An evidence-based approach for setting desired state in a complex Great Barrier Reef seagrass ecosystem: A case study from Cleveland Bay

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ABSTRACT

Implementing management actions to achieve environmental outcomes requires defining and quantifying ecological targets, but this is a complex challenge, and there are few examples of how to quantitatively set them in complex dynamic marine ecosystems. Here we develop a methodology to devise 'desired state' for tropical seagrasses in Cleveland Bay, northern Australia, in the Great Barrier Reef World Heritage Area. Analysis of diverse species assemblages was used to define seagrass communities as indicators of the region's ecological value. Multivariate regression trees assigned 8000 observations of species presence/absence and habitat characteristics from 2007 to 2017 into seven community types. Generalized Linear Models were used to assess annual variation in above-ground biomass of each seagrass community. Reference subsets of the data expressing high biomass and spatial extent were identified, and desired state was defined as the mean and 95% confidence intervals. This approach rests on the assumption that seagrass resilience and its ecosystem services are met when the diverse seagrass communities reach desired state. This method required a data set that spanned a range in seagrass conditions, but which may have been compromised by a history of pressures. Our method for defining desired state provides evidence-based targets that can be used within an adaptive management framework that prioritises and implements management actions.

1. Introduction

Degradation of ecosystems and associated ecosystem services is a pressing issue for humanity (MEA et al., 2005; Steffen et al., 2015). Managing natural resources more sustainably has challenges: urbanization, climate change, coastal development, consumption, and the complexity and uncertainty created by multiple pressures (Grech et al., 2011; Walker and Salt, 2012; Head, 2014). Adaptive management provides a best practice approach to managing natural resources by linking management objectives and actions to ecosystem health through appropriate indicators (Hallett et al., 2016). A fundamental challenge is

defining success (Borja et al., 2013): what is the desired state of an ecosystem that we are aiming to achieve? This ought to be the specific outcome of management actions, and a target for success when considered in context of natural disturbances.

'Desired state' is defined in this study as an aspirational target for guiding management decisions. Defining desired state has been identified as a priority information need for management of the Great Barrier Reef World Heritage Area (GBRWHA) because of an importance in standardizing the evaluation of success and for prioritizing remediation (Great Barrier Reef Marine Park Authority, 2015). Desired state for seagrass habitats ideally would be that which maintains ecosystem services

Fig. 1. Map showing the location of Cleveland Bay within the Great Barrier Reef World Heritage Area, the city of Townsville, coral reefs and the Burdekin River - the largest river influencing water quality in the region.

(Madden et al., 2009). Seagrass ecosystems are of global significance because they provide a range of ecological functions such as food for dugongs and turtles, feed a large proportion of the world's population by providing nursery grounds for fisheries species, sequester vast amounts of carbon, and provide shoreline protection by stabilising sediments (Mtwana Nordlund et al., 2016; Cullen-Unsworth and Unsworth, 2013; Unsworth et al., 2018). In some cases, these ecosystem services are used to define management objectives (Borja et al., 2012; Samhouri et al., 2012). However, quantifying every aspect of ecosystem services is a challenging task, especially when the relationship between services, functions and underlying biodiversity remains poorly understood (Kremen, 2005; Barbier, 2014). Not all ecosystem services have been defined, previously unknown seagrass ecosystem services continue to emerge, such as reducing disease-causing pathogens [e.g. (Lamb et al., 2017)], and trade-offs in seagrass ecosystem services exist (Butler et al., 2013;

Scott et al., 2018). The services also vary among seagrass genera and among community types, adding complexity to basing targets on ecosystem services in multi-specific seagrass habitat (Mtwana Nordlund et al., 2016; Cullen-Unsworth et al., 2014).

Two of the challenges for defining desired state of complex, dynamic ecological systems are: 1. choosing the right indicator/s and metrics for the ecosystem; and, 2. quantitatively defining the desired values of metrics for the indicator (Wicks et al., 2010). We define 'indicator' as seagrass communities which have unique assemblages, ecological value and sensitivity to pressures and 'metric' as a measurable quality of the seagrass community [sensu. 22]. Seagrass habitat has properties of condition and resilience (O'Brien et al., 2017). We define 'condition' as relative quantities of characteristics of the seagrass that can provide ecological services at the time of assessment. 'State' is synonymous with 'condition', but the term state is reserved for use in 'desired state' for

clarity. 'Resilience' is the capacity to provide those services in the future, based on being able to retain condition and function in the face of disturbances (O'Brien et al., 2017; Connolly et al., 2018). Ideally, desired state would encapsulate both condition and resilience, and while the metrics used to quantify these can overlap (Unsworth et al., 2015), simple metrics of condition are generally easier to measure and report against than resilience metrics (Tett et al., 2013; Marbà et al., 2013).

Spatial extent is one indicator of seagrass habitat availability and the provision of ecosystem services that it provides, so knowledge of extent is required before implementation of management strategies to protect these services (Unsworth et al., 2019). Extent can fluctuate for multiple reasons, including from pressures that arise from human activities. For example: it can fluctuate at the deepest limit due to declining water quality and light limitation (Dennison et al., 1993); in shallow water due to thermal anomalies and tidal variability (Rasheed and Unsworth, 2011; Thomson et al., 2015; Massa et al., 2009), which may become more frequent and extreme in the future (Hoegh-Guldberg et al., 2014); and, from increasing patchiness associated with disturbances (Cunha et al., 2005; Kendrick et al., 1999). Extent can also fluctuate naturally, including due to seasonality in annual (York et al., 2015) and perennial species (O'Hara et al., 2002). Seagrass extent can be easily integrated among studies to assess broad-scale change in seagrass habitat, including in global assessments (Waycott et al., 2009). Seagrass presence/absence, species composition, and abundance are other common and simple population-level metrics of seagrass condition and resilience; they encapsulate the effects of multiple human-induced pressures (Madden et al., 2009; Martinez-Crego et al., 2008; Marbá and Duarte, 2010), and may fluctuate independently of extent (Rasheed and Unsworth, 2011). These metrics form the basis of most robust studies investigating the condition and resilience of seagrass meadows [e.g. (Madden et al., 2009; Personnic et al., 2014)] and are applied in monitoring and assessment programs within the Great Barrier Reef [e.g. (McKenzie et al., 2019; Bryant and Rasheed, 2018)].

Determining the desired state of metrics for an indicator is not trivial (Hallett et al., 2016). This is further exacerbated in systems where there is large seasonal and/or inter-annual variability, particularly for biotic indicators with no long-term data sets that encapsulate each metric's variability. Desired state should be ambitious yet realistic (Samhouri et al., 2012; Perrings et al., 2011), and can be based on understanding the functional cause-effect with environmental conditions (Choice et al., 2014; Steward et al., 2005; Steward and Green, 2007; Samhouri and Levin, 2012; Saunders et al., 2017), which likely requires complex analysis specific to the local system. In many cases, targets have been based on historical status or on the maximum value in the region (Borja et al., 2012), providing reference points for management activities, without being specific to one pressure. Irrespective of the approach, setting targets requires supporting data.

The objective of this study was to develop a methodology for defining desired state by selecting indicators and metrics and then defining desired state of each metric. Our paper describes a case study from Cleveland Bay in the GBRWHA where the seagrass habitats are complex because they are dynamic and diverse, but the approach can be applied to habitats with different ecological attributes and adapted to a range of spatial scales. Desired state can be used as a reference point against which to quantitatively assess the influence of human pressures and 'natural' variation thereby enabling the implementation of remediation strategies.

2. Methods

2.1. Study area and management objectives

We chose Cleveland Bay as an appropriate study area for implementing a model of adaptive management because of its highly valued ecological attributes and the well-understood risks to those ecosystem services (Fig. 1). Cleveland Bay lies within a region of international significance — the GBRWHA — where the over-arching management

objective for biodiversity is "The reef maintains its diversity of species and ecological habitats in at least a good condition with a stable to improving trend" (Great Barrier Reef Marine Park Authority, 2015). The GBRWHA protects up to 10% of the world's coral reef ecosystems, but they only cover about 7% of its area. Seagrasses are another of the key ecological attributes of the GBRWHA by virtue of their extensive area and the ecosystem services they provide (Great Barrier Reef Marine Park Authority, 2015), including supporting dugong and green turtle populations (Scott et al., 2018; Marsh et al., 2011; Tol et al., 2016).

Seagrass grows throughout most of the bay, from intertidal banks to deeper subtidal waters (Bryant and Rasheed, 2018). There are seven species of seagrass in Cleveland Bay: *Cymodocea serrulata, Halophila decipiens, Halodule uninervis, Halophila ovalis, Halophila spinulosa, Thalassia hemprichii* and *Zostera muelleri* subsp. *capricorni* and the meadows they form here are a connectivity hotspot in the central GBR (Grech et al., 2018). Cleveland Bay is affected by discharge from the Burdekin River — the second largest river basin on Australia's east coast — as well as several smaller rivers. These rivers discharge fine sediment, nutrients and particulate organic matter during the wet season (October to April), the loads of which have increased in association with agricultural developments (largely beef grazing and sugarcane cultivation) in the catchments (Fabricius et al., 2014; Bainbridge et al., 2012, 2018; Kroon et al., 2012). Discharge from the river has high inter-annual variability in volume of discharge, sediment and nutrient loads, and the direction of plume flow depending on prevailing winds (Fabricius et al., 2014; Lewis et al., 2018). These influence water clarity (Fabricius et al., 2014), and contribute to changes in seagrass extent and biomass (Collier et al., 2012a; Petus et al., 2014; Rasheed et al., 2014). Cleveland Bay is also located adjacent to the city of Townsville presenting multiple threats to seagrass distribution and abundance in the region, including urban and port developments (Grech et al., 2011). The region is exposed to large-scale disturbances from tropical cyclones, and to increasing risk from heat waves (Hughes et al., 2017; Lough et al., 2018).

We use biomass and extent from observations spanning over a decade to quantify desired state, which results in desired states that are ambitious, yet realistic. In general, targets could be based on reference sites or on a reference period of time (Samhouri et al., 2012), such as the designation of the Great Barrier Reef Marine Park in 1981, or on pre-industrial times. However, reliable historical information on the condition of seagrasses in the region is available only from 2007, and developing targets for any time prior to that would be based on scant evidence and require a considerable number of assumptions. Furthermore, the historical predictions could not be validated. Environmental managers responsible for the GBRWHA report on the condition and trend of ecological health and prioritise and implement actions to achieve management objectives in an adaptive management process (Great Barrier Reef Marine Park Authority, 2019). We developed desired state for all communities without being specific to a management action, but our intention is to apply or adapt them to provide an evidence-base for management decisions. The implications of this approach are discussed throughout.

2.2. Define indicators: community types based on species composition and habitat

Setting seagrass desired state in this region required an approach that accommodates the relatively high species diversity and dynamic nature of the seagrass meadows. Therefore, we define the indicators in this study as not just seagrass, but as different community types of seagrass. As the community types were then used as the basis to establish desired states for biomass and spatial extent, it was necessary to exclude data from years when the species assemblages were altered due to the impacts of large events as described below.

2.2.1. Available data

Seagrass biomass and species composition were assessed as part of routine monitoring of benthic habitats for the Port of Townsville.

Table 1
Seagrass species and habitat data used to determine desired state, including collection method, units, data source, resolution, and whether the data was used as a predictor or response variable.

Label	Description	Methods	Units	Source	Data resolution	Predictor/response
Seagrass species presence/absence data						
P/A	Seagrass species presence/ absence	Assessed in three 50 × 50 cm quadrats per 'site' deployed from helicopter, camera drops, or free diving depending on water depth and sea conditions.	0/1	Summarised in Bryant and Rasheed (2018)	Annual data 518–1209 sites/year, median = 626	Response (to habitat predictors)
Habitat data						
Sed$_{dom}$	Dominant sediment type	Recorded in the field and aggregated into broad categories for this analysis based on the dominant sediment type. Coarse Sand, Mud, Reef, Rock, Rubble, Sand.	n.a.	Bryant and Rasheed (2018)	Annual data 518–1209 sites/year, median = 626	Predictor
WCI	Water clarity index	Remote sensing imagery was used to derive a categorical index of water clarity, ranging from 1 (lowest) to 7 (highest). Categories 1–4 represent water that has high levels of total suspended solids, chlorophyll a and coloured dissolved organic matter, leading to high light attenuation coefficients, and low clarity.	# weeks	Petus et al. (2016)	Annual data. Number of weeks (out of 22 weeks) in the previous wet-season (from December to April) that were category 1-4	Predictor
Depth class	Depth class	Habitat classification developed in Carter et al. (2018), a spatially-explicit habitat classification scheme developed for the entire GBR based on water depth and water clarity (using the techniques described for WCI. Only depth categories were relevant to Cleveland Bay analysis: Coastal intertidal and Coastal subtidal (shallow and deep combined).	n.a.	Carter et al. (2018)	Single polygon file	Neither. Used to allocate sites for analysis in subtidal or intertidal models.
RelExp	Relative tidal exposure index	Extracted from the intertidal extents model raster (ITEM v1.0), where 0 is never exposed, and 1–9 is exposed at increasing amounts of time where 1 = exposed at the lowest 0–10% and 9 = exposed at highest 80–100% of observed tidal range.	Relative scale	Geoscience Australia (2017) and Carter et al. (2018)	Single raster file. Uses all Landsat observations (5, 7, 8) for Australian coastal regions, 1987–2015	Predictor (intertidal analysis only)
Depth	Colonisation depth	Depth of the sampling site as determined from Beaman (2010) supplemented by other sources as summarised in (Carter et al., 2018).	m (metres below mean sea level)	Carter et al. (2018)	Single raster file Beaman (2010) and polygon shapefile Carter et al. (2018)	Predictor (subtidal analysis only)
Define metrics						
Biomass	Above-ground biomass	Estimated using a calibrated visual estimation technique during the peak growing season (September to November) for each species at each site.	g DW m^{-2}	Summarised in Bryant and Rasheed (2018)	Annual data 424–1101 sites/year, median = 592	Response (to year)
Spatial Extent	Area of seagrass habitats	Determined by GIS spatial extent analysis of site data for each seagrass community type collected during the peak growing season (September to December).	Ha	Derived from habitat assessment sites in Bryant and Rasheed (2018)	Annual data	Response (to year)
Identify desired state						
Year	Survey year		Factor	Bryant and Rasheed (2018)	Annual data	Predictor

Seagrass biomass and species composition was visually assessed at least annually between 2007 and 2017 (Bryant and Rasheed, 2018). The data is made up of 8122 observations (518–1209 sites/year, median = 626). Sampling was stratified into discrete seagrass meadows and non-seagrass areas in the bay, and the distribution of sites covered most of Cleveland Bay during broad-scale surveys in 2007, 2013, and 2016. A subset of discrete seagrass monitoring meadows was surveyed in the other years. Sites (an area of 5m radius) were haphazardly allocated within each stratified area to ensure good spatial coverage. This method ensured all seagrass monitoring meadows were assessed each year regardless of the annual spatial change. The number of sites needed to represent the variability and patchiness of the communities and detect change in biomass in the original monitoring program was determined by power analysis. Above-ground biomass was visually assessed within three replicate quadrats (50 × 50 cm) randomly placed within each site. Visually estimated above-ground biomass is a widely-used non-destructive method that has been applied in high-precision time-series analysis (Aragones and Marsh, 2000; Rasheed, 1999, 2004) and meadow scale change assessments (Rasheed and Unsworth, 2011; McKenna et al.,

2015). The visual assessment is calibrated for each individual observer against harvested biomass samples at each time of sampling. Biomass for the site was calculated from an average of the three quadrats and scaled up to grams dry weight m^{-2} (g DW m^{-2}). Species composition was the percent contribution of each species to mean biomass within the three quadrats. When defining community types species data was simplified to presence/absence (Table 1).

Habitat requirements including depth range, sensitivity to changing water quality, the benthic substrate suitable for growth, and the frequency of exposure to air at low tide for intertidal communities vary among species (Lee et al., 2007; Erftemeijer and Robin Lewis, 2006; Collier et al., 2016; Waycott et al., 2004; Shafer et al., 2007), and lead to differences in species distributional patterns (Waycott et al., 2004, 2005; Coles et al., 2009). Amongst water quality stressors, light limitation is regarded as the primary cause of seagrass loss in the region, and exposure to turbid flood water and subsequent resuspension of sediments has been linked to declines in seagrass meadow area and biomass in the GBRWHA and Cleveland Bay (Collier et al., 2012a; Petus et al., 2014, 2016). Habitat requirements may also overlap among species, resulting in

multi-species meadows such as those found in Cleveland Bay (Bryant and Rasheed, 2018). Habitat characteristics, such as sediment type, tidal exposure, water quality measured as the clarity of water and/or depth, were therefore used to classify seagrass species assemblages into community types, with separate analyses for intertidal and subtidal sites.

Benthic sediment type at each site was visually assessed and defined according to broad categories (e.g. mud, sand) and listed from most to least dominant; dominant sediment (Sed$_{dom}$) was defined as the most dominant of these categories at a site (Table 1). Water clarity at each site was defined by a Water Clarity Index (WCI) and calculated as the frequency (number of weeks) of exposure to turbid water during the previous wet season which spans 22 weeks from December to April in each 'water year'. Turbid water was identified from water colour as brownish to brownish-green waters in MODIS true colour satellite images and processed according to Álvarez-Romero et al. (2013) and Petus et al. (2019) as part of routine annual water quality monitoring for the GBRWHA (Waterhouse et al., 2018). Sites were defined as intertidal or subtidal using the habitat classification of Carter et al. (2018). Depth below mean sea level was included as a predictor in the subtidal analysis only. The relative frequency of intertidal exposure was included as a predictor in the intertidal analysis only (Table 1).

2.2.2. Define community types

Seagrass species presence/absence (P/A) was used as a response variable to assign the seagrass at each site into a community type with unique species assemblages using multivariate regression trees (Table 1). While there are several other methods for defining species assemblages, multivariate regression trees result in discrete site groups (with distinct environmental affinities) allowing prediction and inference about sites where there is environmental data but no seagrass data. We used presence/absence from each site rather than biomass, which resulted in the community type being defined based on the frequency of occurrence of each species. Regression trees (Breiman et al., 1984; Clark et al., 1992) are a machine-learning method for constructing prediction models and do not include *a priori* assumptions about the relationships between the response and predictor variables. Multivariate Regression Trees (MRTs) (De'ath, 2004);) can be used to describe and predict relationships between multiple species and habitat characteristics (De'ath, 2002). The parameters leading to the splits in the MRTs are interpreted by stepping down the tree. Once the tree has finished splitting the data, the bottom 'leaves' of the tree are nodes that we refer to as community types. As the aim was to cluster the sites spatially (not predict the abundance at a site at a point in time), we did not include 'year' as a factor in the model. Instead we aimed to categorise where each seagrass species is found, on average, through time.

To define seagrass community types, the MRT was fitted to data for all years excluding 2009 to 2012. These data were removed from the analysis because our aim was to identify community types that could be used to set seagrass desired state. There was loss of seagrass area and biomass in this period most likely from significant rainfall and the subsequent discharge of sediment and nutrients, which led to low water clarity and low benthic light levels (Bryant and Rasheed, 2018; Petus et al., 2014). We removed these years from the analysis to avoid defining seagrass community types based on data that overwhelmingly represented a significant environmental impact, rather than more nuanced habitat conditions (e.g. sediment type, water quality) likely to drive community types in relatively normal years and desired state years. To check the effect of this decision, the MRTs were run on the data from years 2009 to 2012 separately. The species assemblages in those years were disproportionally dominated by colonising species indicative of a disturbance event, *Halophila ovalis* at intertidal and *Halophila decipiens* at subtidal sites, leading to an overly simple community classification that was not appropriate for setting desired state. The MRTs were fitted to the intertidal and subtidal sites separately. This analysis identified nine potential seagrass community types, which have been numbered one to nine and the characteristics of these communities are defined in the results.

The models were fitted using the *mvpart* package (De'ath, 2004) in R (available in archive form on CRAN, https://cran.r-project.org). Exploratory analyses and sensitivity testing of the MRTs included: MRTs on biomass, which revealed a similar classification to the seagrass species presence/absence classification (Appendix A); Separate MRTs for each year to test the sensitivity of the community classifications to "good" and "bad" years (i.e. when there were significant rainfall events leading to poor water clarity and low benthic light) years; MRTs for all years combined and not just the "good" years; and, single regression trees for individual species.

The data from 2007–2008 and 2013–2016 was used in the initial analysis to define communities, while the 2017 data was included as it became available. This provided an opportunity to demonstrate how the fitted model can predict membership to a community type for additional data.

2.2.3. Determine spatial extent of each community

The spatial extent of each of the nine community types was assessed annually from 2007 to 2017. The data set is for observations collected from September through to December as this is the peak growing season for seagrasses in the region, and the time-period in which most of the surveys were conducted. Spatial analysis was also restricted to the smaller survey extent of meadows monitored annually, so the results were not biased in years which included the bay-wide surveys and increased sampling effort. (2007, 2013 and 2016). This means that spatial extent desired state could not be determined for deep subtidal community 1 as determined by the MRT classification. Survey extent was calculated from the concave hull (polygon enveloped) of all points based on spatial density in six different sub-regions in the Bay in each year (Geoffrey Bay, Nelly Bay, Cockle Bay, Shelly Beach, Rowes Bay/The Strand, and South Cleveland Bay, which are shown in the results in Fig. 5). The sub-regions were separated by parts of the bay having no seagrass, or not surveyed. Thiessen polygons were created from site data to geostatistically define the area of seagrass in each sub-region for each year using seagrass presence/absence (0/1 data), clipping the polygons to each sub-region's survey extent, then removing polygons where seagrass was absent.

The area of each seagrass community type was determined by calculating the area of the remaining Thiessen polygons (in hectares) then summing these according to community type, sub-region and year. Survey extent (concave hull) analysis was conducted in QGIS v. 3.4.0 (QGIS Development Team, 2018); all other spatial analyses were conducted in ArcMap v.10.4.1 (ESRI, Redlands, CA).

2.2.4. Re-assess community types

There were nine communities identified; however, the species composition and biomass of communities 6 and 7, and of communities 8 and 9 were very similar, varying in their classification between years based only on dominant sediment type or the water quality index, respectively. This led to an inter-annual switch in the occurrence of these community types between years, and was associated with inter-annual fluctuations in the biomass of each community type. Therefore, these community types were re-classified into community 6/7 combined and community 8/9 combined, resulting in seven seagrass communities identified in Cleveland Bay. Combining these very similar communities also meant we could do a more robust analysis on desired state biomass because the number of samples was increased.

2.3. Select metrics

Above ground biomass and geostatistical spatial extent were selected as metrics for setting seagrass desired state because there is substantial evidence that these are ecologically-important attributes of seagrass condition, and are sensitive to environmental change over the spatial-temporal scale of this study, including to the pressures occurring in the region (Marbà et al., 2013; Bryant and Rasheed, 2018; Petus et al., 2014;
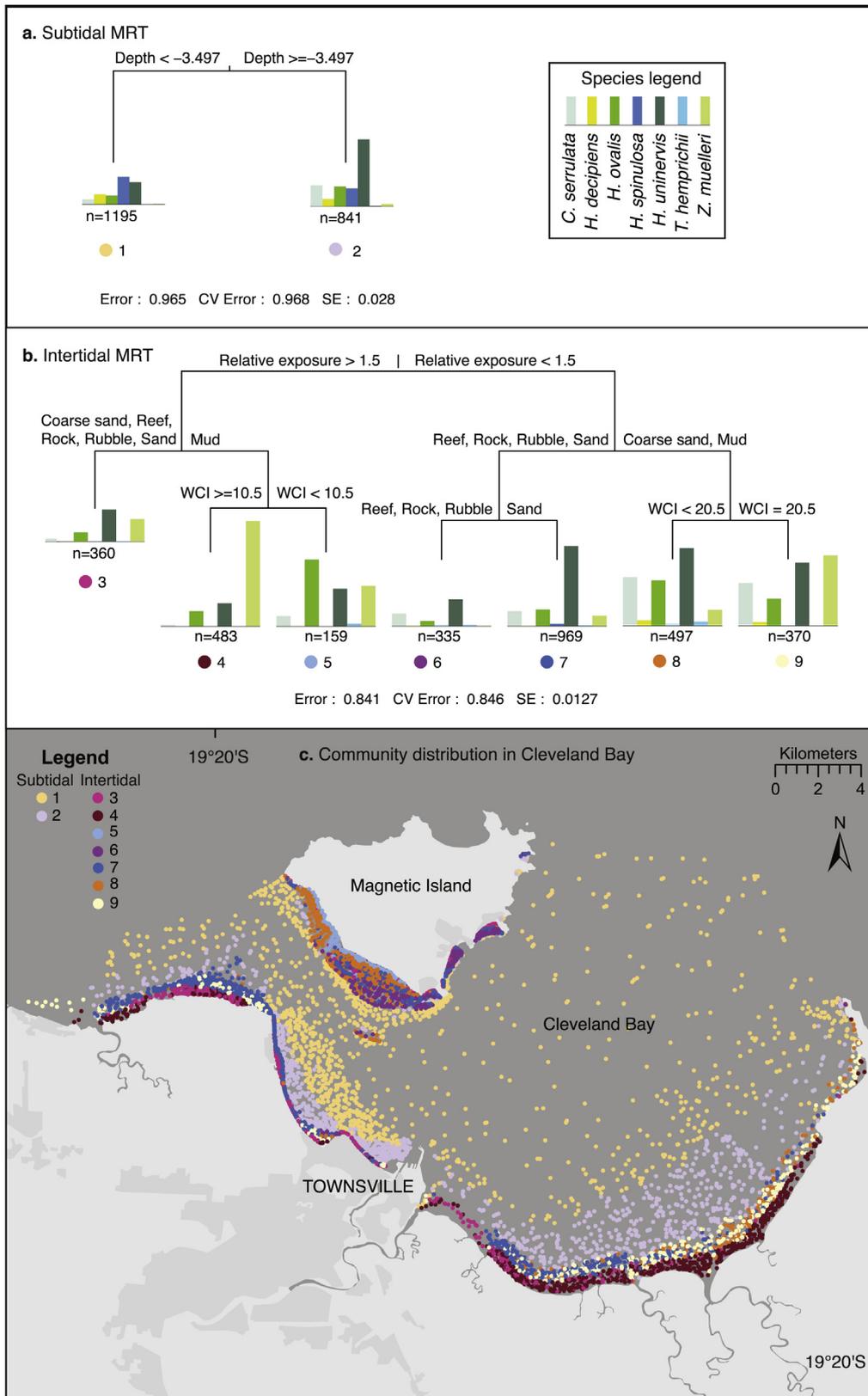
Fig. 2. Multivariate regression tree (MRT) and seagrass communities classified using presence/absence data for a. subtidal sites, b. intertidal sites and c. the spatial distribution of communities in Cleveland Bay, 2007, 2008, 2013–2016. The number below each community is the count of observations that fall into that community. The histogram shows the frequency of occurrence for each species in that community with the height of the bar representing the frequency that each species was observed in that assemblage. The coloured dots represent unique communities one to nine (later grouped into seven communities with 6/7 and 8/9 combined). The CV Error is the cross-validated relative error and is the best indication of the error here.

Table 2
Frequency of occurrence of each species within the nine community types (Com.) identified using multivariate regression tree analysis on site data. Bold type indicates most common species.

Com.	C. serrulata	H. decipiens	H. ovalis	H. spinuolsa	H. uninervis	T. hemprichii	Z. muelleri
1	0.07	0.14	0.12	**0.37**	0.30	0.00	0.01
2	0.15	0.05	0.15	0.13	**0.49**	0.00	0.02
3	0.06	0.00	0.13	0.00	**0.47**	0.01	0.33
4	0.01	0.00	0.10	0.00	0.16	0.00	**0.72**
5	0.07	0.00	**0.42**	0.00	0.24	0.02	0.26
6	0.26	0.01	0.11	0.03	**0.56**	0.03	0.01
7	0.12	0.00	0.13	0.02	**0.64**	0.01	0.08
8	0.24	0.03	0.23	0.01	**0.39**	0.02	0.08
9	0.21	0.02	0.13	0.00	0.30	0.00	**0.34**

Rasheed et al., 2014; McMahon et al., 2013). They are also measured in many monitoring programs, enabling this method to be applied in other regions.

2.4. Identify desired state

2.4.1. Desired state of above-ground biomass

Once the species assemblages were defined using the MRTs, temporal trends in above-ground biomass were examined. Generalized Linear Models (GLMs) were fitted using Tweedie models (Tweedie, 1984). The Tweedie models were compared to Hurdle models (Mullahy, 1986), which performed similarly. Uncertainty was estimated by calculating the 95% confidence interval (CI) of model predictions for each year.

For the determination of above-ground biomass desired state within each community, years with low sample size (number of sites<15) were excluded due to the high variability in biomass estimates for these years. We aimed to set ambitious targets, and acknowledged that the ecological integrity of the bay over the period of time in which data was available was likely to be somewhat compromised relative to a non-impacted baseline. Therefore, a reference data set was compiled for each community from years when biomass was highest. Specifically, the reference data was biomass in the year where maximum seagrass biomass was present, plus those years where biomass was not significantly different from the maximum year using Wald post hoc comparisons. In three of the communities (3, 4 and 5), the reference data set was compiled from three to four years of data for each community. In the remaining four communities (1, 2, 6/7 and 8/9), maximum biomass occurred in 2007, and this was significantly different from all other years. Where this occurred, 2007 was considered an outlier year that was unlikely to represent an achievable desired state, and the reference data set was therefore based on the mean of 2007 and the second and third greatest biomass years. Desired state was determined as average above-ground biomass of the reference data for each community, bounded by the 95% confidence intervals. All plots were created using the *ggplot* package in R (Wickham, 2016).

2.4.1. Desired state of spatial extent

Spatial extent desired state was defined as the mean total seagrass spatial extent (i.e. all communities combined) based on the three years where extent was at its maximum. This was calculated separately for each sub-region because the large range in spatial extent among sub-regions, from tens to thousands of hectares, meant results from the largest meadows, e.g. South Cleveland Bay, masked trends in the sub-regions with small meadows. Desired state mean total extent (hectares) and 95% CI for those three best years, plus the contribution of each community to area desired state for those years, were calculated using the bias-corrected accelerated bootstrap method (repeated 10,000 times) with the *boot* package in R (Canty and Ripley, 2017; Davison and Hinkley, 1997). This approach ensures that the spatial coverage of community types, not just total extent, contributes to desired state.

We could not calculate a desired state of extent for subtidal community 1, as sampling only ever occurred during the broad-scale surveys.

Shelly Beach was removed from the calculation of desired state for both subtidal communities, as even very shallow subtidal sites were only surveyed during broad-scale surveys.

3. Results

Intertidal areas within the Bay supported a greater number of seagrass community types, and the habitat conditions associated with these was more complex. This demonstrates that the common grouping of seagrass habitat as "intertidal" likely underestimates the complexity of conditions and community types in the intertidal zone. The species presence/absence MRTs identified two subtidal communities (communities 1 and 2) and seven intertidal communities (communities 3–9) (Fig. 2, Table 2). All four habitat characteristics were used by the MRTs to determine the different communities: Sed_{dom}, RelExp, WCI and Depth. *C. serrulata*, *H. ovalis*, and *H. uninervis* occurred in all seagrass communities with varying levels of frequency. The most common species were: *Z. muelleri* in communities 4 and 9, *H. ovalis* in community 5, *H. spinulosa* in community 1, and *H. uninervis* in communities 2, 3, 6, 7, and 8 (Table 2). *T. hemprichii* was absent in the two subtidal communities and in the two *Z. muelleri*-dominated intertidal communities, and occurred at low frequency in the remaining intertidal communities. Both *Z. muelleri* and *T. hemprichii* occurred almost exclusively in the intertidal habitats in Cleveland Bay and did not overlap with *H. spinulosa* and *H. decipiens* which were more dominant in the deepest community. For subtidal seagrass, Depth was the only explanatory variable dividing communities (Fig. 2a). In water shallower than 3.5m the community was dominated by *H. uninervis*, while the community deeper than 3.5m was dominated by *H. spinulosa*.

For intertidal seagrass, the first split in the MRT was relative exposure with communities 3–5 exposed relatively more (>1.5 out of 9) than communities 6–9 (<1.5 out of 9) (Fig. 2b). Sediment was the next split, with communities defined predominantly on whether they grew in mud compared with all other sediment types (Fig. 2b). Mud communities were dominated by *Z. muelleri* (communities 4 and 9), *H. ovalis* (community 5), and *H. uninervis* (community 8), while *H. uninervis* was always the dominant species in the three non-mud communities (3, 6, and 7). Mud communities were further defined according to the WCI (Fig. 2b). On the right hand side, there is a second split based on sediment where habitat that has sand substrate separates from habitat that is reef, rock or rubble. Both of these are mixed communities dominated by *H. uninervis*. On the far right, the mud/coarse sand sites were further split based on the WCI (Fig. 2b).

The MRT was repeated with above-ground biomass (square root transformed) as the response variable instead of presence/absence. The splits in the tree (Appendix A) were almost exactly the same as the presence/absence MRT therefore, the results appear to be quite robust to changes in the choice of response variable. The only small differences were that in subtidal habitat, the depth leading to the split is 3.3m compared to 3.5m. At intertidal sites community 6 was combined with community 7, as the final split based on sediment was not important when using the biomass data.
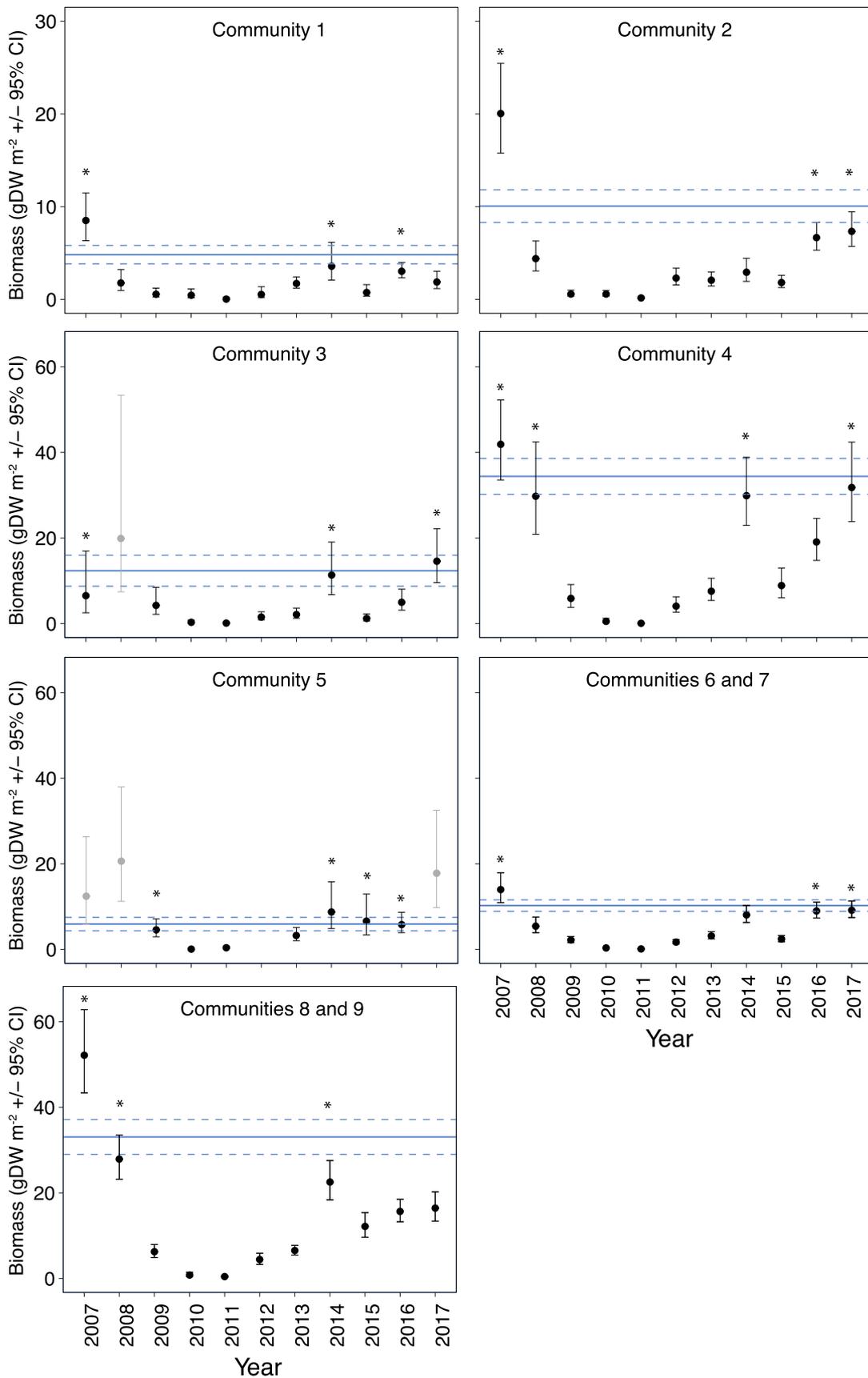
Fig. 3. Annual mean above-ground biomass (±95% CI) for Cleveland Bay seagrass communities, 2007–2017. Greyed values were not included in Tweedie GLM statistical analyses due to low sample size for that year. Seagrass above-ground biomass desired state (solid blue line) with upper and lower 95% CIs (dashed blue lines). Asterisks indicate years used to form the reference data for setting desired state. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
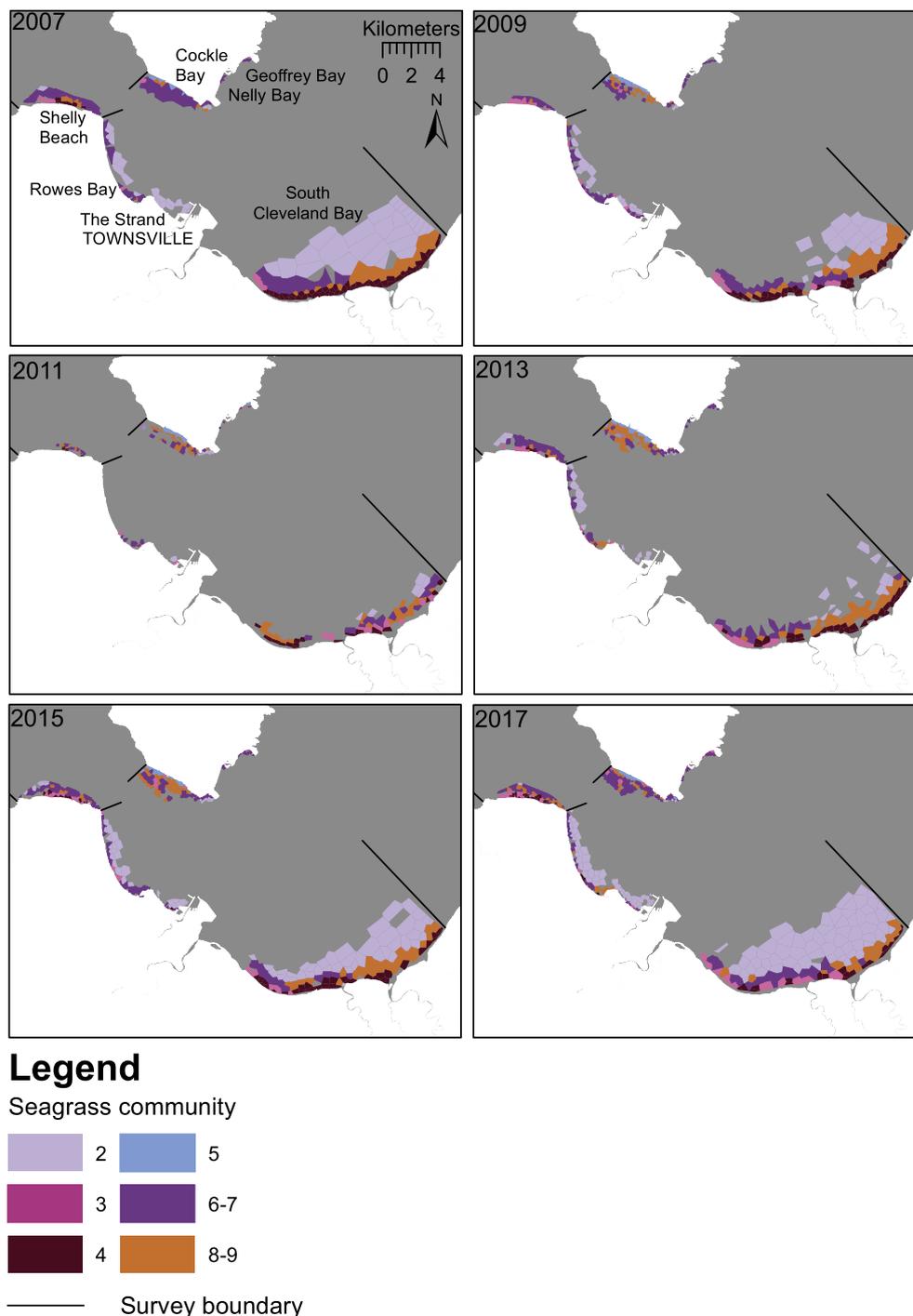
Fig. 4. Temporal change in spatial extent of Cleveland Bay seagrass communities 2, 3, 4, 5, 6/7 and 8/9. Community 1 (deep subtidal) excluded, as sampling only ever occurred during broad-scale surveys. Extent shown for every second year to demonstrate change overtime.

The presence/absence MRT was then applied to the 2017 data, demonstrating that the model can be used to predict community types and the distribution of community types is similar to the preceding years (Appendix A; Figure A2).

3.1. Above-ground biomass desired state

Above-ground biomass desired state in the shallow subtidal community 2 (10 gDW m^{-2}), which was dominated by *H. uninervis,* was double that of deep subtidal community 1, which has a greater dominance of *Halophila* species (Fig. 3, Table 3). For intertidal communities,

above-ground biomass desired state was lowest for community 5 (~6 gDW m^{-2}), the high exposure intertidal *H. ovalis* dominated community at Magnetic Island. Intertidal community desired state biomass was greatest for the high exposure *Z. muelleri* dominated community 4 along the mainland coast (~34 gDW m^{-2}), and the low exposure communities 8 (*H. uninervis* with *C. serrulata*) and 9 (*Z. muelleri* with *C. serrulata*) (~33 gDW m^{-2}) (Fig. 3, Table 3).

Above-ground biomass of all communities significantly varied among years. The highest biomass was observed in 2007 or 2008 in all communities, while biomass reached high levels also in 2017 or 2014 (Fig. 3). The lowest biomass was observed in 2011, but very low biomass was
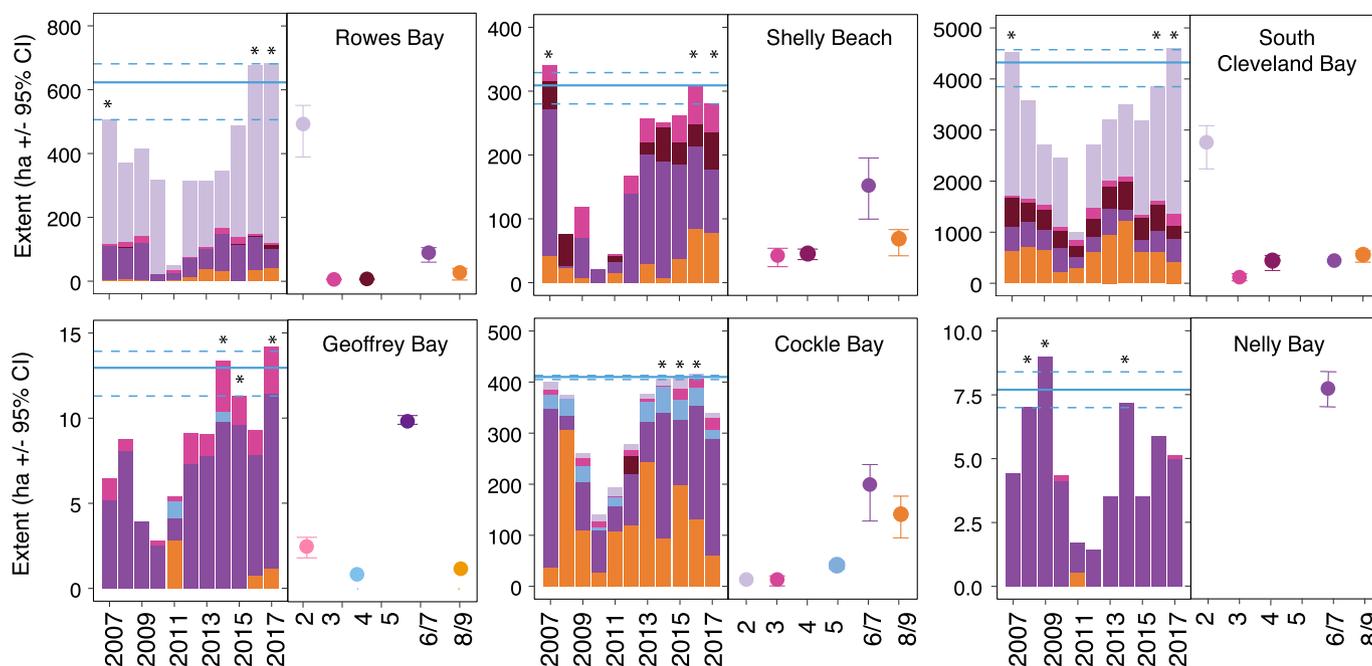
Fig. 5. Annual extent (hectares) for Cleveland Bay seagrass communities in each sub-region, 2007–2017. For each sub-region, bar plots (left) show seagrass extent desired state (solid blue line) with upper and lower 95% CIs (dashed blue lines); dot plots (right) show expected contribution of each seagrass community to extent desired state (±95% CIs). Colour coding of community types match those presented in Fig. 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Seagrass community, dominant habitat requirement (first split in the tree is either depth or tidal exposure), dominant species (most frequently recorded, see Fig. 4), and above-ground biomass desired state (mean with 95% confidence intervals).

Depth	Community	Depth/ exposure	Dominant species	Desired state biomass (gDW m^{-2})	
				Mean	95% CI
Subtidal	1	Deep (>3.5m)	H. spinulosa	4.8	3.8, 5.8
	2	Shallow (≤3.5m)	H. uninervis	10.1	8.3, 11.8
Intertidal	3	High exposure (>1.5)	H. uninervis	12.4	8.7, 16.0
	4	High exposure (>1.5)	Z. muelleri	34.4	30.2, 38.6
	5	High exposure (>1.5)	H. ovalis	5.9	4.4, 7.5
	6/7	Low exposure (<1.5)	H. uninervis	10.2	8.9, 11.6
	8/9	Low exposure (<1.5)	H. uninervis	33.1	29.0, 37.1

observed from 2009 to 2012. The largest variation in biomass occurred in the communities that also reached the highest biomass. These were community 2 (shallow subtidal *H. uninervis* dominated), community 4 (high exposure intertidal, predominantly *Z. muelleri* community) and community 8/9 (low exposure intertidal, mixed species). The lowest variation in biomass occurred in high exposure intertidal communities 3 and 5 (Fig. 3).

3.2. Spatial extent desired state

The years used to form the reference data set for extent differed among sub-regions, but most frequently included the years 2007, 2014, 2016 and/or 2017 (Fig. 5). The years 2010–2013 were not used to define extent desired state for any sub-region, with extent particularly low in

2011 (Figs. 4, 5). Extent desired state varied greatly among sub-regions, ranging from 4323 ha in the large South Cleveland Bay meadow, to 7.7 ha in the small Nelly Bay meadow (Fig. 4). The maximum seagrass extent was limited largely by local topography, such as the reef-top meadow at Cockle Bay. Extent desired state was greatest for South Cleveland Bay where shallow subtidal community 2 was a dominant contributor to seagrass extent (Figs. 4, 5).

Each of the sub-regions had a unique combination of seagrass community types. Community 6/7 was present in every sub-region, and was the most extensive community in Geoffrey Bay, Nelly Bay, Shelly Beach, and the intertidal component of Rowes Bay. Communities 8 and 9 contributed most to extent desired state at Cockle and South Cleveland Bays. Intertidal communities with high intertidal exposure were restricted to a narrow band along the shoreline so contributed least to extent desired state. Community 4 contributed to extent desired state only on the mainland (Rowes Bay, Shelly Beach, and South Cleveland Bay), while community 5 was only recorded in Cockle and Geoffrey Bays at Magnetic Island. Community 3 occurred in all sub-regions but was always a minor contributor to seagrass extent (Figs. 4, 5).

4. Discussion

Using two metrics of seagrass condition measured over more than a decade we present an approach to setting desired state for seagrass communities in a complex and dynamic tropical habitat. Setting targets is one of the most critical, yet challenging aspects of assessing ecological status (Samhouri et al., 2012) but they are needed to assess the progress towards meeting management objectives when considered in context of natural disturbances. We discuss the benefits and limitations of this approach, and considerations for broader assessment of seagrass desired state.

4.1. Setting desired state

There are many attributes that determine whether seagrass habitat has reached a desired state, including both its condition and resilience.

However, environmental managers often require simple indicators and metrics that can provide information on both. Simple condition metrics such as above-ground biomass and extent are important criteria because they are the sum effect of multiple processes (Daan, 2005; Roca et al., 2016), and can be proportional to provisioning of ecosystem services (Scott et al., 2018). They also overlap with some of the metrics recommended for assessment of resilience, which would also require additional metrics not included in our study (O'Brien et al., 2017; Unsworth et al., 2015). They respond to a diverse range of environmental pressures including light availabilty, water temperature, and toxicant concentrations (Chartrand et al., 2016; Collier et al., 2012b; Negri et al., 2015), plus biological processes and pressures (Scott et al., 2018). By contrast, when screening for a specific stress other metrics such as physiological measures can be used (McMahon et al., 2013; Roca et al., 2016; Schliep et al., 2015; Collier et al., 2017), but these are not as relevant to the time-scales considered here. Seagrass communities provide many ecosystem services but different species and community types vary in their contribution to each of the services because of features such as biomass and other structural characteristics (Mtwana Nordlund et al., 2016). Attempting to define desired state for each of those functions would require substantial quantitative information on ecosystem services that is not available. Hence we need to adopt the assumption that resilience and ecosystem function of the habitat will be preserved if desired state of biomass and extent is met in all community types (Tett et al., 2013), which is acknowledged as unsatisfactory if maintaining resilience is the overarching management objective. We therefore recommend inclusion of complimentary resilience metrics such as population structure and measures of sexual reproduction – an inclusion that is not possible at this stage owing to a lack of data.

Pollutant discharge into the GBRWHA has increased following mining and agricultural development that commenced in the 1850s (Bainbridge et al., 2018); the effect of these activities on seagrass communities in Cleveland Bay is not directly known. The earliest comprehensive seagrass surveys conducted within the area were in the 1980s [summarised in 99], but these were snap-shot surveys and cannot be used to gauge trends in seagrass condition since then. However, it is in the opinion of authors engaged in those early surveys that the maximum level of the metrics observed in the 11-year data set (i.e. desired state), is not dissimilar to observations from the 1980s, but the amount of variability at that time is not known (R. Coles pers com, 2015). In the absence of longer-term historical information on seagrass habitat condition, we have used available data from the previous 11 years. During this period, there was extensive declines in biomass and extent associated with multiple impacts, including flooding and cyclones (McKenzie et al., 2019; Bryant and Rasheed, 2018; Petus et al., 2014). Therefore, the highest levels of biomass and areal extent was used as a reference data set to define desired state, which has resulted in targets that are realistic, but also ambitious.

The region is affected by multiple threats, and targets that are linked to any one anthropogenic pressure (e.g. river discharge), may not be relevant for another pressure (e.g. thermal stress). River discharge can affect water clarity (Fabricius et al., 2014) in which case targets for discharge may be focussed on subtidal or deepwater seagrass communities growing near the edge of light requirements (Choice et al., 2014) and/or against other habitats that are sensitive to turbidity including coral reefs. The time-scales over which these environmental pressures affect seagrass condition can range from weeks and months (Collier et al., 2012a; Chartrand et al., 2016) to annual or multi-annual (Lambert et al., 2019), which influences how targets are used or interpreted for management actions. Therefore, indicators and metrics needed to meet sensitivity, responsiveness, and specifity requirements to pressures must be considered (Lambert et al., 2019; Rice and Rochet, 2005). There may be a need to adapt, or even develop complimentary targets that are specific to these time and space-scales for example, defining levels of change (loss or gain) by gradients in pressure (Collier et al., 2012a, 2016; Lambert et al., 2019).

Pressure-response models can be used to prioritise investment into management strategies to protect seagrass condition (Choice et al., 2014; Saunders et al., 2017; Adams et al., 2015) and to identify the cause of any failure to meet desired state. Also needed is the capacity to forecast the trajectories of ecosystems subject to multiple simultaneous pressures and changes. Ecological thresholds and environmental condition boundaries should be identified, and the consequences of crossing them identified as far as possible (Collier et al., 2016; Strange, 2007). However, pressure-response models require locally-specific data on pressures at a scale that is complimentary to the scale of information on seagrass condition and response to the pressures (Wicks et al., 2010; Adams et al., 2015). We have tested an approach to setting desired state that is not constrained by these modelling needs, but which nonetheless can be used for testing management scenarios.

Our study highlights some limitations and considerations when applying this approach in other areas:

1. *Historical data required.* This approach requires a relatively large historical seagrass data set that captures decadal-scale change. In Cleveland Bay, there was large variability in the biomass and extent metrics that enabled us to develop a reference dataset based on years when biomass and extent were high, and significantly different from other years. An independent test of the targets can occur within an adaptive management cycle as more data is collected in annual surveys. In less or more dynamic regions, it may be more difficult to identify an appropriate reference data set or the need to exclude "bad years" for community analysis, and so adjustment to the decision rules may be required.

2. *Decision rules were required.* Setting desired state required informed choices to made by authors most familiar with the data and the study region in conjunction with exploratory analysis e.g. removal of "bad years" for classifying the communities. These decision rules are detailed throughout the methods, and may have been slightly different if this analysis was undertaken by others.

3. *Matching monitoring scale to desired state scale.* Biomass desired state was developed for each community type across a relatively broad area (Cleveland Bay), and extent targets for the sub-region. When bay-wide targets were tested against individual meadows at the sub-region scale, the bay-wide biomass desired state for each community was not applicable for some individual meadows meaning that desired state may never be achieved at some locations. This is likely due to local features that our current model used to define seagrass communities is not able to resolve, such as wave and wind exposure, sediment nutrient concentration, and grazing pressure by green sea turtles (*Chelonia mydas*) and dugong (*Dugong dugon*) that will influence biomass but is less likely to affect extent (Scott et al., 2018). If the reporting and monitoring is matched to the desired state scale (i.e. Cleveland Bay), then small-scale disturbances can occur and the target for that community still be met. These small-scale disturbances and variation in local conditions occurred from 2007 to 2017, and were an inherent component of the data set used to set the targets. Desired state can be refined to increase the spatial resolution of the targets to investigate small-scale processes and pressures, but doing this could also make the desired state less useful as it would result in a greater number of targets, increase complexity, and complicate procedures for tracking progress against targets.

Cleveland Bay is affected by tropical cyclones, extreme rainfall and river discharge events (McKenzie et al., 2019; Bryant and Rasheed, 2018; Cook et al., 2016), and heat waves that have devastated vast swathes of coral reefs in the broader region (Lough et al., 2018; Hughes et al., 2018). Our data confirms that large, event-driven changes in the biomass and extent of seagrass in Cleveland Bay have occurred, as observed in other locations in the GBRWHA (Rasheed et al., 2014; McKenna et al., 2015) and more extreme conditions are projected in the future (Lough and Hobday, 2011). Excursions below desired state will continue in response
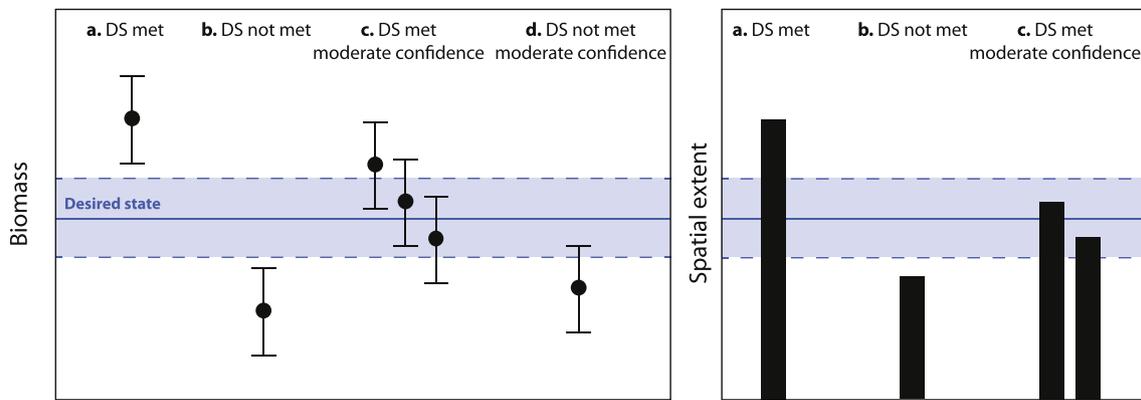
Fig. 6. Interpretation of whether desired state (DS) is met for above-ground biomass (mean ± 95% confidence intervals; left) and spatial extent (right).

to events such as cyclones with frequent occurrence. Under these circumstances, it is the ability for the seagrass communities to rapidly return to the prescribed desired state levels that will be of interest. While it may appear that single targets could make these changes difficult to reach, reporting procedures can be implemented to track trends relative to targets.

While returning ecosystems to a particular historic state is a useful goal, it may not be acheivable. For example, reduced nutrient loading from rivers may be ineffective in the presence of other major stressors such as climate change – the Return to Neverland conundrum (Duarte et al., 2009). Adaptive management frameworks (e.g. Hallett et al. (2016)) include a need to revise targets, however once set, changes should be adopted cautiously and infrequently. It may be necessary to refine the targets to accomodate the resilience needed to withstand changing pressures (Cook et al., 2016). On the other hand, if management actions are effective and there is an increase in the frequency in which targets are reached, then it may be necessary to refine them to a higher level to maintain the ability to understand the conditions associated with when they are met and when they are not. Alternatively, proxies for resilience such as connectivity among seagrass meadows (Grech et al., 2016), could be added to the definition of desired state and used to track progress towards management goals in the face of increasing pressures or improved management strategies.

4.2. Reporting against desired state

Our definition of desired state provides a benchmark against which to assess future annual growing season (September–December) condition, where:

- *Desired state is met* with a high level of confidence placed in that assessment if the mean biomass or spatial extent exceeds desired state and its upper CI (Fig. 6a).
- *Desired state is not met* with a high level of confidence if the mean biomass or spatial extent is lower than the lower CI (Fig. 6b).
- *Desired state is met with a reduced level of confidence* when: 1. the mean biomass of a community is above the upper CI of desired state but the CI overlaps with desired state range; or 2. when the mean biomass of a community or spatial extent is within the desired state range (Fig. 6c).
- *Desired state is not met with a reduced level of confidence* when the mean biomass is lower than the desired state range, but the upper biomass CI falls within the desired state range (Fig. 6d).

The considerations for reporting against desired state will be affected by the monitoring and reporting needs of specific programs, all of which are possible with small adaptations to the framework presented here. These include scaling community types based on dominance or sensitivity, or impacted versus pristine areas. Trends in ecological condition can also be accommodated by applying the biomass models to new

annual monitoring data and a statistically significant increase or decrease in biomass can be determined. A failure to meet desired state doesn't necessarily mean that management actions have failed where there is an improving trend, or if there have been disturbances that are outside of management control. The timeframe over which reporting against desired state occurs will be important in these dynamic habitats with significant interannual variation. Alternatively, consideration can be given to designing management around a relative desired state with better values than currently (i.e. improving trend), but not an absolute desired state. Given the long time lags inherent in improving water quality such as reduction in sediment loads from the Burdekin River, trends in seagrass condition due to management actions will take many years to become evident (Bartley et al., 2014).

4.3. Conclusions

Setting targets is essential for the management of marine ecosystems, but doing so presents multiple challenges, and there are few quantitative examples for benthic habitats. We present an approach to setting seagrass desired state in complex habitat that is both dynamic and diverse. The framework we developed enables flexibility to locally-optimize the analysis to other locations. The process used for setting desired state was tailored towards the system of Cleveland Bay, but could be modified for application in other regions with particular environmental contexts, data availability, and management needs. The study site may be somewhat unusual in having a relatively long decadal scale historical data set with differences among years that could be used to set a reference data set. However, the approach presented herein may be useful in other jurisdictions to adopt this methodology, or to assess how current data collection strategies could be modified to allow for desired state estimates in future. The confidence intervals around desired state can be used for reporting on whether the desired state has been met for future data collections. It is important that the scale of reporting is consistent with the scale over which the reference points were set, and these desired states could be re-scaled as needed. Future research could assess how management scenarios are likely to return seagrass communities to an improving trend towards desired state.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indic.2020.100042.

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