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7	Multiple stressors, nonlinear effects and the implications of climate change impacts on
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24 ABSTRACT

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Global climate change will undoubtedly be a pressure on coastal marine ecosystems, not only 25 affecting species distributions and physiology but also ecosystem functioning. In the coastal 26 zone, the environmental variables that may drive ecological responses to climate change 27 include temperature, wave energy, upwelling events and freshwater inputs, and all act and 28 interact at a variety of spatial and temporal scales). To date we have a poor understanding of 29 how climate-related environmental changes may affect coastal marine ecosystems or which 30 environmental variables are likely to produce priority effects. Here we use time series data 31 (17 years) of coastal benthic macrofauna to investigate responses to a range of climate 32 33 influenced variables including sea surface temperature, southern oscillation indices (SOI, Z4), wind-wave exposure, freshwater inputs and rainfall. We investigate responses from the 34 abundances of individual species to abundances of functional traits and test whether species 35 that are near the edge of their tolerance to another stressor (in this case sedimentation) may 36 exhibit stronger responses. The responses we observed were all nonlinear and exhibited 37 thresholds. While temperature was most frequently an important predictor, wave exposure 38 39 and ENSO-related variables were also frequently important and most ecological variables 40 responded to interactions between environmental variables. There were also indications that species sensitive to another stressor responded more strongly to weaker climate-related 41 42 environmental change at the stressed site than the unstressed site. The observed interactions between climate variables, effects on key species or functional traits, and synergistic effects 43 44 of additional anthropogenic stressors have important implications for understanding and predicting the ecological consequences of climate change to coastal ecosystems. 45

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47 INTRODUCTION

Anthropogenically induced global climate change has profound implications for marine 48 49 ecosystems. Globally, the marine environment is changing rapidly (Hoegh-Guldberg & 50 Bruno, 2010; Doney et al., 2012) with unprecedented rates of change in sea water 51 temperature throughout much of the globe occurring in the last decade (Philippart et al., 52 2011). Changes also include the loss of sea ice cover in the Arctic and Antarctic, rising sea 53 level, increased storm events, more variable precipitation with more frequent intense rainfall events and earlier occurrence of springtime phytoplankton blooms (IPCC, 2007; Solomon et 54 al., 2007; Hoegh-Guldberg & Bruno, 2010). Although marine species and ecosystems have 55 responded to such variations in their environment throughout evolutionary history, a primary 56

57 concern is the rapid rate of change currently observed (Root *et al.*, 2003; Philippart *et al.*,

58 2011).

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60 Seminal reviews in the early 1990s (Fields et al., 1993; Lubchenco et al., 1993) summarised the understanding of climate change impacts on marine systems. At that time, research on the 61 62 effects of rising temperatures focused on organismal and, to a lesser extent, population level processes, suggesting that the distribution and abundance of species would shift according to 63 64 their thermal tolerance and ability to adapt. In 2006, Harley et al. suggested that for marine systems it was time to move on from effects of temperature alone, and identified a number of 65 66 other important aspects that deserved study, e.g., ocean chemistry and circulation, UV, and sea level rise. Despite this, many marine studies still focus on temperature predicting changes 67 68 in distributional boundaries of species and replacement of cold-water taxa by others with warm-water affinities, over decades (Southward et al., 1995; Holbrook et al., 1997; Sagarin 69 et al., 1999), associated with El Nino-Southern Oscillation events (Pearcy & Schoener, 1987; 70 Dayton et al., 1999), and extreme events (Wethey et al., 2011; Smale & Wernberg, 2013; 71 Boucek & Rehage, 2014). 72

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In coastal environments, the effects of waves and freshwater inputs on benthic processes can be expected to have important consequences. Moreover coastal environments are frequently high use areas by humans, impacted by multiple land and sea based human activities. In such cases, the potential for interaction between climate and other anthropogenic variables affecting responses exists (Harley *et al.*, 2006; Schindler, 2006, Walther, 2010) but these are not so frequently studied (Darling & Côté, 2008; Wernberg *et al.*, 2012).

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Efforts to manage and conserve living coastal systems in the face of climate change requires research that investigates community and functional attributes, synergistic effects with other anthropogenic variables, and ecological thresholds. While laboratory experiments can generally be used to investigate organism responses/sensitivities to single (or at most a few) variables at small scales, field-based manipulative experiments at an appropriate scale are generally impossible. Time series data offer the opportunity to develop and test general hypotheses and to observe correlative patterns that may be used for large-scale predictions.

- Within this study, we use a time series of 17 years in the abundances of coastal benthic
 macrofauna to investigate biological responses. The 17 years covers a time period of strong
 southern oscillation, with winter water temperatures that varied from 13 to 16 °C (Figure 1ac). The following hypotheses were investigated:
- The majority of responses will be nonlinear, and on occasion exhibit thresholds (i.e., a
 sudden drop in abundance or a change from increasing to decreasing abundance).
- Responses to many variables, not just temperature, will be observed and interactions
 between variables will drive the responses.
- 96 3. Species that are near the edge of their tolerance to another stressor will exhibit
 97 responses with a lesser degree of change of climate- driven environmental variables.
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 99 such that thresholds are only detected at more extreme conditions, than those detected
 100 for individual species.

We focus on benthic macrofauna as this group has been demonstrated to: affect benthic 101 microphyte communities and primary productivity (e.g., Thrush et al., 2006; Colen et al., 102 2008; Volkenborn et al., 2009); modify hydrodynamics, nutrient recycling and benthic 103 pelagic coupling (e.g., Eckman et al., 1981; Pilditch et al., 1997; Nikora et al., 2002; Lohrer 104 et al., 2004; Newell, 2004); and provide food for fish and birds. Benthic macrofauna are 105 frequently used throughout the world in marine health and quality indices (e.g., Alden *et al.*, 106 2002; Borja & Dauer, 2008; Villnäs & Norkko, 2011; Rodil et al., 2013). We move beyond 107 impacts to single species by considering effects on two key species which thus have the 108 potential to impact on the larger community (Harley et al., 2006; Thrush et al., 2009; Thrush 109 110 et al., 2014). Finally, we use biological trait analysis to focus on some key functional traits that would alter ecosystem function and, therefore, ecosystem services (Sara et al., 2014). 111

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113 MATERIALS AND METHODS

114 Macrofaunal Data

Data on macrofaunal abundances were available from two study sites in Mahurangi Harbour (174 degrees 45 minutes E, 36 degrees 30 minutes S), North Island, New Zealand. One near where a major river enters the harbour (hereafter called mud) and one further out towards the harbour entrance (called sand). The mud site had a sandy-mud substrate with up to 54% mud 119 (<63 μ m). The sand site generally had little mud and a higher percentage (up to 88%) of fine 120 to medium sand (63 to 500 μ m). Twelve replicate core samples (13 cm diam. by 15 cm 121 depth) were collected every three months at each site from July 1994 to April 2012. The 122 replicates were randomly allocated sample positions within 12 strata of equal size. Sites were 123 located in the low to mid intertidal (tidal range 2 – 3 m).

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Samples were sieved on a 0.5 mm mesh sieve and preserved in 50% IPA before being sorted to remove macrofauna. Macrofauna were identified to the lowest practical level (generally species, but at least to family level, with the exception of nemerteans and oligochaetes) and

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then counted.

Taxa were allocated to the following four functional groups based on biological traits: (1)
suspension feeder; (2) bioturbators (subsurface or surface dwellers that move particles and
pore water); (3) sediment stabilisers (sedentary surface dwellers or infauna that produce
protruding tube mats); and (4) sediment destabilisers (mobile surface dwellers that produce
holes, pits or mounds in the sediment surface).

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To identify individual responses of species that are often numerically dominant, four species 136 that were present at both sites were selected for analysis. When selecting these four we also 137 used criteria that ensured they covered a range of responses to mud content; from a 138 preference for sand, through neutral, to a preference for high mud content. Unfortunately, we 139 140 were unable to find a species with a preference for high mud content that occurred at both sites. Two of these species (Macomona liliana (Iredale, 1915) and Austrovenus stutchburyi 141 (W. Wood 1828)) have been identified as key species on New Zealand's estuarine intertidal 142 143 flats.

Macomona liliana is a deposit-feeding bivalve that lives 5 – 10 cm below the
 sediment surface as an adult and feeds on the surface, influencing the densities of
 other species, nutrient recycling and sediment oxygenation (Thrush *et al.*, 1997;
 Thrush *et al.*, 2006; Volkenborn *et al.*, 2013). For the functional group analyses it was
 allocated to bioturbation and sediment destabilisation. *Macomona* prefers sandy
 sediment and is sensitive to terrestrial sediment deposition and suspended sediment

(Thrush *et al.*, 2003; Thrush *et al.*, 2005; Ellis *et al.*, 2006; Anderson, 2008). It was
found in higher numbers at the sand site and its abundance at the mud site decreased
markedly over part of the time series, possibly as a response to increased sediment
deposition at this site.

- Austrovenus stutchburyi, the New Zealand cockle, is a suspension feeder living close
 to the sediment surface, influencing primary productivity and nutrient cycling (Thrush
 et al., 2006; Sandwell *et al.*, 2009). For the functional group analyses it was allocated
 to suspension feeding, bioturbation and sediment destabilisation. Austrovenus prefers
 a sand to muddy sand substrate and is less sensitive to terrestrial sediment deposition
 and suspended sediment (Thrush *et al.*, 2003; Thrush *et al.*, 2005) than Macomona.
- Anthopleura aureoradiata (Stuckey, 1909) is an anemone that lives on cockle shells.
 For the functional group analyses, it was allocated to suspension feeding, as it filters
 zooplankton from the water column. Anthopleura always occurred in higher densities
 at the sand site.
- *Heteromastus filiformis* (Claparède, 1864) is a capitellid polychaete that feeds at
 depth in the sediment and defecates on the surface. In New Zealand, it appears to be
 one of the Capitellidae more sensitive to pollution (Hewitt unpub data). *Heteromastus* is found across a wide range of sediment mud contents (Thrush *et al.*, 2003; Thrush *et al.*, 2005) but in this study was found in higher densities at the mud site. For the
 functional group analyses it was allocated to bioturbation and sediment
 destabilisation.

For each replicate core sample, the number of taxa and abundance of organisms in the four
functional trait groups were calculated. Then for each site/time, the average number of taxa,
abundance of the four functional traits and abundance of the four species was calculated.
Plots over time of the variables are presented in Figures 1h, 2 and 3.

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177 Environmental Data

178 Two indices of broad-scale temporal variability in climate were used (monthly estimates of

the southern oscillation index (SOI) and the mean sea level pressure difference between

180 Raoul and Chatham Islands (Z4, which represent the strength of westerly wind patterns).

Monthly sea-surface temperature (SST) records were available until April 2011 from the 181 nearby Leigh Marine Laboratory (University of Auckland). Monthly rainfall records were 182 available from NIWA's CliFlo website, for a site (-36°26'3.66", +174°40'3.58") south of 183 Warkworth, 10 km from the harbour. Daily discharge values for Mahurangi River were 184 obtained from Auckland Council. This data was used to calculate an average monthly 185 freshwater discharge volume. Wind exposure for both sites was calculated using input 186 records of wind measurements. The wind rose data was used for both sites (mud and sand), 187 assuming a constant wind field across the study domain. For each site the fetch was measured 188 from a map in eight cardinal directions. Wind speed in km.h⁻¹ was binned into these eight 189 classes, squared and multiplied by the fetch values to generate wave disturbance from eight 190 directions (Burrows et al., 2008). 191

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As macrofaunal core data was collected every three months, corresponding physical data for
each month was extracted for all physical variables (SOI, Z4, SST, wind exposure, freshwater
input and rainfall). Plots of the information are available in Figure 1a-g.

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While a 17 year time period is not long, the variables we use are likely to exhibit extremes in 197 a short time series. For example, although the Pacific Decadal Oscillation occurs over 60 – 198 199 70 years, NZ has undergone a shift within our time series. Moreover, changes in the intensity and strength of El Nino/La Nina, events (one of the strongest climate oscillations on earth) 200 201 occur around New Zealand at much shorter time scales and control wind, rainfall and ocean upwelling and thus influence coastal ecosystems. A very intense El Nino event occurred in 202 1998/1999 and annual mean sea level pressure for 1996, 1998, 2007, 2010 and 2012 differed 203 from the average over the 1961 – 1990 period by 2 standard deviations. A series of datasets 204 205 were searched to provide evidence that the time period of our data did encompass environmental fluctuations that were similar to longer time periods. Air temperature and 206 rainfall were available from a nearby site from 1972, SOI was available from 1876 and Z4 207 was available from 1938. Maxima, 90th percentiles, 10th percentiles and minima were 208 calculated for each time period (Supporting information S1). While the monitored time 209 period did not encompass the maximum or minimum of the longer SOI or Z4 time series, the 210 90th and 10th percentiles were similar, and the maximum and minimum found for the SOI and 211 Z4 data from 1972 (40years) were similar to those observed in our shorter time period. The 212

monitored time period also encompassed the daily rainfall and the daily minimum and
maximum temperatures from 1972- 2012.

215 Statistical Analysis

216 Regression trees were used to investigate responses to environmental drivers (Breiman et al., 1984; De'Ath et al., 2000). Initially slow to be used in ecology, their ability to deal with non-217 218 linear relationships and interactions has seen their use increase markedly since 2000. Trees explain variation in a single response variable by repeatedly splitting the data into two more 219 homogeneous groups, using the best explanatory variable in each case. Regression tree 220 221 analyses were conducted for each site separately, using the rpart package (Therneau *et al.*, 222 2014 available in R (R Core Team, 2013)). Tree growth was constrained to have a minimum of 20 observations in a node (group) before attempting a split; the split had to increase the fit 223 (represented by the R^2) by > 0.03 and each terminal node (final most homogeneous group) 224 had to contain at least 6 observations. Tenfold cross validation was used to prune and 225 produce the optimum tree. 226

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Due to correlations between SOI and Z4, the regression trees were constrained to only use whichever of these appeared first in the tree. Lagged variables were included, but once the lag of a variable was chosen, subsequent tree structure was constrained to using that lag (full tree structures are given in S1). As regression tree analysis does not have any distributional assumptions, no transformations were used.

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As regression trees will split the data into trees even if a linear model would fit the data 234 (Breiman et al., 1984), models were checked to determine whether the regression tree 235 approach was valid by: (1) comparing the % explained by the regression tree (1 – relative 236 error) with a linear multiple regression (model deviance/total deviance); (2) visual inspection 237 of residuals from a linear multiple regression and (3) scatter plots highlighting the regression 238 tree splits. Multiple regression models were derived using generalised linear modelling 239 techniques (normal or poisson error structures) with backwards selection. If these models 240 explained as much variation as did the regression tree, we would assume that no 241 242 nonlinearities, thresholds or interactions occurred.

244 RESULTS

245 *Hypothesis1- were responses to environmental variables linear?*

No. Multiple linear regression models explained less of the variability than the regression

trees for all but *Anthopleura* at the mud site, which had very low abundances and was not

well explained by either method (Table 1). *Anthopleura* at this site was thus dropped from

further analysis and discussion. The increase in % explained by the regression tree approach

ranged from 4% (sediment stabilisers at the mud site) to 41% (sediment destabilisers at the

mud site) with an average increase of 25%. The magnitude of change in densities (highest

group – lowest group as a % of the average, Table 1), predicted by the first three tree levels,

varied from 30.1 - 171.8% at the mud site and 29.8 - 173.1% at the sand site.

254 Hypothesis 2- which variables were most important and did interactions occur?

Similar results were found at both sites. SST was the environmental variable most likely to form the first split, followed by SOI or wave exposure (Table 2). These first splits explained % magnitude changes from 15 to 123 (Table 1), leaving between 18 to 54% of the changes still to be explained. SOI was also most likely to form the second split. Wave exposure was the next most likely variable overall, whereas freshwater input was never identified as a driver within the first two nodes of a tree.

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262 There were no models that used all five environmental variables (i.e., waves, rainfall, freshwater, SST and either SOI or Z4). However, interactions between 4 environmental 263 variables did occur for bioturbators and Macomona at both sites and number of taxa and 264 265 Heteromastus at the sand site (Table 3). For example, wave exposure provided a first level split for bioturbators at the mud site, followed by SOI at the second level, freshwater at the 266 third level and SST at the fourth. Interactions between a single pair of environmental 267 variables only occurred for Austrovenus (SOI and rain) at the mud site and for suspension 268 269 feeders and Austrovenus (SST and SOI) at the sand site. Pairwise interactions generally involved SST with either SOI or rain, followed by SOI and wave exposure. No pairwise 270 interactions between waves and Z4, freshwater or rain were observed, nor between Z4 and 271 freshwater. 272

- Occasionally a tree would reuse a variable in another split further down the tree. Examination 274
- of the mean densities associated with these splits revealed that none of these were coincident 275
- with a monotonic change in the response variable (Table 4). For example, the number of 276
- destabilisers at the mud site had three splits associated with SOI, occurring at SOI values of -277
- 1.45, 0.55 and 1.05. The lowest mean abundances occurred between SOI values of 0.55 278
- 1.05, and the highest with SOI values >1.05. 279
- Hypothesis 3- comparison of sensitive species responses between sites 280
- Macomona at the mud site had highest densities when SST <14.1 °C (low winter 281
- temperatures), while at the sand site, high densities did not appear to be affected by SST at 282
- 283 all. Rainfall had an influence on lowest densities at both sites for Macomona, with lower
- splitting values at the mud site ($<77 \text{ m}^3/\text{s}$) than the sand site ($<223 \text{ m}^3/\text{s}$). Highest densities of 284
- 285 Austrovenus were found with a strongly negative SOI in the previous month at the mud site
- but at an even stronger negative SOI at the sand site. 286
- *Hypothesis* 4- *functional trait responses and number of taxa versus individual species* 287
- Functional trait groups did not produce less complex trees, interactions or non-monotonic 288 responses than individual species (Tables 3 and 4), although the variables selected as good 289 290 predictors did vary. Functional trait groups were more likely to have wave exposure as an important factor than individual species (8 nodes across all traits cf. 0 at the mud site and 6 291 versus 1 at the sand site). There was also no consistent difference between functional traits 292 and individual species in the magnitude of the change between highest and lowest values 293 294 predicted by the trees. For the sand site, the % magnitude change was greater for individual species than for functional traits (one sided t-test with equal variance, p = 0.0375), but there 295 was no significant difference for the mud site (one sided t-test with equal variance, p =296 0.2032).
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Number of taxa was the response variable best predicted at both sites (Table 1), with wave 299 exposure, temperature, ENSO and rainfall all important predictors of variation (Table 3). At 300 the sand site, wave exposure was the most important factor, with the highest number of taxa 301 found with more waves in years with a positive SOI (Table 5). Lowest numbers of taxa were 302 303 observed in years with a low numbers of waves. At the mud site, where waves were low, SST 304 was the most important factor. Highest numbers of taxa were observed with lower SST when

rainfall was high, lowest numbers were observed with higher SST and a strongly negative Z4.

306 DISCUSSION

307 Our results have important implications for how we should consider ecological responses to climate change. We observed responses to climate change at all levels from individual 308 309 species to community level responses such as species richness and functional traits. Interestingly, the number of taxa was the response variable best predicted at both sites, 310 suggesting that species richness has the potential to be strongly affected by climate change. 311 We observed indications that species that are near the edge of their tolerance to another 312 313 stressor may have a lower threshold. Thus, intact communities may be more resilient to climatic disturbances, and may minimize the risk of population collapses and biodiversity 314 315 loss due to climate change (Hughes *et al.*, 2003). Although the magnitude of these effects we observed were weak, they do imply that this is an important avenue for future research on 316 how communities respond to change. 317

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Our fourth hypothesis related to the potential for ecosystem level responses to be smoother than species-level responses, with fewer nonlinear, threshold responses and interactions between variables. We found no evidence of this, which does not bode well for the resilience of function in the face of climate change. This may have been a result of the time scales we were analysing over, only 17 years. Longer time scales may allow dispersal and recruitment of other species to build resilience in functional traits.

325

Definite nonlinear responses to environmental variables were observed (hypothesis 1), with 326 all but one of our ecological response variables being better explained by regression tree 327 models than multiple linear regression. These nonlinearities usually involved thresholds, with 328 329 highest or lowest densities of biological response variables found nearer to the centre of the observed environmental range, rather than occurring at either end. Importantly our results 330 suggest that responses are a result of interactions occurring between climate change-related 331 variables and highlight the potential for sudden changes. There is a body of marine literature 332 333 that suggest that interactive and non-independent effects may be important (Hoffman et al., 2003; Reynaud et al., 2003; Pörtner et al., 2005). 334

As per our second hypothesis, all trees had more than one level, demonstrating that 336 interactions occurred. While temperature was the most likely predictor forming the primary 337 338 split at both sites, ENSO variables and wave exposure were also frequently important. In coastal zones, wave disturbance is an important driver of species distributions (e.g. Hewitt & 339 Thrush, 2009; Pedersen et al., 2012; Tam & Scrosati, 2014). In particular, estuarine and 340 near-shore species may be exposed to synergistic effects where wave disturbance increased 341 by increasing storm frequency/intensity is further increased by changing water depth as sea 342 levels rise. Further, changes in broad scale processes such as wave climate can have 343 important implications for local ecological interactions. For example, field experiments have 344 demonstrated that wave climate influenced the strength of negative ecological interactions 345 346 among adult and juvenile bivalves (Thrush et al., 2000).

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Changes in the abundance of key species may result in far reaching effects, as frequently such 348 species perform more than a single function. For both sites, lower densities of Macomona 349 (up to 140% of average) were predicted to occur with increasing temperatures, in 350 combination with lower rainfalls and low SOI values. Similarly, low SOI values in 351 352 combination with lower rainfall were predicted to decrease densities of Austrovenus at the sand site, but at the mud site increasing temperatures would result in increasing densities. 353 354 These changes would result in differences in the way nutrients are processed and exchanged 355 between the sediment and the water column and the degree of primary productivity. Adult Macomona control macrofaunal community composition, pore water pressure gradients, the 356 357 presence of anoxic water at the sediment – water interface and nutrient fluxes (Thrush *et al.*, 2000; Thrush et al., 2006; Volkenborn et al., 2013; Thrush et al., 2014). Austrovenus, while a 358 359 lesser driver of macrofaunal community composition, does control primary productivity, 360 nutrient fluxes and sedimentation rates (Thrush et al., 2001; Thrush et al., 2006; Sandwell et 361 al., 2009; Hewitt & Cummings, 2013). A positive feedback loop has been demonstrated to exist between mud content, sediment chlorophyll a and Austrovenus density in clear water 362 363 that is broken when light levels are decreased (Thrush et al., 2014). Thus, changes in these key dominants may control the potential for threshold responses and regime shifts in 364 ecosystem functioning in response to land-use change induced sediment inputs into the 365 366 coastal zone.

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535 SUPPORTING INFORMATION

- S1: Maxima, 90th and 10th percentiles and minima of selected environmental variables for
 different time periods.
- 538 S2: Regression trees structure for each response variable at the two sites separately.
- 539
- 540
- 541 FIGURES
- 542 Figure 1. Time series plots of environmental variables and number of taxaat both sites.
- 543 Number of taxa is given as average per 12 cores (13 cm diam x 15 cm deep).
- 544 Figure 2. Time series plots of abundance of biological response variables at the sand site.
- 545 Abundance is average abundance of 12 cores (13 cm diam x 15 cm deep).
- 546 Figure 3. Time series plots of abundance of biological response variables at the mud site.
- 547 Abundance is average abundance of 12 cores (13 cm diam x 15 cm deep).
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Table 1. Percent explained by multiple linear regression vs regression tree models at each site. Blank cells are where final models explained < 10% of the variance. Also given is the magnitude of the difference between the highest value and lowest value group (as a % of the average) predicted by the tree down to three split levels (3S) and the first level only (1S).

Mud site					Sand site			
Linear	Tree	3S	1 S	Linear	Tree	3S	1 S	
Austrovenus 13	23	172	123		30	173	79	
Heteromastus	30	94	69	14	23	105	63	
Macomona 19	41	146	88		27	107	86	
Anthopleura				16	33	168	99	
Stabilisers 17	21	146	111		23	126	76	
Destabilisers	41	116	93		38	58	34	
Suspension 16 feeders	40	108	85		22	94	52	
Bioturbators	39	96	79		30	65	46	
No. of taxa 24	42	30	15		39	30	17	
0								

Table 2. Variables driving the first two nodes in the regression trees summed over all
response variables at each site. Supporting Information S2 shows the complete tree for each
variable at both sites.

	SST	SOI	Waves	Rain	Z4	Freshwater
Mud Site						
1st split	4	2	2			
2nd split		5	2	2	1	
Total	4	7	4	2	1	0

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Sand site

	1st split	5	2	1	1		
	2nd split	1	5	2	1	1	
	Total	6	7	3	2	1	0
559	-						
560							

Table 3. Environmental variables important for the regression tree models at each site. The
presence of two-way interactions are indicated by 'y', blank cells indicate no two way
interactions. T= SST, W = wave exposure, R = rainfall, F = freshwater.

1	I	1	1	T	SOI	SOI	SOI	F	R
SOI	W	F	R	Z4	W	F	R	R	Z4
							У		
			у				У		
У							У	у	
	У				У				
					у		У		
	У				У				
		у			У	У			
			у	У					у
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- Table 4: Environmental variables with splits occurring more than once in the tree. Where the
- lowest or highest densities of the response variable show a unimodal response, the range of
- the environmental variable is given.

Mud Site		
Response variable	Environmental variable	Range
Austrovenus	SOI	Lowest 0.15 to -1.35
Heteromastus	SOI	Highest -0.25 to -1.45
Macomona	Freshwater	
Stabilisers	Waves	Lowest 0.16 to 0.72
Destabilisers	SOI	
Suspension feeders	SOI	Lowest -0.7 to -1.65
Bioturbators	Freshwater	Lowest 0.69 to 0.31
No. of taxa	Rain	
Sand Site		
Response variable	Environmental variable	Range
Anthopleura	Z4	Lowest 53 to 19
Austrovenus	SOI	Lowest -0.75 to -1.45
Heteromastus	SOI	Lowest 0.45 to -1.15
Macomona	SST	
Stabilisers	SST	Lowest 19.3 to 14.3
Destabilisers	Waves	Highest 0.40 to 0.14
Suspension feeders	SST	Lowest 19.3 to 14.5
No. of taxa	SOI	Lowest 0.25 to 0.95

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- 569 Table 5: Summary of key environmental variables and split values identified at the mud and
- 570 sand sites for which highest and lowest values of response variables occurred.

Response	Muc	l site	Sand	1 site
variable	Highest abundance	Lowest abundance	Highest abundance	Lowest abundance
Anthopleura			SST lag <u>></u> 17.2	SST lag<17.2
			Waves<0.41	Z4 lag 53 to -19
Austrovenus	SOI lag <u><</u> -1.35	SOI lag > 0.15	SOI< -1.45	SOI -1.45 to -0.75

SOI>-0.25 Rain < 131.6 SST lag > 18.3	SOI lag<1.15	SOI lag <u>></u> 1.15 Rain<176.6
Rain < 131.6 SST lag > 18.3		Rain<176.6
SST lag > 18.3		
		SST <u>></u> 19.5
SST <u>≥</u> 14.1	Rain <u>></u> 223	Rain <223
SOI lag <u>></u> -1.15		SOI lag \geq -1.15
Rain <u><</u> 76.5		SST lag<18.1
SST <u>></u> 14.1	SST<14.3	SST <u>></u> 14.3
Waves 0.72 to 0.17		SOI <1.65
SOI lag ≥1.65		Waves>0.49
Waves<0.17	SST <u>></u> 14.5	SST <u>></u> 14.5
	Waves 0.13 to 0.40	Waves<0.13
	SOI lag≥0.4	
SST <u>></u> 14.1	SST<14.5	SST <u>></u> 14.5
Waves <u>></u> 0.17		SOI 0.95 to 1.65
SOI -0.7 to -1.65		
Waves<0.17	SST<14.5	SST <u>></u> 14.5
		SOI lag<1.25
		FW<0.64
		Rain<61.6
SST <u>></u> 15.7	Waves<0.14	Waves>0.14
Z4 lag<-26.5	SOI <u>></u> 0.95	
	SST ≥14.1 SOI lag≥-1.15 Rain \leq 76.5 SST \geq 14.1 Waves 0.72 to 0.17 SOI lag ≥1.65 Waves $<$ 0.17 SOI -0.7 to -1.65 Waves $<$ 0.17 SOI -0.7 to -1.65 Waves $<$ 0.17	SST ≥14.1Rain≥223SOI lag>-1.15 Rain≤76.5Rain≤76.5SST SST≥14.1Waves 0.72 to 0.17SST SST Maves<0.17





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