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Using modelling to predict impacts of sea level rise and increased turbidity on seagrass distributions in estuarine embayments

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ABSTRACT

Climate change induced sea level rise will affect shallow estuarine habitats, which are already under threat from multiple anthropogenic stressors. Here, we present the results of modelling to predict potential impacts of climate change associated processes on seagrass distributions. We use a novel application of relative environmental suitability (RES) modelling to examine relationships between variables of physiological importance to seagrasses (light availability, wave exposure, and current flow) and seagrass distributions within 5 estuarine embayments. Models were constructed separately for *Posidonia australis* and *Zostera muelleri* subsp. *capricorni* using seagrass data from Port Stephens estuary, New South Wales, Australia. Subsequent testing of models used independent datasets from four other estuarine embayments (Wallis Lake, Lake Illawarra, Merimbula Lake, and Pambula Lake) distributed along 570 km of the east Australian coast. Relative environmental suitability models provided adequate predictions for seagrass distributions within Port Stephens and the other estuarine embayments, indicating that they may have broad regional application. Under the predictions of RES models, both sea level rise and increased turbidity are predicted to cause substantial seagrass losses in deeper estuarine areas, resulting in a net shoreward movement of seagrass beds. Seagrass species distribution models developed in this study provide a valuable tool to predict future shifts in estuarine seagrass distributions, allowing identification of areas for protection, monitoring and rehabilitation.

1. Introduction

Habitat loss in marine environments has been linked to loss of biodiversity (Stuart-Smith et al., 2015; Harasti, 2016) and species extinctions (Dulvy et al., 2003). Estuaries, in particular, are suffering habitat loss from anthropogenic impacts (e.g. coastal development, pollution, eutrophication), due to the concentration of human activities within and around estuarine systems (Duarte, 2002; Lotze et al., 2006). Anthropogenic impacts are often compounded by disturbances from extreme weather events (e.g., storm waves, flooding), which are predicted to become more severe due to climate change (Hoegh-Guldberg and Bruno, 2010; Emanuel, 2013), and climate-induced sea level rise (Short and Neckles, 1999). There is, therefore, a clear need to improve our understanding of the relationships between estuarine habitats and their environment, to inform management actions targeted at mitigating habitat loss.

Seagrass meadows are productive estuarine ecosystems that support substantial biodiversity and provide valuable ecosystem services (Barbier et al., 2011). While data on seagrass distributions can be obtained using a combination of aerial/satellite imagery and ground truthing (Kendrick et al., 2002; Creese et al., 2009), these data do not provide insights into how species distributions will change in response to future climate change. To address this, species distribution modelling (SDM) provides a tool that can be used to examine how species are likely to respond to future environmental changes, allowing identification of areas most likely to facilitate long-term species survival (Guisan and Thuiller, 2005). Numerous techniques have been used for SDM including: presence/absence based methods such as generalised linear modelling (GLM) (Kelly et al., 2001), and generalised additive modelling (GAM) (Downie et al., 2013); and methods using presence-only data such as maximum entropy (Maxent) (Poulos et al., 2015), relative environmental suitability (RES) (Kaschner et al., 2006), and the genetic

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algorithm rule-set procedure (GARP) (West et al., 2008).

Often, seagrass SDMs are not developed to be generally applicable, but are constructed for specific objectives within localised regions, such as predicting responses to changes in turbidity (Lathrop et al., 2001) or identifying sites suitability for restoration (Kelly et al., 2001). However, models with applicability across a range of estuarine systems are useful for developing regional management strategies (Van der Heide et al., 2009), and using explanatory variables with direct linkages to the ecological requirements of species is recommended where broader applicability is an objective (Guisan and Zimmermann, 2000).

Within well-mixed estuarine embayments, temperature and salinity are relatively uniform, and the dominant variables influencing seagrass distributions are light availability (Abal and Dennison, 1996; Duarte et al., 2007), wave exposure (Fonseca et al., 2002; Grech and Coles, 2010), current flows (Bridges et al., 1982; Fonseca and Bell, 1998), and tidal location (Van der Heide et al., 2009). Seagrasses only occur where there is sufficient light for photosynthesis (Duarte et al., 2007), with light availability at the seabed influenced by water depth and turbidity (Anthony et al., 2004; Greve and Krause-Jensen, 2005). Furthermore, seagrasses are influenced by tidal location with some species occurring intertidally, while others are predominantly subtidal (Van der Heide et al., 2009). Waves influence seagrass distributions through damaging and uprooting established plants, and preventing settlement of seeds (Carruthers et al., 2002), with negative effects concentrated in shallow areas where waves generate substantial forces at the seabed (Rohweder et al., 2012). Currents also negatively impact seagrasses (Fonseca and Bell, 1998), with strong currents, driven by tidal and river flows, generating substantial forces at the seabed (Jiang et al., 2011).

Here, we developed RES models for large estuarine embayments in New South Wales (NSW), Australia, using variables of physiological importance to seagrasses (i.e. light availability, wave exposure, and current flow), with the objective of testing model transferability, in terms of the ability to use models created in one estuary to predict seagrass distributions for other estuaries. Models were created using data from Port Stephens and tested in four other NSW estuarine embayments, spanning over 570 km of the NSW coastline. This represents the first application of RES to prediction of estuarine seagrass distributions, with RES previously primarily used for predicting global distributions of marine species (Ready et al., 2010).

Although broad-scale reviews of the probable response of seagrasses to climate change have been conducted (Short and Neckles, 1999; Björk et al., 2008), relatively few studies have examined changes in seagrass distributions at a regional scale in response to sea level rise and increased turbidity (but see Carr et al., 2011). It has been projected that climate change will lead to substantial sea level rise over the coming century (Church et al., 2013) and may also lead to regional increases in wind velocities, waves, currents, and turbidity through increased storm activity and floods (Björk et al., 2008). We therefore used the RES models to calculate changes in seagrass distributions for projected climate change induced sea level rises, and for changes in turbidity. This allowed us to assess locations where seagrass loss is likely to occur, and to identify areas of high resilience where seagrasses will be relatively unaffected.

2. Material and methods

2.1. Study sites

This study examined five micro-tidal (tidal range < 2 m) estuarine embayments in NSW, Australia (Table 1, Fig. 1). Each estuary contained substantial areas of subtidal seagrasses (i.e. *Posidonia australis*, *Zostera muelleri* subspecies *capricorni* (hereafter *Z. muelleri*), and *Halophila ovalis*) (Creese et al., 2009). Separate RES models were constructed for *P. australis* and *Z. muelleri* using data from Port Stephens (Fig. 1), as this embayment contained both seagrass species, and the embayment had widely varying levels of turbidity, wave exposure, and tidal currents, making it ideally suited for developing models with general applicability. A RES model for *H. ovalis* was not constructed as this species generally has sparse cover and displays seasonal changes in distribution (Stewart and Fairfull, 2007). Current seagrass distributions for *P. australis* and *Z. muelleri* within Port Stephens were obtained from recent surveys (Davis et al., 2016). Distribution maps were generated from high-resolution (7.5 cm), geo-referenced aerial photographs from August 2014 (Nearmap, 2014) which were ground-truthed using towed video (Davis et al., 2015). Seagrass distributions for other estuaries were obtained from the study by Creese et al. (2009), with maps generated from orthorectified aerial photographs with boundary locations and species presence verified in the field.

2.2. Calculation of explanatory variables

Light availability (*Light*), tidal velocity (*Current*), and orbital velocity at the seabed due to waves (*Waves*) were calculated for use as explanatory variables in RES models. Light availability was defined using the ratio of photosynthetically-available radiation (PAR) at the seabed (E_z) to PAR at the surface (E_0), and calculated using Beer-Lambert's law: $Light = E_z/E_0 = e^{-K_d(PAR)z}$ where; z = water depth, and $K_d(PAR)$ = irradiance attenuation coefficient. Values of $K_d(PAR)$ were calculated from measured Secchi depths (Z_{SD}) using the relationship ($Kd(PAR) = 1.4/Z_{SD}$) derived for turbid coastal waters by Holmes (1970). Secchi depth data were obtained as point measurements at multiple sites within each estuary, over extended periods (>12 months), allowing derivation of time-averaged Secchi depth distributions, with interpolation of Secchi depths between measurement sites. For Port Stephens, average Secchi depths varied from 8.8 m at the estuary entrance to 2.2 m at the western end of the embayment (pers. obs.). Secchi depths for Wallis Lakes and Lake Illawarra were obtained as point measurements from the online data repository OzCoasts (2015), with Secchi depths in Wallis Lakes varying from 2.6 m at the estuary entrance to 0.5 m in the Wallingat River, and those in Lake Illawarra varying from 2.4 m to 1.2 m. Secchi depths for Merimbula and Pambula lakes were supplied by Bega Valley Shire Council (Elgin, 2014a; 2014b), varying from 5.5 m to 4.6 m in Merimbula Lake, and from 3.1 m to 2.0 m in Pambula

Table 1
Study estuaries in New South Wales, Australia, with locations, water area (km^2) and prevalence (% cover) of *Zostera muelleri* and *Posidonia australis*.

Estuary	Location	Water area	*Z. muelleri* prevalence	*P. australis* prevalence
Wallis Lake	152.510 E, 32.174 S	93.82	31.4%	2.6%
Port Stephens	152.190 E, 32.708 S	52.04	8.1%	5.1%
Lake Illawarra	150.873 E, 34.544 S	35.81	22.3%	Nil
Merimbula Lake	149.922 E, 36.896 S	4.89	9.8%	23.5%
Pambula Lake	149.916 E, 36.948 S	3.70	9.7%	14.1%