

Original Articles

Temporal and spatial variability in the cover of deep reef species: Implications for monitoring



Nicholas R. Perkins^{a,*}, Scott D. Foster^b, Nicole A. Hill^a, Martin P. Marzloff^a,
Neville S. Barrett^a

^a Institute of Marine and Antarctic Studies, University of Tasmania, Australia

^b Commonwealth Industrial and Scientific Research Organisation, Hobart, Australia

ARTICLE INFO

Article history:

Received 11 November 2016

Received in revised form 17 February 2017

Accepted 19 February 2017

Available online 6 March 2017

Keywords:

AUV

Benthic monitoring

Ecological monitoring

Imagery

Survey design

Sampling design

ABSTRACT

Imagery collected from Autonomous Underwater Vehicles (AUVs) provides a novel means of monitoring changes in benthic ecosystems over large spatial scales and depth ranges. However, for many benthic ecosystems there is little baseline data to quantify temporal and spatial variance for key indicator species. This information is crucial for isolating background “noise” from long-term “signals”. Here we quantify components of variance for five key deep-water sessile invertebrate species across four long-term benthic monitoring sites in a region undergoing strong climate-driven changes. We use linear mixed models to estimate the contribution of sources of spatial and temporal variance in species covers from empirical data. We then combine this information with projected long-term climate-driven changes in the cover of these groups and test the power of various survey designs to detect change through time. Large short-term temporal and spatial variability in the cover of a gorgonian octocoral results in high components of variance that limit the detectability of the projected long-term trend for this species. Conversely, for three of the sponge species high power is achievable with revisits to the four original sites every two years until 2060. By including more sites in the revisit design, high power can be achieved with less frequent revisits. For the fifth species, we find high power is unachievable due to the small trend predicted. Overall, we highlight how examination of components of variance in a system can aid in the selection of suitable indicators and the establishment of effective monitoring programs.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Marine benthic ecosystems are under increasing pressure from widespread threats such as climate change, over-fishing, pollution and invasive species (Jackson et al., 2001; Halpern et al., 2008; Hoegh-Guldberg and Bruno, 2010). These pressures can induce localised extinctions, changes in the distribution of species, including climate-driven range-shifts, and hence they affect local community composition (Poloczanska et al., 2013). Monitoring programs are essential to quantify the effects of these pressures and to assess the effectiveness of conservation measures such as marine reserves. Studies that cover large spatial scales over long time periods are required to robustly detect ongoing large-scale changes, such as those related to climate change (Brown et al., 2011). However, baseline information on abundance and natural

levels of variation in key benthic species is often lacking, in particular for deeper-water marine systems below SCUBA diving depths, which have been historically under-sampled.

Image-based methods provide a non-intrusive approach to sampling natural systems, with modern technologies such as remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) allowing the routine surveying of deeper benthic communities over large spatial scales. These approaches generate a large volume of imagery that has the potential to greatly enhance our understanding of these environments and our ability to monitor long-term changes. However, image-based underwater surveys have challenges: image scoring is time-consuming, and the effectiveness of AUV survey design (spatial and temporal replicates) to detect long-term changes remain largely untested (but see Ling et al., 2016).

Assessing approaches for appropriate sampling designs, and sub-sampling of acquired imagery, has been an area of recent research (Molloy et al., 2013; Foster et al., 2014; Perkins et al., 2016, 2017). This research has contained important messages regarding the level of within site sampling likely to be required to bring

* Corresponding author at: Institute of Marine and Antarctic Studies, Private Bag 49, University of Tasmania, Hobart 7001, Australia.

E-mail address: Nicholas.Perkins@utas.edu.au (N.R. Perkins).

uncertainty in percentage cover estimates down to an acceptable level. At a site-level this will involve consideration of the interplay between transect design (or number of transects), the image sub-sampling approach, the scoring approach for individual images, and the properties of target groups such as their mean cover and spatial distribution (Perkins et al., 2016). Broad-scale long-term ecological monitoring programs will typically deploy a survey design that involves multiple sites nested within regions of interest that are revisited through time (Larsen et al., 2001; Urquhart, 2012). Therefore, there is also a need to take into account variability introduced into the time-series of data that are produced across larger scales. Indeed, spatial and temporal variation in ecological dynamics is typically large for most indicators (Skalski, 2012) and can compromise the ability of monitoring programs to detect long-term trends in group abundance, or community composition (Urquhart and Kincaid, 1999; Larsen et al., 2001).

Monitoring programs generally have two concerns: (i) estimating status; and (ii) estimating trends. Information about status is gained through gathering data on the geographical distribution of biota, whereas information about trend requires repeat visits over time (McDonald, 2003; Urquhart, 2012). The best survey designs for status estimation will cover the spatial extent of the survey area more effectively by including as many sites as is practical within budgetary constraints. On the other hand, designs with the highest power for detecting trends include planned revisits to sites across the entire survey period (Urquhart and Kincaid, 1999). Under a restricted budget, program designers need to balance the trade-off between spatial replication and temporal revisits. Various designs, termed panel designs, exist that aim to provide a balance between increasing the spatial extent of surveys for status estimation, and the benefit of revisits to sites for trend estimation (Duncan and Kalton, 1987). A panel in this sense is a set of selected units, such as sites, that enter and leave the sample at the same time, for example by being visited in the same year (for a review of different designs see McDonald, 2003). Regardless of the panel design employed, understanding the components of variance across the system and the influence they can have on survey outcomes is an essential element in order to effectively design the monitoring program (Elston et al., 2011).

When considering a long-term monitoring program with multiple sites, the components of variance at a minimum include: (i) site-to-site differences (some sites have, on average, higher/lower measurements than others for all measurement times); (ii) temporal variance that is expressed at all sites for example due to a trend; (iii) inter-annual differences, some years are higher/lower than others for reasons not related to trend; and (iv) the residual variance (Larsen et al., 2001). Even for the best sampling schemes, if there is high inter-annual variation in the response that is not driven by the trend, then detecting the trend will be challenging at best (Urquhart and Kincaid, 1999; Larsen et al., 2001; Urquhart, 2012).

Here we use data collected from AUV imagery in the early stages of a long-term deep-water benthic monitoring program in order to quantify the components of variance and their influence on the programs ability to detect climate-change-driven trend. Strong climate-driven ocean changes in SE Australia over recent decades (Ridgeway, 2007) have resulted in a large range of species undergoing a poleward redistribution in the region (Johnson et al., 2011; Robinson et al., 2015; Marzloff et al., 2016a,b). Given forecasts for ongoing warming (Oliver et al., 2014), further range shifts are expected, with populations of sessile benthic invertebrates being no exception. We focus our study on five deep water benthic indicator species with distributions that span at least the extent of the east coast of Tasmania (James et al., 2017). We analyse the results of repeat AUV surveys conducted to date at four deep-water monitoring sites in order to estimate the components of variance for

these indicators. We then combine this information with predicted changes in abundance until 2060 (Marzloff et al., 2016b) to examine whether various revisit designs can detect the expected impacts of climate driven trends in abundance. Monitoring designs that vary in both the frequency of revisits and the number of sites included are simulated. Using the example of five key species in our study system, our aim is twofold: (i) to provide a baseline quantification of the components of variance in our system, in particular aspects of temporal variance, and (ii) to examine the power of various revisit designs to detect the declining regional trend in abundance predicted from the SDMs. While our focus is on key species in our study system, these species exhibit attributes common to many benthic taxa, and our approach and results will be informative for researchers aiming to establish benthic monitoring programs elsewhere.

2. Methods

2.1. Overview

The percent cover of five key deep-water invertebrate species was quantified in AUV imagery from repeat transects across four sites on the east coast of Tasmania, Australia (Fig. 1). The combined sessile invertebrate fauna below photic depth in this region often constitutes up to 100% benthic cover, however, few individual species exceed more than 2% of overall cover at any one survey location, and power to detect change is in part, a function of this rarity (Skalski, 2012). The species utilised here are representatives of the most abundant and readily recognised species in eastern Tasmanian surveys. They typify the species that may be monitored in any long-term program examining change in deep reef assemblages through time, and include a gorgonian, erect branching sponge, palmate sponge, massive sponge and a cup sponge species. Data on the percent cover of these species at four sites over two sampling events were analysed with generalised linear mixed models (GLMMs) in order to obtain estimates of the components of variance within this system for each species. Current cover estimates and predicted changes by 2060s derived from regional scale distribution models were combined to simulate scenarios of future changes in cover for our species. A set of monitoring designs were tested where the frequency of surveys and the number of sites revisited in any given panel varied. For each species, power was assessed by testing whether the climate trend induced by the predicted trend could be detected at any given point in time, or with any particular revisit design.

2.2. Data collection

AUV imagery was collected by the Australian government funded Integrated Marine Observing System (IMOS) program, which includes the long-term deployment of an AUV to monitor benthic ecosystems around Australia's coastline (Williams et al., 2012). This program was launched in 2007, with the intent of regular revisits to national reference sites as part of ongoing long-term benthic monitoring. We focussed our study on four sites on the east coast of Tasmania (Fig. 1) where repeat transects have been conducted: the western boundary of the Flinders Commonwealth marine reserve (CMR; 40°36'S, 148°35'E, mean depth 46 m), a deep water reef offshore from Bicheno in the Freycinet CMR (41°54'S, 148°26'E, mean depth 74 m), a site off the Lanterns on the Tasman Peninsula (43°08'S, 148°00'E, mean depth 50 m) and a site in the Huon CMR (43°37'S, 146°55'E, mean depth 62 m). The Flinders site was first surveyed in June 2011, and again in June 2013 (2 years apart); the Bicheno site in June 2011, and again in June 2014 (3 years apart); the Lanterns site in May 2012, and again in June 2014

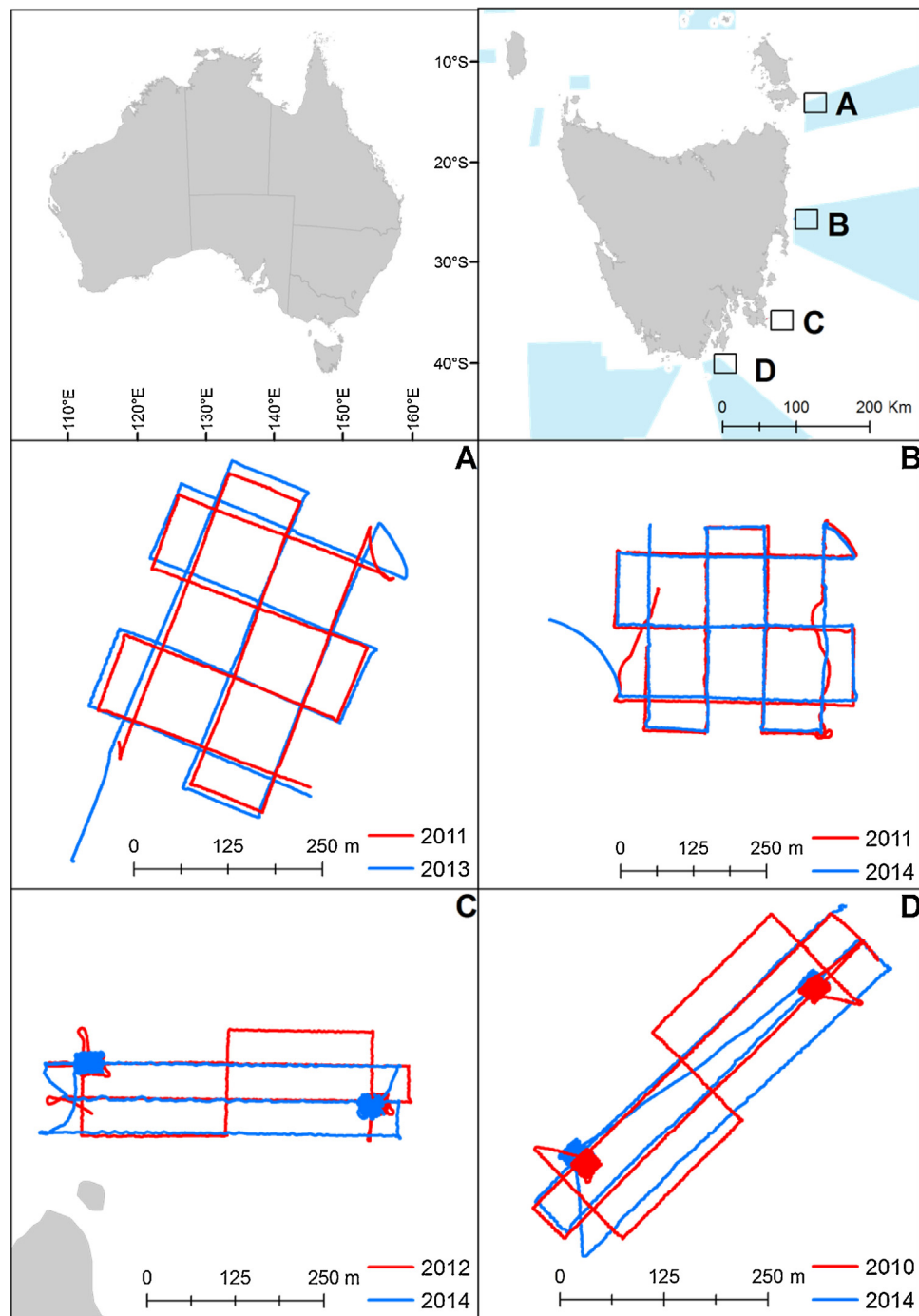


Fig. 1. The three sites and repeat transects on the east coast of Tasmania used for the study: (A) Flinders, (B) Bicheno, (C) the Lanterns and (D) Huon. Red lines mark the original transects and blue lines the repeat transects. Blue shaded areas indicate Commonwealth Marine Reserves. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(2 years apart); and the Huon site in June 2010 and again in June 2014 (4 years apart).

Five key 'morphospecies' were scored at each site across both repeat transects in order to examine changes over time and quantify components of variance. Morphospecies here refers to groups identified from imagery that have characteristically different morphologies and/or colours than others within the same taxonomic grouping. These morphospecies are characteristic in deep waters (>30 m) across the region and were selected due to being distinctive and having been identified in imagery across a large latitudinal gradient (see James et al., 2017). For example, taxonomic records indicate that the gorgonian species is likely to be *Pteronisia plumacea*

(Alderslade, 1998), a species typically found in depths greater than 50 m (Andrew, 1999). Hereafter we will refer to these morphospecies as species. It should be noted that these five species were selected and scored prior to any knowledge of their predicted responses under climate change (see Section 2.3 below).

Scoring of the imagery for each site was conducted using Transect Measure software, developed by SeaGIS (<http://www.seagis.com.au/transect.html>). The AUV typically collects thousands of images on each deployment. This imagery is then subsampled and scored by overlaying random points on each image. The number of points that fall on a species of interest within each image is recorded and used to calculate percentage cover, which can then be sum-

Table 1
Output from the species distribution model used to model climate-related changes in abundance of each of the five species over the four sites. Trends represent the change in probability of presence for each species and site between 2016 and 2060. Mean regional trend is simply the mean (and sd) of the three site values.

Site	Species	Site level trend in probability of presence (2016–2060)	Mean ($\pm$ sd) regional trend in probability of presence (2016–2060)
Flinders	Gorgonian sp.	−0.408	−0.237 $\pm$ 0.163
Bicheno	Gorgonian sp.	−0.3	
Lanterns	Gorgonian sp.	−0.216	
Huon	Gorgonian sp.	−0.022	
Flinders	Erect sponge sp.	−0.324	−0.229 $\pm$ 0.128
Bicheno	Erect sponge sp.	−0.342	
Lanterns	Erect sponge sp.	−0.176	
Huon	Erect sponge sp.	−0.072	
Flinders	Palmate sponge sp.	−0.192	−0.235 $\pm$ 0.031
Bicheno	Palmate sponge sp.	−0.266	
Lanterns	Palmate sponge sp.	−0.238	
Huon	Palmate sponge sp.	−0.242	
Flinders	Massive sponge sp.	−0.438	−0.312 $\pm$ 0.231
Bicheno	Massive sponge sp.	−0.406	
Lanterns	Massive sponge sp.	−0.438	
Huon	Massive sponge sp.	0.034	
Flinders	Cup sponge sp.	−0.052	−0.013 $\pm$ 0.099
Bicheno	Cup sponge sp.	0.044	
Lanterns	Cup sponge sp.	−0.132	
Huon	Cup sponge sp.	0.090	

marised over the site. Previous work has shown that for the target species, scoring 50 points within every 20th image along the transect should be sufficient to provide high precision in within site estimates of cover (see Perkins et al., 2016, 2017).

2.3. Predicted climate-driven trend

Projected climate-driven changes in probabilities of presence were contrasted across the five species and across the study sites, allowing an examination of various climate-change effect sizes. The expected change in the probability of presence for each of our species at each site until 2060 was obtained from the SDM developed by Marzloff et al. (2016b). Briefly, this consisted of modelling the current distribution of our 5 species (among others) using Random Forests models based on a set of environmental variables characterising local oceanographic and biogeochemical climatology from a downscaled global ocean circulation model (Chamberlain et al., 2012; Oliver and Holbrook, 2014) and seafloor features (e.g. depth, slope). Each model was fitted across a wide latitudinal gradient (25°S–45°S) and cross validated overall classification error rates were 0.14, 0.25, 0.12, 0.14 and 0.43 for gorgonians, erect sponges, branching sponges, massive sponges and cup sponges, respectively. Local changes in the presence of each species were then estimated using the distribution models under projected climate-driven ocean changes by 2060s based on dynamically downscaled climate change projections from a coupled ocean-atmosphere climate model taking account of CO₂ increases according to the IPCC AR4 ‘business as usual’ A1B scenario (Table 1; Matear et al., 2013). Changes in the average predicted probability of presence at each site were used as estimates of rates of change in abundance by adjusting the site level binomial proportions based on how far the sample was in the future for any given species. Rates of change were assumed constant over time. For clarity purposes, we did not account for uncertainty around these mean estimates of projected changes in probability of presence.

2.4. Generalised linear mixed modelling and simulation to determine power

Power analysis provides a useful way of assessing different possible survey and sampling designs, as it provides a relative measure of the ability of different designs to meet program objectives. Power analysis requires five components: (i) a number of samples over

time, (ii) measures of components of variation that are not the trend of interest, (iii) the effect size to detect, (iv) the significance level, and (v) the desired power (one minus the probability of making a type II error). Conventionally, significance levels are set to a default of 0.05, and power to 0.8. Here we are interested in exploring the components of variance not attributable to the trend and their effect on power over time.

While a trend may be non-linear over short time frames, longer term declines or increases in abundance may manifest a large linear component (Urquhart et al., 1993; Urquhart, 2012). Here, we treat the changes in abundance due to climate change taken from the SDM as acting linearly over time. To analyse our data we use an approach similar to that outlined in Urquhart (2012), where a linear mixed modelling approach is used to characterise the various components of variance. These components of variance can then be utilised to test the effect of differing levels of variation, and different temporal revisit plans on power to detect trend (see also Urquhart et al., 1993).

It is likely, particularly when considering large spatial scales, that individual sites will display deviations from the overall regional trend due to localised factors interacting with the general trend. This implies a situation where there will be a different slope at each site. The output of the SDM used (Table 1) shows that while most species are predicted to decline over the region under climate change projections, different sites are indeed likely to have different responses. In particular, expected declines were generally smaller in the more southern sites (Huon and Lanterns, Table 1) which are likely to act as a refuge for many species under poleward redistribution. It was therefore necessary to incorporate a site-specific trend term in our model for the individual site response to the trend, as well as an overall regional trend.

As our data are binomial (i.e. the number of points out of 50 that fall on a given species within an image), we use a generalised linear mixed model, with a logit link function. Also, there are two sources of residual variation: (i) image-to-image, that is, a within site residual variance for one survey, and (ii) transect-level residual variance, which captures the variance between transects conducted at different sites and at different times that is not accounted for by the site or temporal effects. The following model was used for each species:

$$Y_{ijkl} \sim \text{Binomial}(n, p(i, j, k, l)) \quad (1)$$

$$\log \left(\frac{p(i, j, k, l)}{1 - p(i, j, k, l)} \right) = \mu + \lambda_i + \beta + j * \alpha + T_j + E_{ij} + e_{ijk} \quad (2)$$

Where: i indexes site

j indexes year

k indexes transect

l indexes image

μ = mean parameter

λ_i = the site effect

β = the slope of the linear time trend over years for the region

α = deviations of each site from β

T_j = random time effect not captured by the linear trend

E_{ij} = random residual for transect-to-transect error

e_{ijk} = random residual for image-to-image binomial sampling error within a transect

and: $T_j \sim N(0, \sigma_{YEAR}^2)$, $E_{ij} \sim N(0, \sigma_{RESID.TRANS}^2)$, and $e_{ijk} \sim N(0, \sigma_{RESID.IMG}^2)$.

All modelling was conducted using the glmer function in the lme4 package in R (Bates et al., 2015b). Site (λ_i) was treated as a fixed effect in order to gain unbiased estimates of the intercept (i.e. mean percent cover for each species) at each site. The time effect (T_j) and the residual variance (E_{ij}) were treated as random effects. Models were run for each species based on the scored data in order to gain estimates of the intercepts (i.e. mean percentage cover for each species at each site), and the estimates of components of variance: time (σ_{YEAR}^2), and the transect-level residual variance ($\sigma_{RESID.TRANS}^2$). The initial models based on the empirical data excluded the trend effects β and α which corresponds to the assumption that any changes captured by our time component T_j represents inter-annual variation as opposed to long-term trend.

Our model and simulation based approach aims to incorporate the best information currently available. While more complex models, that allow better estimates of temporal or spatial correlation (e.g. geostatistical random effects models) may be appealing, the current scope of our data does not support such analysis. It should also be noted that variance components are themselves estimates, which have uncertainty, and several studies note the value of incorporating the uncertainty of the variance components into the power analysis (e.g. Sims et al., 2007; Elston et al., 2011). Our simulation approach takes samples from the estimated distribution of variance values. In this way we incorporate the uncertainty in our variance estimates, thereby integrating over this uncertainty with multiple simulations.

Temporal revisit plans tested were: every year, every 2 years, every 5 years and every 10 years. Data simulated with various revisit plans was then analysed with a GLMM to test whether the climate change trend could be detected. Our simulations took the below steps:

- 1 A design matrix was specified that delineated the panel revisit plan between 2016 and 2060.
- 2 For a given species, site and time in the future:
 - (a) Climate-driven changes in species abundance, as estimated by the SDM until 2060, were calculated for the given site;
 - (b) Random draws were taken from the relevant time (σ_{YEAR}^2) and site-level residual variance ($\sigma_{RESID.TRANS}^2$) for the particular species. Each draw was taken from a normal distribution with mean zero, and the standard deviation from the associated component of variance from the initial model.
 - (c) The mean intercept at the starting time from the initial model was added to the two random effects described in (b) to obtain a linear predictor. This linear predictor was then inverse-logit transformed in order to obtain the binomial proportion p (see Eq. (1)). This proportion was multiplied by the expected change in probability of presence calculated in (a) to gain the expected binomial proportion for any given image and species at that time.

- (d) The new binomial proportion calculated in (c) was used to generate the binomial outcomes for each image within the transect for a given species (i.e. Y_{ijkl}). This was done by taking a random binomial draw where $n = 50$ (the number of points used to score each image), and $p(i, j, k, l)$ is the binomial proportion calculated in (c) (see Eq. (1)). In this way e_{ijk} was incorporated.

- 3 A complete data set was built for each species, over all times and sites by repeating steps 2 (a)–(d).

For each design matrix, 1000 simulations were conducted, drawing new random components for each simulation. The output of each simulation was analysed using the generalised linear model outlined in Eq. (2). Power was assessed as the proportion out of 1000 simulations where a significant effect ($\alpha = 0.05$) was detected for the temporal effect β_j . That is, power was assessed as a function of the ability of the GLMM to detect the change. This procedure was carried out for each panel design and for each species.

A separate simulation was conducted to examine power accumulation with ongoing sampling through time. This simulation employed steps 2 and 3 as outlined above. However, data was generated based on annual revisits up until 2060. Power was assessed at each 5 year time-step into the future (i.e. 5, 10, 15, 20, 25, 30, 35, 40 and 44 years from 2016). For each time interval, 1000 simulations were conducted for each species. Power was once again assessed as the proportion of GLMM models run for each of the 1000 simulations where a significant trend for the region, β , was detected.

2.5. Power simulation with additional sites

Another factor influencing the power of a monitoring program is the number of sites included in the revisit design (Urquhart, 2012). In order to test the effect of including more sites in the panel we simulated a survey design with additional sites, approximately equally spaced between the original four sites along the east coast of Tasmania. Once again, predictions from the SDM were used to model the linear decline at each site. The location of these additional sites and the predictions from the SDM for these sites are outlined in Appendix A. We tested a design with all 21 sites and a subset of 10 sites. Both designs included the original four sites. For the simulated sites, 200 images were used as this represents an average number of images scored in the real transects.

In order to create starting covers at each simulated site, a weighted average based on the distance from the two closest of the four scored sites was calculated. For example, the Ansons Bay site (Appendix A), was assigned a cover that was forty percent of the Flinders site cover and sixty percent of the Bicheno site cover for any given species.

The same steps (1–3) outlined above were used, once again testing revisit designs of every 1, 2, 5 and 10 years. Power was once again assessed as the proportion of 1000 simulations where a significant temporal trend effect β_j was detected.

3. Results

3.1. Estimates of components of variance in our study system

Percent cover of all four sponge species included in this study proved to be reasonably stable over the two to four year period between survey times (Table 2). The stability in the cover of the sponge species over this time is reflected in the generalised linear mixed model estimate of temporal component T_j^* over all sites (σ_{YEAR}^2 ; Table 2) for the four sponge species, which were either zero or extremely low except for the massive sponge sp. which

Table 2
Empirical results from the scored transects at each site and estimates of the temporal and transect-level residual variance for each species from the generalised linear mixed model based on the scored data. Here the temporal variance (σ^2_{YEAR}) refers to the short-term temporal variance, not the long-term trend.

Species	Site	Initial transect cover (%)	Repeat transect cover (%)	$\sigma^2_{\text{RESID. TRANS}}$	σ^2_{YEAR}
	Flinders	0.03	0		
Gorgonian sp.	Bicheno	3.40	1.45	0.1778	0.0896
	Lanterns	2.47	0.58		
	Huon	0.60	0.83		
	Flinders	1.63	2.26		
Erect sponge sp.	Bicheno	0.95	0.97	0.0039	0
	Lanterns	1.67	1.53		
	Huon	0.36	0.34		
	Flinders	1.36	0.79		
Palmate sponge sp.	Bicheno	0.24	0.52	0.0456	0
	Lanterns	0.62	0.82		
	Huon	0.14	0.17		
	Flinders	0.008	0.008		
Cup sponge sp.	Bicheno	0.42	0.32	1.0701e-13	2.4923e-14
	Lanterns	0.25	0.29		
	Huon	0.23	0.21		
	Flinders	0.49	0.38		
Massive sponge sp.	Bicheno	0.51	0.62	0.0046	0.0005
	Lanterns	0.39	0.59		
	Huon	0.35	0.36		

had a very small component of inter-annual variance. In contrast, the time estimate for gorgonian sp. ($\sigma^2_{\text{YEAR}} = 0.0896$; Table 2), was much higher than for any of the sponge species reflecting the short-term variability in cover. A large decline in abundance was observed for the gorgonian species at three of the sites (Flinders 100% decline, Bicheno 50% decline and the Lanterns 75% decline) and a 40% increase was observed at the Huon site (Table 2).

The residual variance due to transects being conducted at sites at different times ($\sigma^2_{\text{RESID. TRANS}}$; Table 2) varied among the species by several orders of magnitude. The estimate for transect-level residual variance was an order of magnitude higher for the gorgonian species than any of the four sponge species. This reflects the afore-mentioned contrast in site level responses between the initial and repeat transects. The palmate sponge sp. had a much higher transect-level residual variance than any of the other sponge species, with fluctuations in cover between survey times recorded for Flinders (approx. 40% decline) and Bicheno (approx. 50% increase; Table 2).

3.2. Simulation results: power to detect the regional climate change trend depending on revisit design

Our simulations treating the four original sites as a panel showed that high power (>80%) could be achieved in detecting a regional trend for three of the sponge species (erect sponge sp., massive sponge sp. and palmate sponge sp.), provided the panel of four original sites were visited at least every 2 years up until 2060 (Fig. 2). We provide the outputs of one simulation in the Supplementary Materials, which highlights how the current variance estimates are likely to influence long-term survey results over these four sites. Both the erect sponge sp. and massive sponge sp. had low inter-annual temporal variance and residual transect-level variance estimates (Table 2), and reasonably strong regional trends for declining abundances (Table 1). For the erect sponge sp., >80% power could still be achieved with repeat surveys conducted every 5 years. For the palmate sponge sp., which exhibited relatively high transect-level residual variance, power declined markedly when sites were visited less frequently than every two years. This is despite the palmate sponge sp. having a zero estimate for unexplained temporal variance. For the gorgonian species, which exhibited high inter-annual

variance and high residual transect-level variance, greater than 50% power could not be achieved, even when visiting the four sites every year until 2060. Power also remained very low regardless of the revisit design for the cup sponge sp., which had low and varied projected site-level trends and hence an extremely low mean regional trend, making detection problematic.

Including more sites in the panel increased power for all species when equivalent temporal revisit designs were employed (Fig. 2). For the erect sponge sp. and massive sponge sp. >80% power was achieved with revisits of every 10 years with both 10 and 21 sites in the panel. However, 21 sites were required to reduce the revisit frequency to every 5 years for the palmate sponge sp. Adding more sites had the most pronounced effect on power for the palmate sponge sp., for which high power could be achieved with a revisit design of every 5 years with 21 sites, and every 2 years with 10 sites. For the cup sponge sp., even with 21 sites and annual visits the small regional trend could not be detected with high power. For the gorgonian species, only with the most intensive panel and revisit design (annual revisits and 21 sites) could the regional trend be detected with power >80%.

When considering the accumulation of power over time with annual revisits for each species (Fig. 3), power accumulated relatively quickly for the erect sponge sp. and massive sponge sp., with >80% power being achieved in a shorter time frame when more sites were employed (e.g. approximately 15 years with 21 sites as opposed to 25 years with 4 sites). For the palmate sponge sp., power accumulated more slowly, and >80% power was not reached until after approximately 25 years, regardless of the number of sites. For the gorgonian species power accumulated very slowly over the survey period and required the largest number of sites tested (21 sites) in order for >80% power to be achieved. For the cup sponge sp. power remained low across the entire survey period for all number of sites, although it did accumulate more rapidly with more sites.

4. Discussion

Given the rapid increase in the effects of climate change on ecosystems globally, there has never been a more important time to establish question-driven, statistically designed monitoring programs (Field et al., 2007; Lindenmayer and Likens, 2010). An

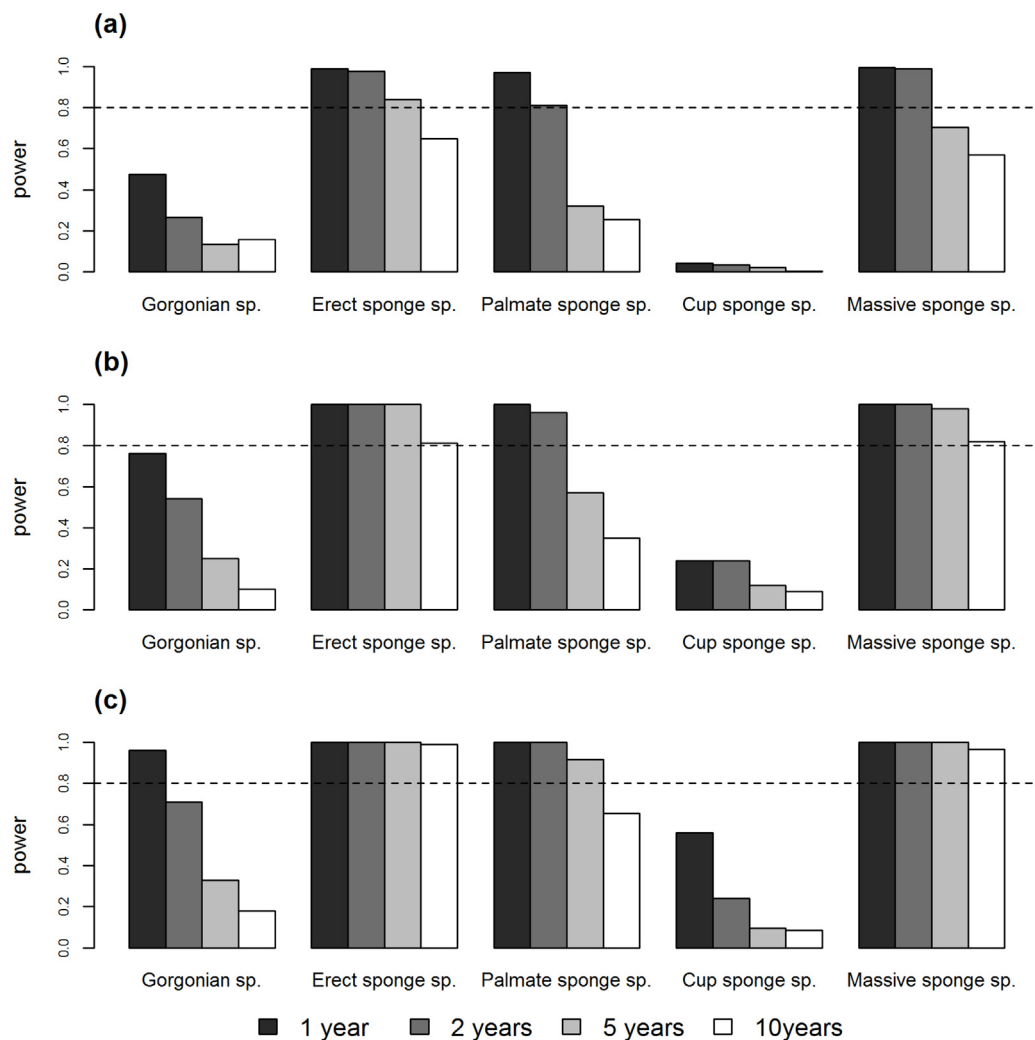


Fig. 2. Power of various revisit designs to detect the regional climate change trend for each of the five species when surveying from 2016 to 2060. (a) A panel design based on the original 4 sites; (b) A panel design based on 10 sites; and (c) A panel design based on 21 sites. The dashed line marks 80% power.

essential early component of an effective monitoring program is the determination of sample sizes that take into account both spatial and temporal replication as well as within-site measurement error (Skalski, 2012). Here we build on previous work examining the level of within site sampling required (Perkins et al., 2016, 2017). We turn consideration to temporal aspects of variation in our data and the potential influence that these components of variance have on the power to detect predicted climate-change driven trends (see Marzloff et al., 2016b). Our results provide the first assessment of the temporal variability in deeper water ecosystems in our study region. We find that the four sponge species assessed all display relatively low levels of short-term temporal variance, whereas the gorgonian species showed a high variability in cover over the survey period, and a corresponding larger temporal variance. Our simulations show that the temporal revisit plan necessary to deliver >80% power for the sponge species varied, with the predicted regional trend and site-deviations from this trend, and the residual variance all playing important roles in determining the revisit design necessary for high power. These findings indicate that early and rigorous statistical assessment of a monitoring program can aid in both the

selection of suitable indicators and the survey design necessary to adequately monitor them.

4.1. Estimates of components of variance in our study system

Our results regarding the levels of temporal variance across the four sites studied provides the first assessment of shorter-term (2–4 years) stability in the cover of five key deep-water species. These results therefore not only provide interesting ecological insights into the dynamics of our study system, but also vital baseline data for long-term monitoring. Monitoring designs for deep water reef systems must ensure adequate within-site sampling for taxa which typically have very low cover (<2%; Perkins et al., 2017), as well as incorporating information about larger-scale spatial and temporal variability. Deeper meso-photic and sub-photic marine ecosystems are often thought to show considerable stability compared to shallower ecosystems, in particular due to the less dynamic nature of physical factors such as exposure and temperature anomalies in deeper water (e.g. Slattery et al., 2011). However, very little is known about the temporal variability of sponges and many other invertebrates, even in shallower ecosystems (Berman and Bell, 2016). Some studies indicate a high degree of stability in abundance and slow growth rates (e.g. Hughes, 1996), while other studies have found dynamic seasonal cycling in composition and abundance (e.g. Berman and Bell, 2016). All of our four sites were surveyed in

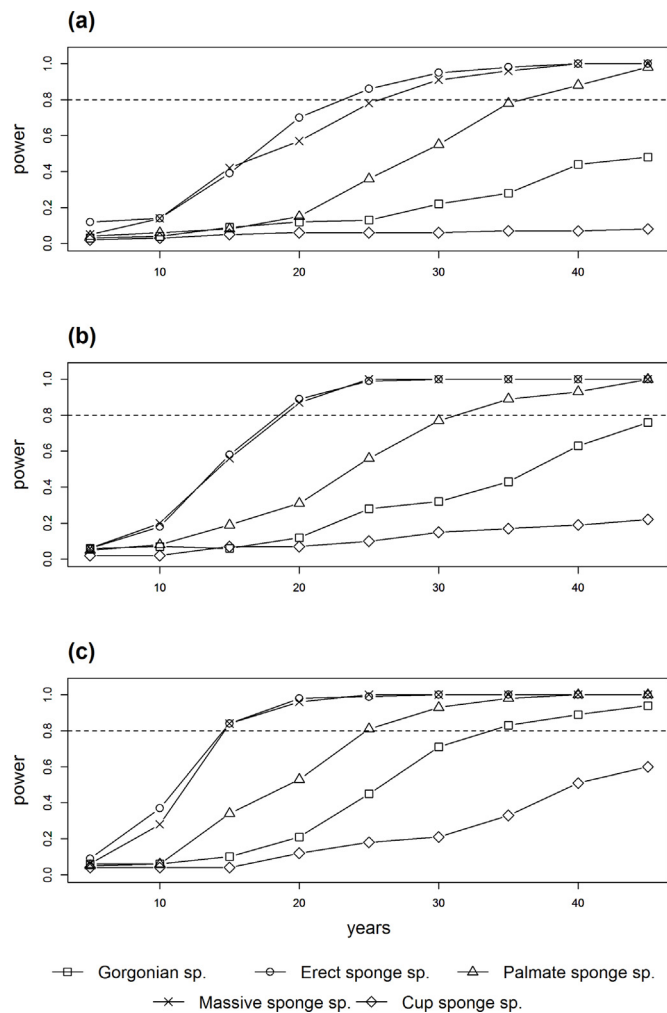


Fig. 3. Power accumulation over survey time for each of the five species, with (a) 4 sites; (b) 10 sites; and (c) 21 sites in the panel. Power was calculated based on annual revisits. The dashed line indicates 80% power.

Tasmanian winter, and therefore our results are likely to display minimal amounts of within-year seasonal fluctuations in abundance of our selected species if they do occur. We found differences in abundance of some of the sponge species between survey years. However, some of this difference is likely to be accounted for by sampling variability. The lack of any time effect found for two of our sponge species, and small effects found for the other two, indicate a high degree of annual stability in the cover of these species across the region. Whether this pattern holds true for other sponge species in our study system requires further research.

We observed a large variability in the cover of the gorgonian species (likely to be *Pteronisia plumacea*) included in our study over all our sites. There is currently nothing in the literature regarding growth or reproductive rates for this species, although a biodiversity survey of Bathurst Harbour in Tasmania noted a marked decline in cover of this species between surveys conducted in 2002 and 2010 (Barrett et al., 2010). Our results suggest that this species is likely to have a life cycle in the order of years rather than decades. However, our findings are based on only two survey times, and until a longer time-series is established it is unclear to what extent the observed variability represents typical natural short-term variability. Research elsewhere has suggested that temperate gorgonians may be susceptible to thermal stress, with anomalous temperatures causing mass mortalities (e.g. Santangelo et al., 2015). However, examination of fine-scale model temperature predictions for our

sites (Eric Oliver, personal communication) didn't indicate any events that would amount to a 'marine heatwave' (Hobday et al., 2016) at our sites over the time-period of the study.

4.2. Power of an image-based monitoring program to detect long-term regional trends in deep-water benthic species

Ensuring sufficient statistical power is the cornerstone of an effective monitoring program, as without it changes of interest can go by without being detected, or past points where critical intervention thresholds have already been met (Field et al., 2007; Hewitt and Thrush, 2007). For survey and sampling designs to have sufficient power, rigorous statistical assessment of the program needs to occur early and be ongoing (Lindenmayer and Likens 2009, 2010). We provide here an important assessment of the IMOS AUV benthic monitoring program, and direct feedback to managers regarding the level of future sampling likely to be required to ensure an effective program. We find that given our current knowledge, at a minimum the four sites in our study would need to be visited every 2 years until 2060 to detect projected climate change driven changes for 3 of the 5 species. Including more sites within the panel design allowed increased power with less frequent revisits for all species. By including a larger number of real sites, as opposed to our simulated sites, an improved characterisation of the regional spatial distribution and temporal variance of our indicator species could be achieved. However, programs must act within budgetary constraints, and additional sites are not always feasible. Given our current knowledge, adequate power for two of the species may be unachievable by 2060 given the predicted changes and estimates of variance. Designing an effective monitoring program to detect change in deep water benthic ecosystems in this region, which is characterised by high biodiversity with low cover of individual species, will require informed and adaptive decision making regarding the temporal and spatial replication necessary.

When designing a long-term monitoring program, researchers must balance the desire to survey more sites in order to better understand status, with the need to ensure sufficient temporal replication to detect trends (Rhodes and Jonzén, 2011). We found, in concordance with research by Urquhart (2012), that increasing the number of sites in a panel will generally increase power for all indicators, but will have the most pronounced effect on power for indicators with the highest residual variance (the gorgonian sp. and palmate sponge sp. in our case). However, for the gorgonian sp. the monitoring design required to provide high power is likely to be prohibitively high given our current knowledge. Also, increasing the number of sites is unlikely to provide sufficient power for indicators that exhibit small trends (e.g. the cup sponge sp.). Indeed, if *a priori* knowledge exists that a species is unlikely to show a strong response to the trend of interest, then it is unlikely to be selected as an indicator. In the case of the present study, species were selected for scoring prior to knowledge of their responses under the SDM. For the remaining 3 species tested, a relatively small panel of just 4 sites, if visited at least every 2 years could provide high power. Increasing the number of sites decreased the frequency of temporal revisits required, but where variances are relatively high such as for the palmate sponge sp., the number of additional sites required to reduce revisit frequency may be significant. Balancing the number of sites and the revisit frequency will ultimately be defined by program goals and budgets, with the length of the program being of particular importance.

Ecological monitoring programs that are designed to detect chronic impacts such as the impacts of climate-change are likely to require a commitment that spans decades in order to accumulate sufficient data (Lindenmayer et al., 2015). Regardless of other effects, power to detect trend will increase with the number of years included in the survey, which can be increased by either

increasing the frequency of revisits or extending the length of the survey (Urquhart, 2012). We find that revisits that are more frequent increased the power to detect change for all species, and that power increased for all species the longer the survey carried on. However, even for species that had high power with less frequent visits, the program would need to run for at least 15–20 years until >80% power was achieved to detect the climate change trend.

4.3. Selecting indicator species

Indicators of ecological change must be sensitive to the pressure of interest, and the natural cycles in the indicator must also be able to be separated from the trend due to that pressure (Noss, 1990). However, ecologists are becoming increasingly aware of the limited knowledge regarding temporal changes in ecological communities (Magurran et al., 2010). For monitoring programs, this situation must be remedied, as it is well known that components of variance in a system such as large short-term temporal variance or large residual variances in indicators can have a large impact on the power to detect trend (Urquhart et al., 1993; Urquhart and Kincaid, 1999; Skalski, 2012). We show that 3 out of the 5 species tested are likely to be suitable indicators given the projected changes and current estimates of variance, provided sufficient revisits are undertaken. Improving the baseline data regarding the natural temporal and spatial variability of other potential indicators is likely to prove essential in narrowing down suitable indicators by ruling out those that cannot be monitored effectively within budgetary constraints.

Previous work has shown that a number of other species are capable of being surveyed with similar levels of precision to the 5 species used here (Perkins et al., 2017). We therefore suggest the expansion of the present study to cover other species, or potentially community groupings, and incorporating as frequent revisits as possible to the sites included here in the next 5–10 years to improve on the estimates of variance. Elston et al. (2011) note the importance of frequent visits in the initial stages of monitoring to provide good baseline estimates. Program designers can then potentially reduce the frequency of visits as time goes on allowing more sites to be included in the network. In this way, rotating-panel designs can be created that allow greater coverage of the region and better estimation of the regional status of species in question as well as detecting any climate change driven trend.

Consideration of the spatial scale of the monitoring program and how this relates to indicator species distributions and climate change trends is another essential component of designing an effective program (Bates et al., 2015a). Our study has focussed on the ability to detect regional trends in indicators on the east coast of Tasmania. However, AUV surveys have been conducted far more extensively, and climate driven trends are affecting other regions in SE Australia. The three indicators we were able to detect trends with a reasonable monitoring effort all had truncated distributions of latitudes >35°S (James et al., 2017), and show general trends of poleward re-distribution. Indicator species whose distributions

are more closely tied with that of a region of interest are likely to make better indicators for change than those with broader distributions (Butler et al., 2012). However, further consideration of the relationship between distributional shifts and the monitoring effort required across these distributions will be an ongoing requirement for long-term monitoring programs (Bates et al., 2014).

5. Conclusion

Long-term monitoring programs are crucial for the effective management and conservation of the environment. For monitoring programs to be successful, sampling designs need to be underpinned by ongoing rigorous statistical evaluation, and refinement of the design where necessary based on the findings (Field et al., 2007). We show that when monitoring to detect change, there is a need to factor in the effects of relevant components of spatial, temporal and residual variance in the early stages of planning (Urquhart and Kincaid, 1999; Skalski, 2012; Urquhart, 2012). Doing so will allow the determination of where sampling effort should be directed in both space and time. This need is particularly acute in the case of deep-water marine ecosystems, where little is currently known about important components of variance. In such cases, assessments such as outlined here may not only aid in determining necessary sampling designs and panel revisit plans, but also in determining likely candidate species or groups that are suitable indicators. Simulation based approaches such as conducted here are an important tool for monitoring program design, and can provide researchers with the ability to assess various design aspects and their impact on power to detect trends of interest. As data accumulates, ongoing assessments of sampling design, panel-revisit schemes and expected changes can be incorporated and power and the suitability of indicators reassessed.

Acknowledgements

This work was undertaken for the Marine Biodiversity Hub, a collaborative partnership supported through funding from the Australian Government's National Environmental Science Programme. We thank Prof Stefan Williams and his IMOS AUV facility team, and collaborating research agencies in eastern Australia (NSW Marine Parks Authority and IMAS, University of Tasmania) for supporting the collection and collation of deep reef imagery in the region and making it available for this study. We also thank Justin Hulls, Lainey James and the numerous technical staff that have assisted in the field programs, and post-processing of the acquired imagery to allow the analysis presented here. MPM's work on climate-driven redistribution of reef habitat-formers in SE Australia was funded by a 2011 SuperScience Fellowship from the Australian Research Council (project FS110200029).

Appendix A.

See Fig. A1

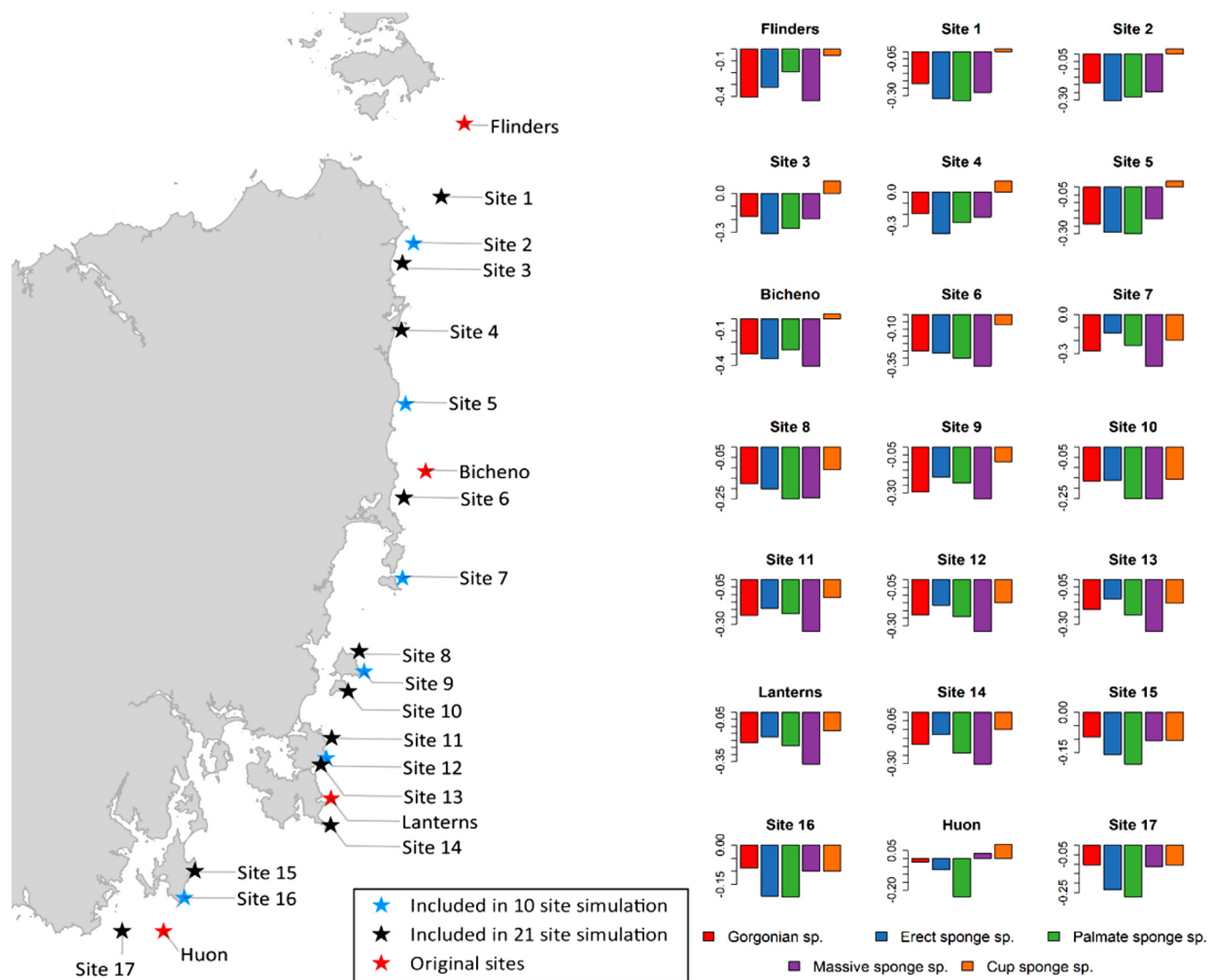


Fig. A1. Map showing the east coast of Tasmania and the survey sites used for the power simulation. Bar plots show the output from the species distribution model used to model climate related changes in the probability of presence of each of the five species at each site until 2060. The four original sites were always included in the panel designs (red stars). The sites marked with blue stars were included in the simulation with 10 sites. All sites were included in the simulation with 21 sites. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecolind.2017.02.030>.

References

- Alderslade, P., 1998. Revisionary systematics in the gorgonian family Isididae, with descriptions of numerous new taxa (Coelenterata: Octocorallia). In: McNamara, K.J., Harvey, M.S. (Eds.), *Records of the Western Australian Museum. Western Australian Museum*, p. 360.
- Andrew, N.L.E., 1999. *Under Southern Seas: The Ecology of Australia's Rocky Reefs*. UNSW Press, Sydney, NSW.
- Barrett, N., Oh, E., Meyer, L., Jones, D., Edgar, G.J., 2010. *A Biological Monitoring Survey of Reef Biota Within Bathurst Channel, Southwest Tasmania 2010*. Institute of Marine and Antarctic Studies, Hobart, Tasmania, pp. 111.
- Bates, A.E., Pecl, G.T., Frusher, S., Hobday, A.J., Wernberg, T., Smale, D.A., Sunday, J.M., Hill, N.A., Dulvy, N.K., Colwell, R.K., Holbrook, N.J., Fulton, E.A., Slawinski, D., Feng, M., Edgar, G.J., Radford, B.T., Thompson, P.A., Watson, R.A., 2014. Defining and observing stages of climate-mediated range shifts in marine systems. *Glob. Environ. Change* 26, 27–38.
- Bates, A.E., Bird, T.J., Stuart-Smith, R.D., Wernberg, T., Sunday, J.M., Barrett, N.S., Edgar, G.J., Frusher, S., Hobday, A.J., Pecl, G.T., Smale, D.A., McCarthy, M., Richardson, D.M., 2015a. Distinguishing geographical range shifts from artefacts of detectability and sampling effort. *Divers. Distrib.* 21, 13–22.
- Bates, D., Machler, M., Bolker, B.M., Walker, S.C., 2015b. Fitting linear mixed-effects models using lme4. *J. Stat. Softw.* 67, 1–48.
- Berman, J., Bell, J.J., 2016. Short-term temporal variability in a temperate sponge assemblage. *Mar. Biol.* 163.
- Brown, C.J., Schoeman, D.S., Sydeman, W.J., Brander, K., Buckley, L.B., Burrows, M., Duarte, C.M., Moore, P.J., Pandolfi, J.M., Poloczanska, E., Venables, W., Richardson, A.J., 2011. Quantitative approaches in climate change ecology. *Glob. Change Biol.* 17, 3697–3713.
- Butler, S.J., Freckleton, R.P., Renwick, A.R., Norris, K., 2012. An objective, niche-based approach to indicator species selection. *Methods Ecol. Evol.* 3, 317–326.
- Chamberlain, M.A., Sun, C., Matear, R.J., Feng, M., Phipps, S.J., 2012. Downscaling the climate change for oceans around Australia. *Geosci. Model Dev.* 5, 1177–1194.
- Duncan, G.J., Kalton, K., 1987. Issues of design and analysis of surveys across time. *Int. Stat. Rev.* 55, 97–117.
- Elston, D.A., Nevison, I.M., Scott, W.A., Sier, A.R.J., Morecroft, M.D., 2011. Power calculations for monitoring studies: a case study with alternative models for random variation. *Environmetrics* 22, 618–625.
- Field, S.A., O'Connor, P.J., Tyre, A.J., Possingham, H.P., 2007. Making monitoring meaningful. *Aust. Ecol.* 32, 485–491.
- Foster, S.D., Hosack, G.R., Hill, N.A., Barrett, N.S., Lucieer, V.L., Spencer, M., 2014. Choosing between strategies for designing surveys: autonomous underwater vehicles. *Methods Ecol. Evol.* 5, 287–297.

- Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C.V., Micheli, F., D'Agrosa, C., Bruno, J.F., Casey, K.S., Ebert, C., Fox, H.E., Fujita, R., Heinemann, D., Lenihan, H.S., Madin, E.M.P., Perry, M.T., Selig, E.R., Spalding, M., Steneck, R., Watson, R., 2008. A global map of human impact on marine ecosystems. *Science* 319, 948–952.
- Hewitt, J.E., Thrush, S.F., 2007. Effective long-term ecological monitoring using spatially and temporally nested sampling. *Environ. Monit. Assess.* 133, 295–307.
- Hobday, A.J., Alexander, L.V., Perkins, S.E., Smale, D.A., Straub, S.C., Oliver, E.C.J., Benthuyssen, J.A., Burrows, M.T., Donat, M.G., Feng, M., Holbrook, N.J., Moore, P.J., Scannell, H.A., Gupta, Sen, Wernberg, T., 2016. A hierarchical approach to defining marine heatwaves. *Progress Oceanogr.* 141, 227–238.
- Hoegh-Guldberg, O., Bruno, J.F., 2010. The impact of climate change on the world's marine ecosystems. *Science* 328, 1523–1528.
- Hughes, T.P., 1996. Demographic approaches to community dynamics: a coral reef example. *Ecology* 77, 2256–2260.
- Jackson, J.B.C., Kirby, M.X., Berger, W.H., Bjørndal, K.A., Botsford, L.W., Bourque, B.J., Bradbury, R.H., Cooke, R., Erlandson, J., Estes, J.A., Hughes, T.P., Kidwell, S., Lange, C.B., Lenihan, H.S., Pandolfi, J.M., Peterson, C.H., Steneck, R.S., Tegner, M.J., Warner, R.R., 2001. Historical overfishing and the recent collapse of coastal ecosystems. *Science* 293, 629–638.
- James, L.C., Marzloff, M.P., Barrett, N., Friedman, A., Johnson, C.R., 2017. Changes in deep reef benthic community composition across a latitudinal and environmental gradient in temperate Eastern Australia. *Mar. Ecol. Progress Ser. (forthcoming)*.
- Johnson, C.R., Banks, S.C., Barrett, N.S., Cazassus, F., Dunstan, P.K., Edgar, G.J., Frusher, S.D., Gardner, C., Haddon, M., Helidoniotis, F., Hill, K.L., Holbrook, N.J., Hosie, G.W., Last, P.R., Ling, S.D., Melbourne-Thomas, J., Miller, K., Pecl, G.T., Richardson, A.J., Ridgway, K.R., Rintoul, S.R., Ritz, D.A., Ross, D.J., Sanderson, J.C., Shepherd, S.A., Slotvinski, A., Swadling, K.M., Taw, N., 2011. Climate change cascades: shifts in oceanography, species' ranges and subtidal marine community dynamics in Eastern Tasmania. *J. Exp. Mar. Biol. Ecol.* 400, 17–32.
- Larsen, D.P., Kincaid, T.M., Jacobs, S.E., Urquhart, N.S., 2001. Designs for evaluating local and regional scale trends. *BioScience* 51, 1069–1078.
- Lindenmayer, D.B., Likens, G.E., 2009. Adaptive monitoring: a new paradigm for long-term research and monitoring. *Trends Ecol. Evol.* 24, 482–486.
- Lindenmayer, D.B., Likens, G.E., 2010. The science and application of ecological monitoring. *Biol. Conserv.* 143, 1317–1328.
- Lindenmayer, D.B., Burns, E.L., Tennant, P., Dickman, C.R., Green, P.T., Keith, D.A., Metcalfe, D.J., Russell-Smith, J., Wardle, G.M., Williams, D., Bossard, K., deLacey, C., Hanigan, I., Bull, C.M., Gillespie, G., Hobbs, R.J., Krebs, C.J., Likens, G.E., Porter, J., Vardon, M., 2015. Contemplating the future: acting now on long-term monitoring to answer 2050's questions. *Aust. Ecol.* 40, 213–224.
- Ling, S.D., Mahon, I., Marzloff, M.P., Pizarro, O., Johnson, C.R., Williams, S.B., 2016. Stereo-imaging AUV detects trends in sea urchin abundance on deep overgrazed reefs. *Limnol. Oceanogr. Methods* 14, 293–304.
- Magurran, A.E., Baillie, S.R., Buckland, S.T., Dick, J.M., Elston, D.A., Scott, E.M., Smith, R.I., Somerfield, P.J., Watt, A.D., 2010. Long-term datasets in biodiversity research and monitoring: assessing change in ecological communities through time. *Trends Ecol. Evol.* 25, 574–582.
- Marzloff, M.P., Melbourne-Thomas, J., Hamon, K.G., Hoshino, E., Jennings, S., van Putten, I.E., Pecl, G.T., 2016a. Modelling marine community responses to climate-driven species redistribution to guide monitoring and adaptive ecosystem-based management. *Glob. Change Biol.* 22, 2462–2474.
- Marzloff, M.P., Oliver, E.C.J., Barrett, N., Holbrook, N.J., James, L., Wotherspoon, S., 2016b. Differential Vulnerability of Deep-Reef Habitat-Forming Organisms to Climate Change (in preparation).
- Matear, R.J., Chamberlain, M.A., Sun, C., Feng, M., 2013. Climate change projection of the Tasman Sea from an Eddy-resolving Ocean Model. *Geophys. Res. - Oceans* 118, 2961–2976.
- McDonald, T.L., 2003. Review of environmental monitoring methods: survey designs. *Environ. Monit. Assess.* 85, 277–292.
- Molloy, P.P., Evanson, M., Nellas, A.C., Rist, J.L., Marcus, J.E., Koldewey, H.J., Vincent, A.C.J., 2013. How much sampling does it take to detect trends in coral-reef habitat using photoquadrat surveys? *Aquat. Conserv.: Mar. Freshw. Ecosyst.* 23, 820–837.
- Noss, R.F., 1990. Indicators for monitoring biodiversity—a hierarchical approach. *Conserv. Biol.* 4, 355–364.
- Oliver, E.C.J., Holbrook, N.J., 2014. A statistical method for improving continental shelf and nearshore marine climate predictions. *J. Atmos. Ocean. Technol.* 31, 216–232.
- Oliver, E.C.J., Wotherspoon, S.J., Chamberlain, M.A., Holbrook, N.J., 2014. Projected Tasman Sea extremes in sea surface temperature through the 21 st century. *J. Clim.* 27, 1980–1998.
- Perkins, N.R., Foster, S.D., Hill, N.A., Barrett, N.S., 2016. Image subsampling and point scoring approaches for large-scale marine benthic monitoring programs. *Estuar. Coast. Shelf Sci.* 176, 36–46.
- Perkins, N.R., Hosack, G.R., Foster, S.D., Hill, N.A., 2017. What can be considered a repeat transect? Repeat spatial precision needed for monitoring change in benthic species. *Ecol. Appl.* (in review).
- Poloczanska, E.S., Brown, C.J., Sydeman, W.J., Kiessling, W., Schoeman, D.S., Moore, P.J., Brander, K., Bruno, J.F., Buckley, L.B., Burrows, M.T., Duarte, C.M., Halpern, B.S., Holding, J., Kappel, C.V., O'Connor, M.I., Pandolfi, J.M., Parmesan, C., Schwing, F., Thompson, S.A., Richardson, A.J., 2013. Global imprint of climate change on marine life. *Nat. Clim. Change* 3, 919–925.
- Rhodes, J.R., Jonzén, N., 2011. Monitoring temporal trends in spatially structured populations: how should sampling effort be allocated between space and time? *Ecography* 34, 1040–1048.
- Ridgway, K.R., 2007. Long-term trend and decadal variability of the southward penetration of the East Australian Current. *Geophys. Res. Lett.* 34.
- Robinson, L.M., Gledhill, D.C., Moltschanivskyj, N.A., Hobday, A.J., Frusher, S., Barrett, N., Stuart-Smith, J., Pecl, G.T., 2015. Rapid assessment of an ocean warming hotspot reveals high confidence in potential species' range extensions. *Glob. Environ. Change-Hum. Policy Dimens.* 31, 28–37.
- Santangelo, G., Cupido, R., Cocito, S., Bramanti, L., Priori, C., Erra, F., Iannelli, M., 2015. Effects of increased mortality on gorgonian corals (Cnidaria, Octocorallia): different demographic features may lead affected populations to unexpected recovery and new equilibrium points. *Hydrobiologia* 759, 171–187.
- Sims, M., Elston, D.A., Harris, M.P., Wanless, S., 2007. Incorporating variance uncertainty into a power analysis of monitoring designs. *J. Agric. Biol. Environ. Stat.* 12, 236–249.
- Skalski, J.R., 2012. Estimating variance components and related parameters when planning long-term monitoring programs. In: Gitzen, R.A., Millsaugh, J.J., Cooper, A.B. (Eds.), *Design and Analysis of Long-term Ecological Monitoring Studies*. Cambridge University Press, pp. 174–199.
- Slattery, M., Lesser, M.P., Brazeau, D., Stokes, M.D., Leichter, J.J., 2011. Connectivity and stability of mesophotic coral reefs. *J. Exp. Mar. Biol. Ecol.* 408, 32–41.
- Urquhart, N.S., Kincaid, T.M., 1999. Designs for detecting trend from repeated surveys of ecological resources. *J. Agric. Biol. Environ. Stat.* 4, 404–414.
- Urquhart, N.S., Overton, W.S., Birkes, D.S., 1993. Comparing Sampling Designs for Monitoring Ecological Status and Trends: Impact of Temporal Patterns. *Statistics for the Environment*. Wiley Lisbon, Portugal, pp. 71–85.
- Urquhart, N.S., 2012. The role of monitoring design in detecting trend in long-term ecological monitoring studies. In: Gitzen, R.A., Millsaugh, J.J., Cooper, A.B., Licht, D.S. (Eds.), *Design and Analysis of Long-term Ecological Monitoring Studies*. Cambridge University Press.
- Williams, S.B., Pizarro, O.R., Jakuba, M.V., Johnson, C.R., Barrett, N.S., Babcock, R.C., Kendrick, G.A., Steinberg, P.D., Heyward, A.J., Doherty, P.J., Mahon, I., Johnson-Roberson, M., Steinberg, D., 2012. Monitoring of benthic reference sites using an autonomous underwater vehicle. *Ieee Robot. Autom. Mag.* 19, 73–84.