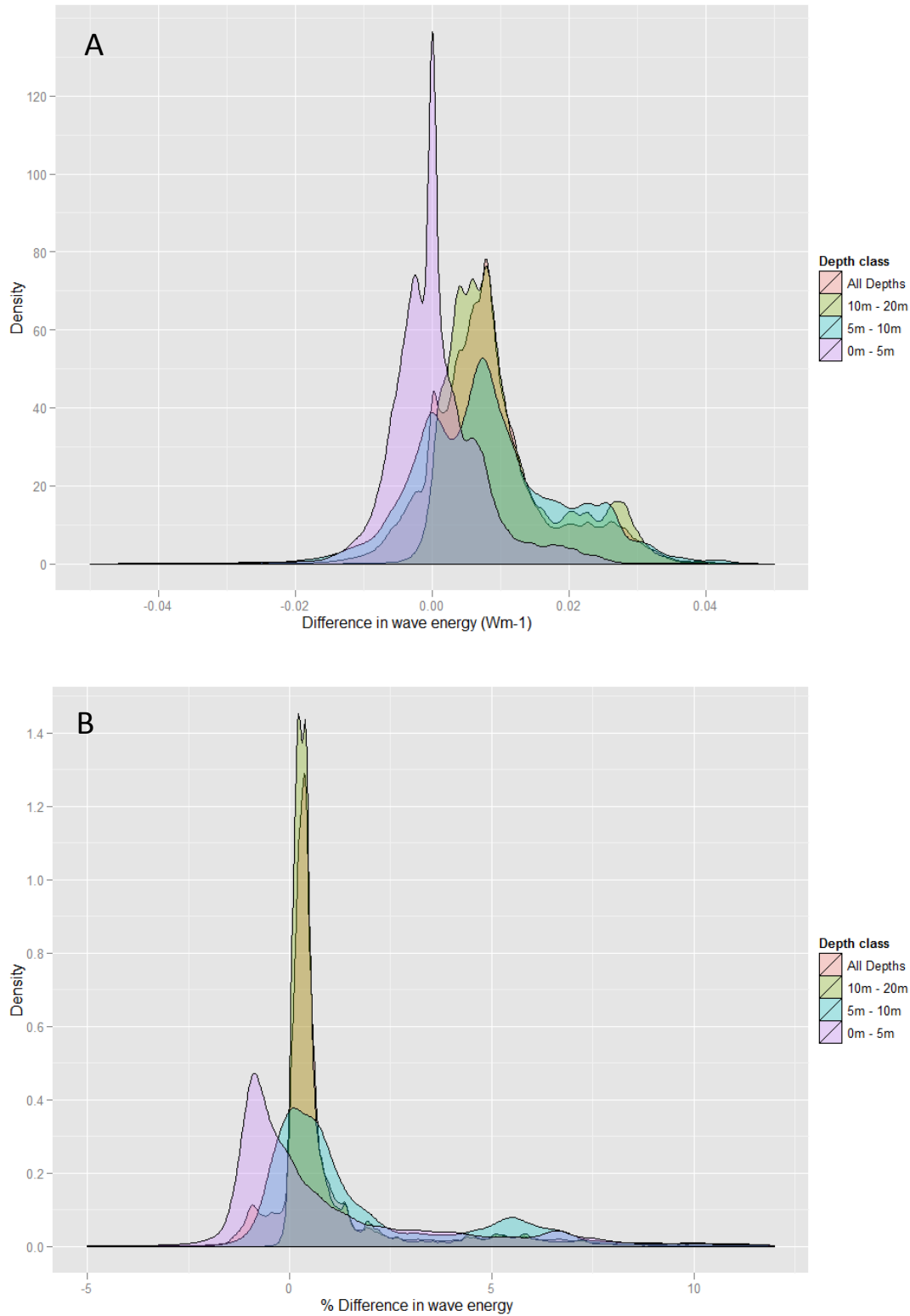


Figure C2.26. Density profiles of the differences in predicted wave energy for wave class 18 in nested grid #12 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

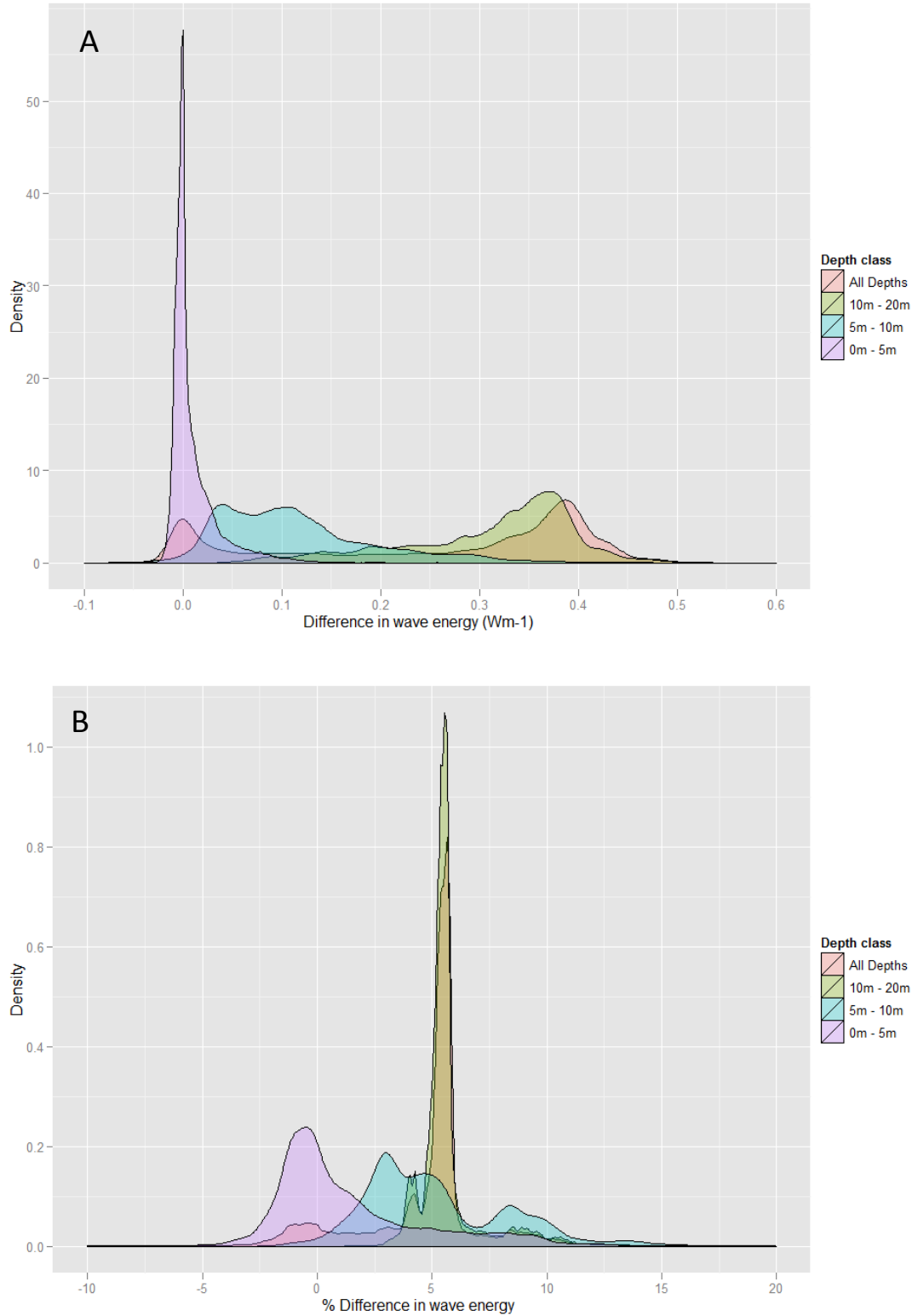


Figure C2.27. Density profiles of the differences in predicted wave energy for wave class 21 in nested grid #12 for model runs with the WAM 3 versus the WAM 4 formulation of wind growth and whitecapping processes. Results are expressed as absolute difference in wave energy (A) and as a % of the mean wave energy (B). Differences are calculated as: $\Delta_i = v_{(WAM4)i} - v_{(WAM3)i}$.

2C.3.5 – Sensitivity of *Macrocystis pyrifera* stipe breaking predictions

The percent-area with stipe breaking probability in each of the eleven probability bins were similar across formulations of the two physical processes examined (Table C2.6). As a reflection of the proportionally lower orbital velocities predicted by the Madsen versus the JONSWAP formulation, there was a larger area with very low breaking probabilities (difference between formulations in terms of the %-area with breaking probabilities $< 0.1\%$ was $0.8 - 2.2\%$ across locations) and marginally smaller area with higher breaking probabilities (difference between formulations in terms of the %-area with breaking probabilities $5 - 10\%$ was -0.15 to -0.646%) when comparing areas across formulations (Table C2.6). A similar pattern is also apparent when comparing the results between WAM 3 and WAM 4 results, whereby the marginally larger orbital velocities produced by WAM 4 lead to slightly greater areas with higher breaking probabilities, and smaller areas with low breaking probabilities (Table C2.6). This pattern was consistent across locations, but the largest difference in the low probability bands was observed in nested location #12, whereas #4 had larger differences in the higher probability bands, likely associated with the overall lower and higher overall breaking probabilities for each of these locations, respectively (Table C2.6). Overall the difference in percent-area for each probability band is marginal with most differences in the low probability bands ($< 1\%$) being $\sim 0 - 2\%$ and $0 - 0.6\%$ in the higher probability bands (Table C2.6).

The differences in percent-area in each band between alternative formulations were predominantly due to grid-cells being classified in either the band one above or one below the probability band in question (Figures C2.28-C2.30). Misclassifications were typically less than 15% in the $< 0.1\%$ to $2.5 - 5\%$ probability bands, but could be up to 25% in the $5 - 10\%$ to $50 - 75\%$ bands when comparing bottom-friction formulations. Predictions produced by the Madsen formulation, when not assigned to the same band as the JONSWAP formulation, were typically assigned to the probability class one lower compared to the JONSWAP formulation across all probability bands (Figures C2.28 to C2.30). In contrast, WAM 3 predictions, when not assigned to the same band as WAM 4, were typically assigned to a higher probability band for bands $0.1 - 0.25\%$ to $1 - 2.5\%$, but a lower band for bands $2.5\% - 5\%$ to $50 - 75\%$ in nested location #4 and #5 (Figures C2.28 to C2.30), but always assigned to a higher band in #12 (Figure C2.30). Overall however, the proportion of mismatch was far lower for alternative formulations of wind-generation/whitecapping ($< 10\%$ across all bands)

than formulations of bottom friction (up to 25%), likely due to the larger discrepancies produced by alternative formulations of bottom friction in orbital velocity predictions.

Even the discrepancies produced by alternative formulations of bottom friction are unlikely to change the conclusions drawn in Chapter 4 as the discrepancies are relatively minor. In the worst case scenario, the change in the area where the probability of breakage is greater than 5% is less than 1% of the overall area investigated (nested location #4 – see Table C2.6), and constitutes a marginal expansion of the areas previously highlighted in Chapter 4 rather than a wholesale change in distribution of potentially destructive wave forces.

Table C2.6. Results of applying the *Macrocystis* bio-mechanical model to the predicted orbital velocities for each location and formulation of bottom friction (JONSWAP and Madsen) and wind-generation/whitecapping (WAM cycle 3 and WAM cycle 4). Values indicate the %-area of each location where predictions were within each of 11 bands of stipe breakage probability. Differences between formulations were also calculated as %_{Madsen} - %_{JONSWAP} for bottom friction formulations and %_{WAM4} - %_{WAM3} for wind-generation and whitecapping formulations.

	Probability of Breakage (%)										
	<.1	.1-.25	.25-.5	.5-1	1-2.5	2.5-5	5-10	10-20	20-50	50-75	75-100
Nest 4											
Friction: JONSWAP	38.530	12.977	8.713	8.232	12.448	14.687	3.536	0.729	0.148	0.001	0.000
Friction: Madsen	39.394	13.090	8.721	8.333	12.652	14.225	2.890	0.582	0.112	0.001	0.000
Difference	0.864	0.113	0.008	0.101	0.204	-0.462	-0.646	-0.147	-0.036	0.000	0.000
Wind: WAM 3	39.394	13.090	8.721	8.333	12.652	14.225	2.890	0.582	0.112	0.001	0.000
Wind: WAM 4	40.009	13.160	8.628	8.199	12.494	13.962	2.840	0.592	0.115	0.001	0.000
Difference	0.615	0.070	-0.092	-0.134	-0.159	-0.263	-0.050	0.010	0.003	0.000	0.000
Nest 5											
Friction: JONSWAP	50.457	13.228	7.448	7.321	9.452	6.639	3.738	1.312	0.345	0.036	0.023
Friction: Madsen	52.009	12.804	7.377	7.393	9.413	6.292	3.294	1.081	0.283	0.034	0.020
Difference	1.552	-0.425	-0.071	0.072	-0.039	-0.347	-0.444	-0.231	-0.062	-0.003	-0.003
Wind: WAM 3	52.009	12.804	7.377	7.393	9.413	6.292	3.294	1.081	0.283	0.034	0.020
Wind: WAM 4	52.854	12.587	7.303	7.349	9.216	6.079	3.190	1.089	0.280	0.034	0.020
Difference	0.845	-0.217	-0.074	-0.045	-0.197	-0.213	-0.104	0.008	-0.003	0.000	-0.001
Nest 12											
Friction: JONSWAP	68.615	11.249	5.240	4.799	5.494	2.593	1.325	0.510	0.160	0.014	0.001
Friction: Madsen	70.862	9.914	5.225	4.650	5.235	2.344	1.175	0.450	0.130	0.012	0.001
Difference	2.247	-1.335	-0.015	-0.149	-0.259	-0.249	-0.150	-0.060	-0.030	-0.002	0.000
Wind: WAM 3	70.862	9.914	5.225	4.650	5.235	2.344	1.175	0.450	0.130	0.012	0.001
Wind: WAM 4	72.880	8.372	5.169	4.594	5.054	2.258	1.115	0.423	0.121	0.012	0.001
Difference	2.018	-1.542	-0.056	-0.056	-0.181	-0.086	-0.059	-0.027	-0.009	0.000	0.000

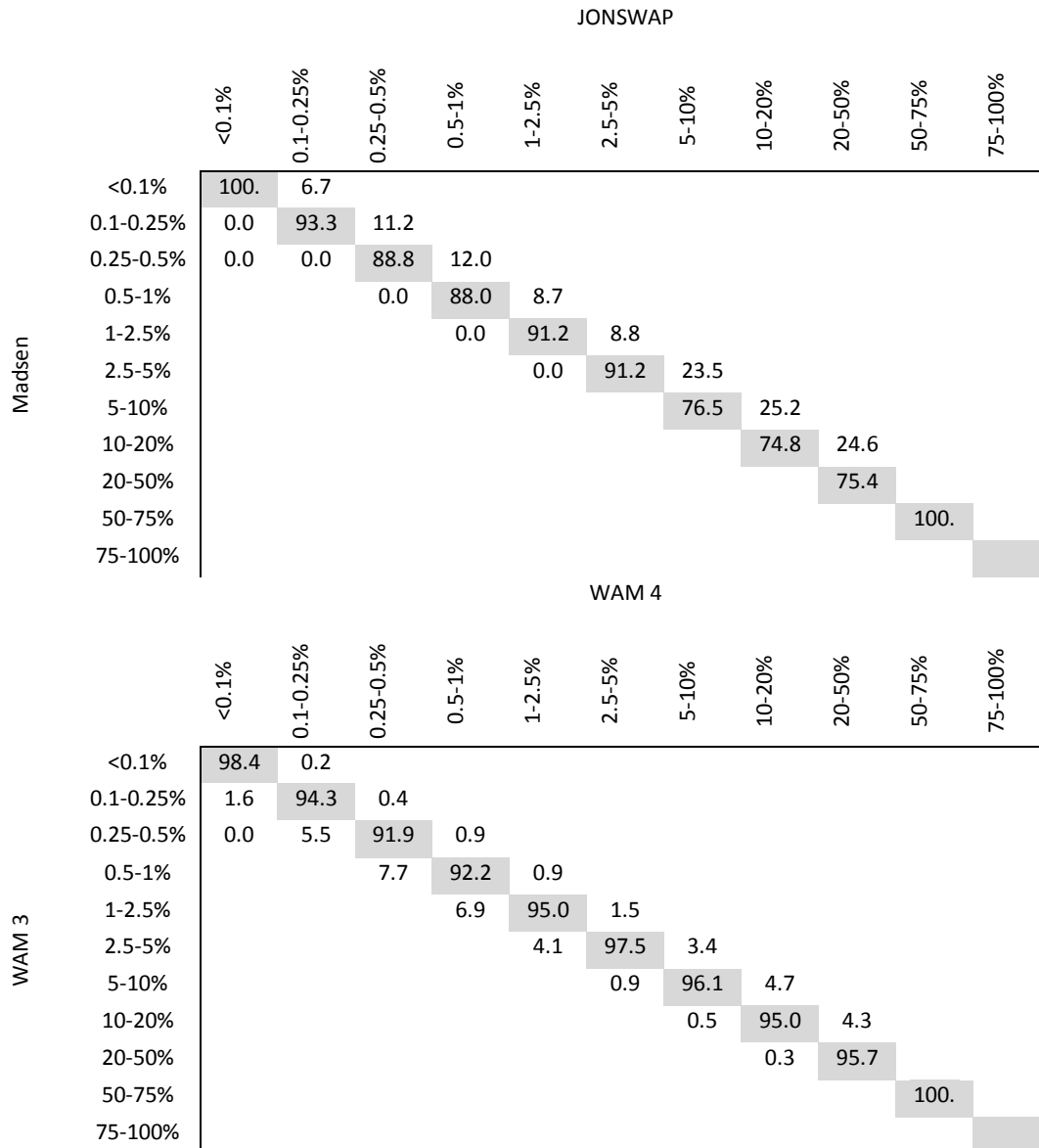


Figure C2.28. Similarity matrices for location #4. Values indicate the % match/mismatch of model predictions for each stipe breakage probability band across formulations of bottom friction (upper) and wind-generation/whitecapping processes (lower). Percentages are calculated as $100 \times x_{i,j} / \sum_{i=1}^{11} x_{i,j}$, where $x_{i,j}$ is the number of cells with predicted probabilities in probability band i in formulation 1 (corresponding to Madsen and WAM 3 respectively) and band j in formulation 2 (JONSWAP and WAM 4 respectively) and are therefore standardised to the sum-total of each column.

		JONSWAP										
		<0.1%	0.1-0.25%	0.25-0.5%	0.5-1%	1-2.5%	2.5-5%	5-10%	10-20%	20-50%	50-75%	75-100%
Madsen	<0.1%	100.0	11.7									
	0.1-0.25%	0.0	88.2	15.2								
	0.25-0.5%		0.0	84.8	14.4							
	0.5-1%			0.0	85.6	11.9						
	1-2.5%		0.0		0.0	88.0	16.4					
	2.5-5%					0.0	83.6	19.8				
	5-10%						0.0	80.2	22.7			
	10-20%								77.3	19.4		
	20-50%									80.6	14.6	
	50-75%										85.4	11.7
	75-100%											88.3
		WAM 4										
		<0.1%	0.1-0.25%	0.25-0.5%	0.5-1%	1-2.5%	2.5-5%	5-10%	10-20%	20-50%	50-75%	75-100%
WAM 3	<0.1%	98.3	0.3									
	0.1-0.25%	1.7	94.4	0.6								
	0.25-0.5%		5.3	91.0	0.8	0.0						
	0.5-1%			8.4	91.3	0.7						
	1-2.5%				7.8	95.0	1.3					
	2.5-5%					4.3	95.7	2.5				
	5-10%						2.9	96.3	3.9			
	10-20%							1.2	95.4	1.5		
	20-50%								0.7	98.3	0.9	
	50-75%									0.2	96.5	1.5
	75-100%										2.6	98.5

Figure C2.29. Similarity matrices for location #5. Values indicate the % match/mismatch of model predictions for each stipe breakage probability band across formulations of bottom friction (upper) and wind-generation/whitecapping processes (lower). Percentages are calculated as $100 \times x_{i,j} / \sum_{i=1}^{11} x_{i,j}$, where $x_{i,j}$ is the number of cells with predicted probabilities in probability band i in formulation 1 (corresponding to Madsen and WAM 3 respectively) and band j in formulation 2 (JONSWAP and WAM 4 respectively) and are therefore standardised to the sum-total of each column.

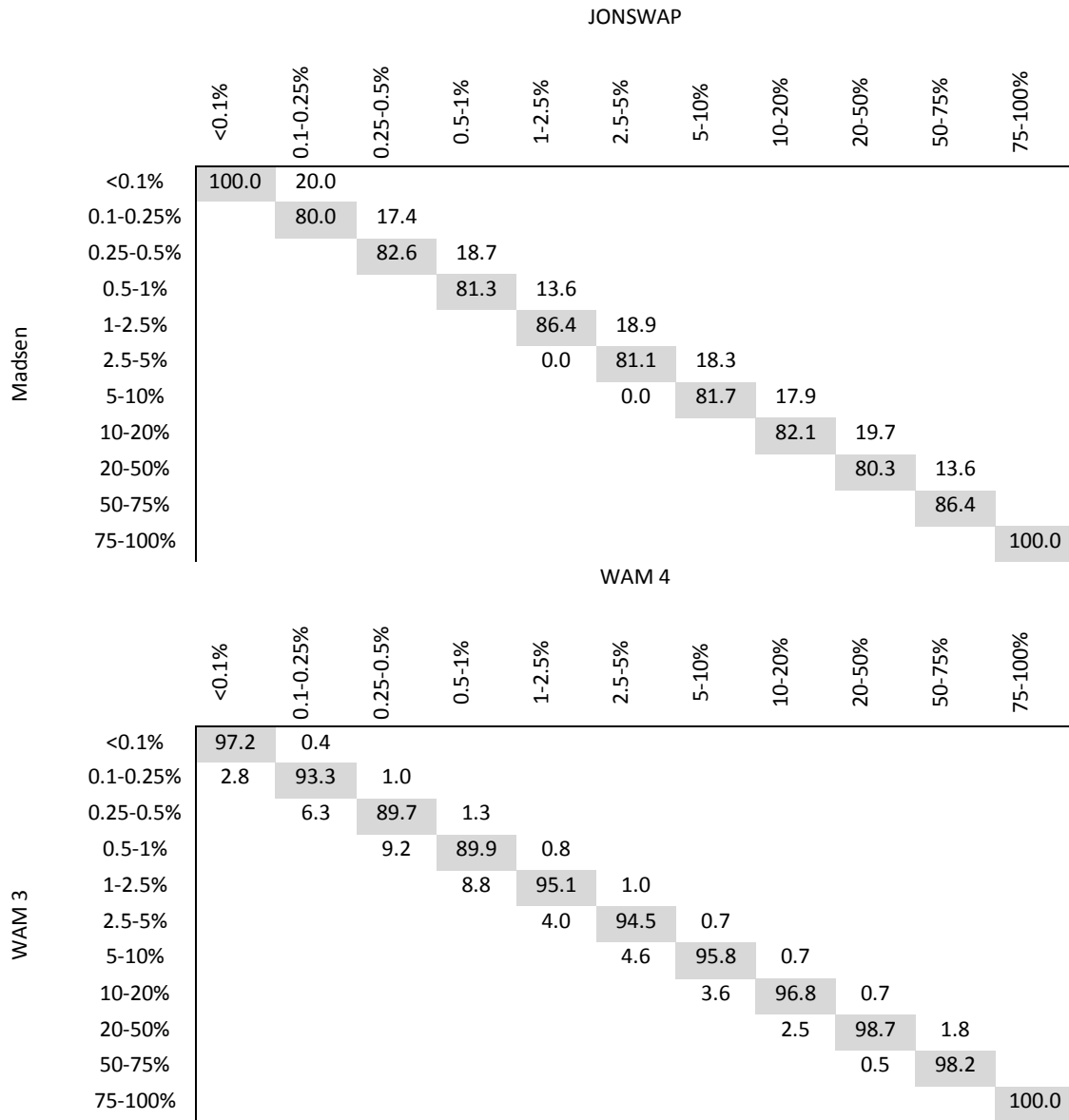


Figure C2.30. Similarity matrices for location #12. Values indicate the % match/mismatch of model predictions for each stipe breakage probability band across formulations of bottom friction (upper) and wind-generation/whitecapping processes (lower). Percentages are calculated as $100 \times x_{i,j} / \sum_{i=1}^{11} x_{i,j}$, where $x_{i,j}$ is the number of cells with predicted probabilities in probability band i in formulation 1 (corresponding to Madsen and WAM 3 respectively) and band j in formulation 2 (JONSWAP and WAM 4 respectively) and are therefore standardised to the sum-total of each column.

Appendix 3A - Additional partial dependency plots from Chapter 5

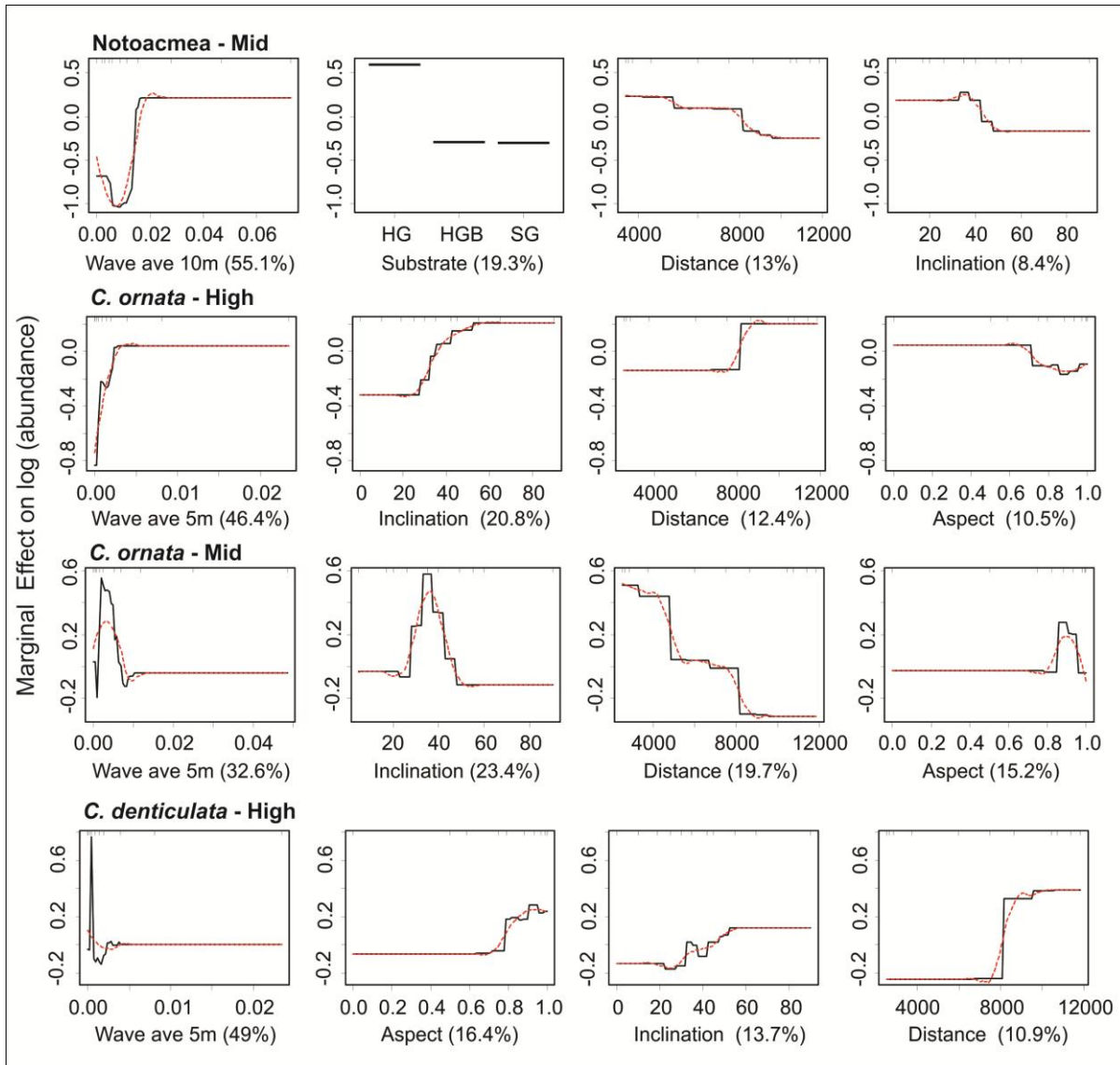


Figure A3.1. Partial dependency plots of BRT models for mobile invertebrate species where models achieved a $D^2 < 0.2$. Black lines illustrate the fitted function of the marginal effect of each predictor on the log transformed abundance, while dotted red lines indicate a smoothed fit to the fitted function. Values in parentheses next to x axis labels indicate predictor relative importance.

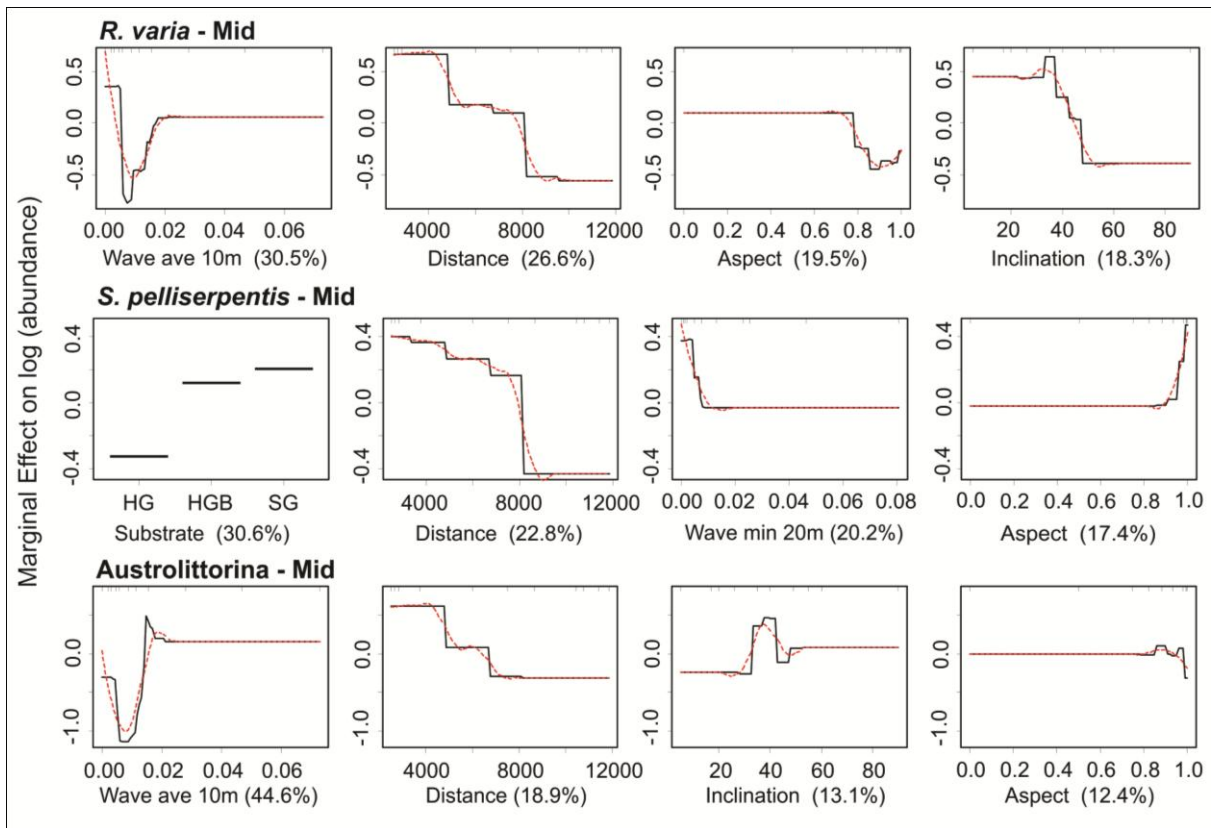


Figure A3.2. Partial dependency plots of BRT models for mobile invertebrate species where models achieved a $D^2 < 0.2$. Black lines illustrate the fitted function of the marginal effect of each predictor on the log transformed abundance, while dotted red lines indicate a smoothed fit to the fitted function. Values in parentheses next to x axis labels indicate predictor relative importance.

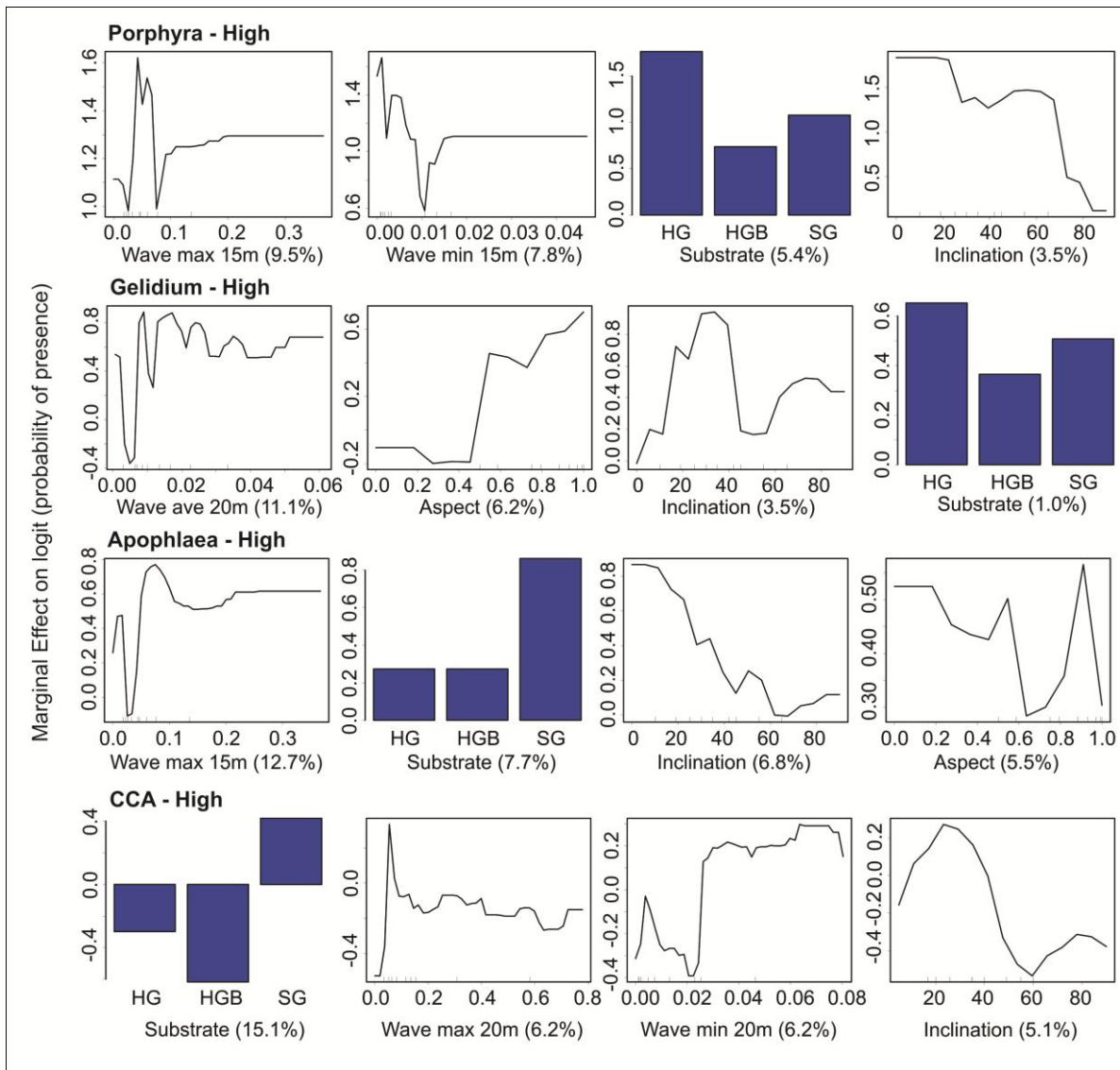


Figure A3.3. Partial dependency plots for high intertidal algal species presence/absence based on relationships obtained from random forests analyses for species models with κ -values < 0.5 . Plotted functions illustrate the logistic transformed probability of each species being present as a function of each predictor for the top four predictors ranked by predictor importance. Values in parentheses next to x axis labels indicate predictor importance.

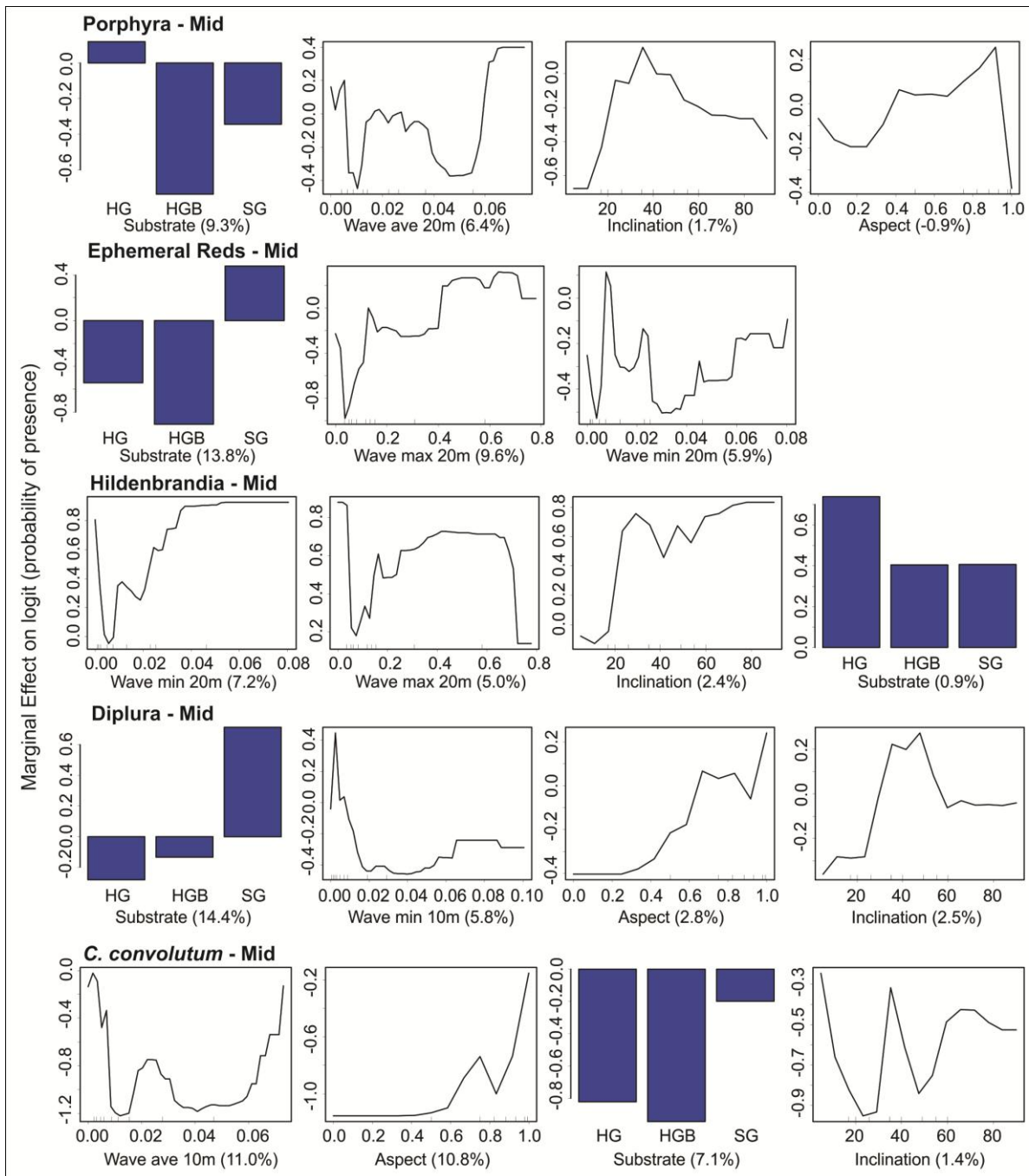


Figure A3.4. Partial dependency plots for mid intertidal algal species presence/absence based on relationships obtained from random forests analyses for species models with κ -values < 0.5. Plotted functions illustrate the logistic transformed probability of each species being present as a function of each predictor for the top four predictors ranked by predictor importance. Values in parentheses next to x axis labels indicate predictor importance.

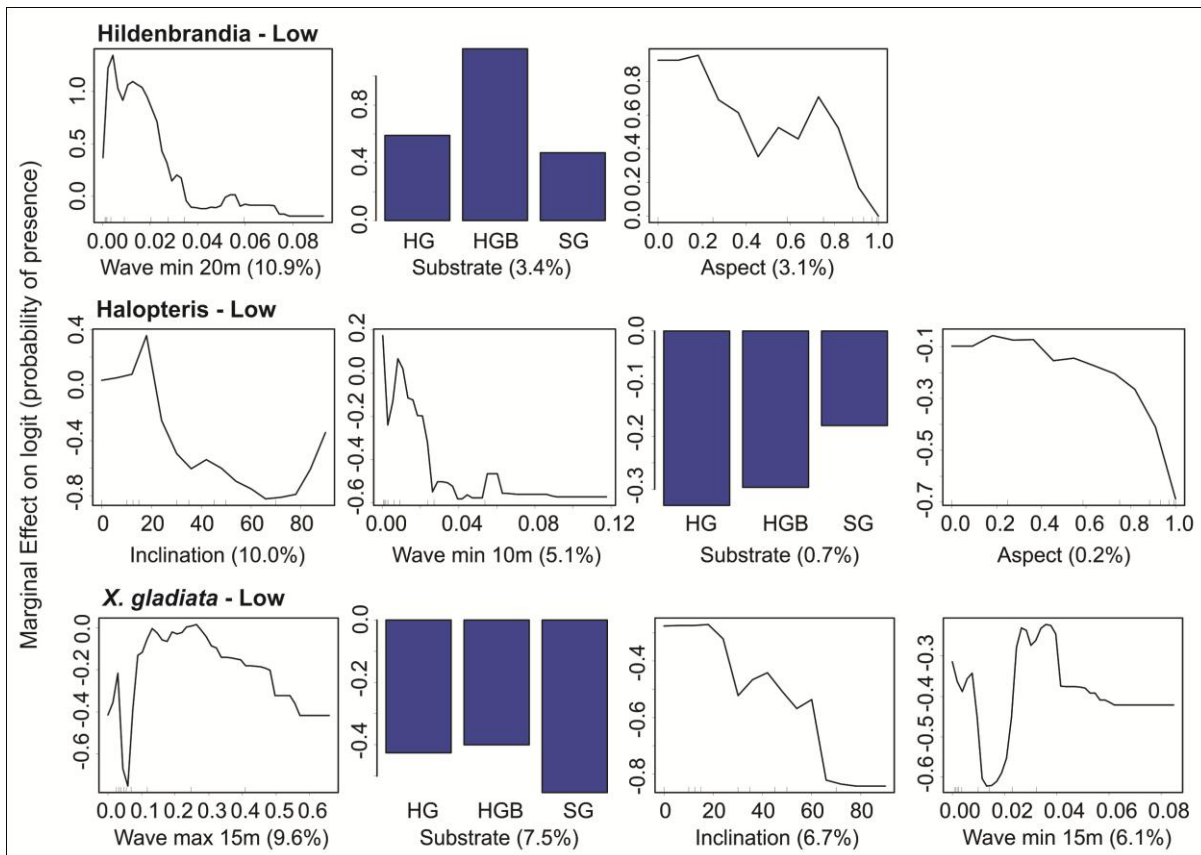


Figure A3.5. Partial dependency plots for low intertidal algal species presence/absence based on relationships obtained from random forests analyses for species models with κ -values < 0.5. Plotted functions illustrate the logistic transformed probability of each species being present as a function of each predictor for the top four predictors ranked by predictor importance. Values in parentheses next to x axis labels indicate predictor importance.

Appendix 3B – Additional data relevant to Mussels on the south coast

3B.1 – Description of data

Although the larger mussels *Mytilus galloprovincialis* and *Perna canalicula* were only observed singularly in south coast quadrats on a few occasions (Table B3.1) the smaller *Limnoperna pulex* was observed in 58% of high intertidal quadrats and 22% of mid intertidal quadrats. The majority of *M. galloprovincialis* and *P. canalicula* individuals were observed at Palmer Head and some individuals persisted for several seasons.

Table B3.1. Sighting location, quadrat details and date for observations of *Mytilus galloprovincialis* and *Perna canalicula*. Site abbreviations are BB – Breaker Bay, PH – Palmer Head and IB – Island Bay. * indicates same individual observed over multiple seasons.

<i>Mytilus galloprovincialis</i>		<i>Perna canalicula</i>	
Site – Height - ID	Survey	Site – Height - ID	Surveys
BB – M – 1	11/09	PH – L – 1	07/10
PH – H – 2	02/11*, 05/11*		
PH – H – 3	04/10*, 07/10*		
PH – H – 4	07/10		
PH – M – 1	05/11		
PH – M – 3	11/09*, 02/10*		
PH – L – 2	11/10		

3B.2 – Analysis of relationship between *L. pulex* and *C. brunnea*

The relationship between *L. pulex* % cover and *C. brunnea* % cover was investigated as initial observations suggested their abundances were correlated. Firstly the relationship between the presence/absence of *L. pulex* and *C. brunnea* % cover was investigated. Fitting a generalised linear model to *L. pulex* presence absence (binomial glm with logistic link function) in R v12.1 (R Development Core Team 2011) revealed a significant positive correlation ($R^2 = 0.078$, $z_{2,45} = 2.458$, $p = 0.014$), with *L. pulex* more likely to be present at higher % cover of *C. brunnea* (Figure B3.1).

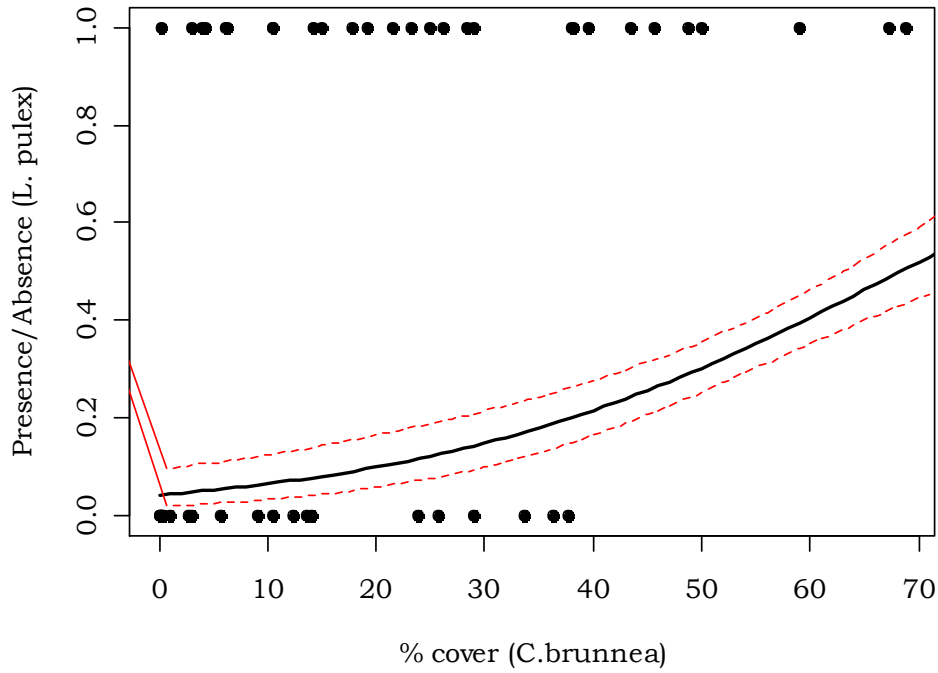


Figure B3.1. Presence/absence of *L. pulex* plotted against % cover of *C. brunnea*, along with the fitted GLM. The black line is the fitted relationship whilst the dotted red lines indicate the upper and lower 95% confidence interval of the fitted function.

Subsequently the relationship between *L. pulex* abundance and *C. brunnea* abundance was investigated. *Limnoperna pulex* % cover was $\ln(X+1)$ transformed to achieve normality and a generalised linear model (gaussian distributed errors with log link function) was fitted in R v12.2 (R Development Core Team 2011). A significant positive correlation ($R^2 = 0.50$, $z_{2,45} = 6.27$, $p = 1 \times 10^{-7}$) was found between *L. pulex* abundance and *C. brunnea* (Figure B3.2).

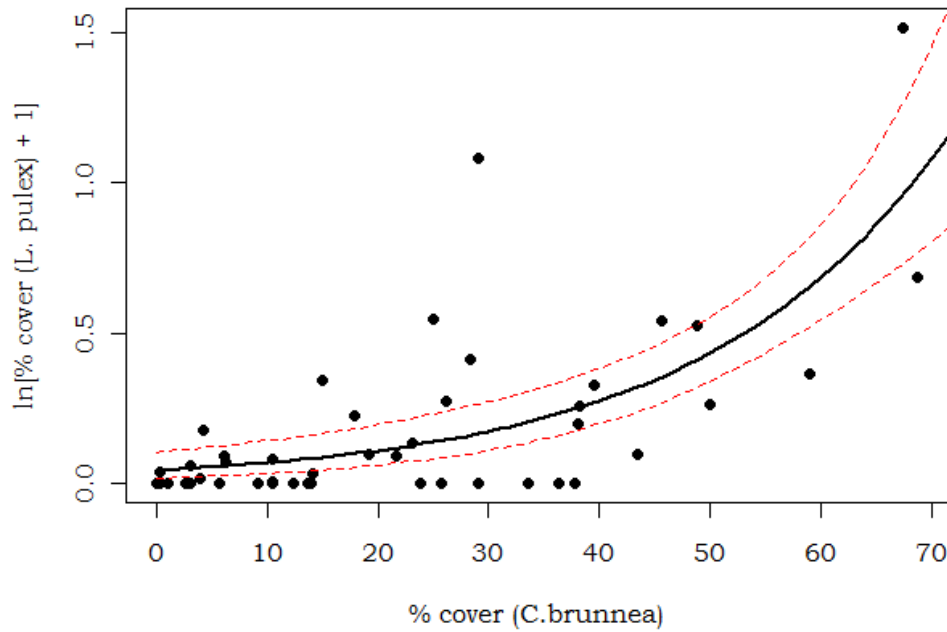


Figure B3.2. Log (X+1) transformed *L. pulex* % cover plotted against % cover of *C. brunnea*, along with the fitted GLM. The black line is the fitted relationship whilst the dotted red lines indicate the upper and lower 95% confidence interval of the fitted function.

This evidence suggests that the conditions necessary for *C. brunnea* are similar to those for *L. pulex*. However, whether *L. pulex* can survive under conditions that cause *C. brunnea* abundance to be low cannot be assessed from this information alone because it is possible that *L. pulex* choose to settle preferentially at locations with *C. brunnea*. Rather these relationships illustrate that *L. pulex* are capable of surviving under the same conditions as *C. brunnea* and are suggestive of increased capacity for *L. pulex* survival and growth under similar conditions that promote greater *C. brunnea* abundance.