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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.

Keywords

Climate change; Seagrass; *Posidonia australis*; Australia, New South Wales; Species distribution modelling

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 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 inter-tidally, 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 < 2m) estuarine embayments in NSW, Australia (Table 1, Figure 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 (Figure 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.

Table 1: Study estuaries in New South Wales, Australia, with locations, water area (km²) and prevalence (% cover) of *Zostera muelleri* and *Posidonia australis*

Estuary	Location	Water area	<i>Z. muelleri</i> prevalence	<i>P. australis</i> 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%

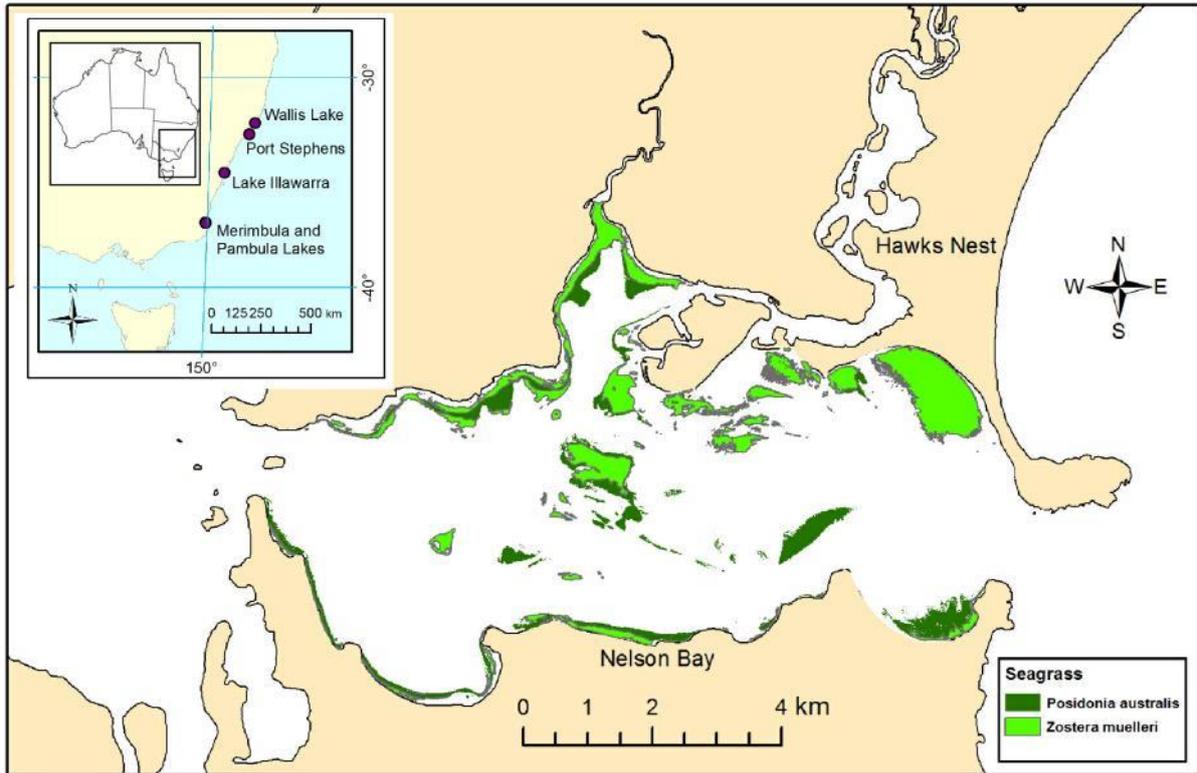


Figure 1: Maps showing the location of study estuaries (●) in New South Wales, Australia and, as an example, the spatial extent of seagrass beds from Port Stephens, which were used to develop species distribution models.

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 ($K_d(PAR) = 1.4/Z_{SD}$) 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; Elgin 2014b), varying from 5.5 m to 4.6 m in Merimbula Lake, and from 3.1 m to 2.0 m in Pambula Lake.

Maximum tidal current velocities (*Current*) were influenced by tidal range, depth, and estuarine geometry, and were calculated for each estuary using two-dimensional hydrodynamic models constructed using TELEMAC-2D (Hervouet 2000). The accuracy of the modelling methodology was validated using measured tidal velocity data (DPWS 1998). Each tidal model included an entire estuary and a section of the coastal waters immediately adjacent to the estuary entrance, and currents were calculated for spring tides with a range of 2.0 m.

Maximum wave-induced orbital velocities at the seabed (*Waves*) were calculated by taking the maximum orbital velocity at each point for wind-driven waves and ocean swells for wave and swell directions at 45° increments from 0–360°. Orbital velocities at the seabed were calculated from wave heights using the relationships defined in Rohweder et al. (2012) with assumed wave breaking heights of $0.55 \times \text{depth}$ as per Nelson (1994). Wind-driven wave heights were calculated from wind speeds, fetches (the distance travelled over water by the wind), and water depths using the relationships defined in Rohweder et al. (2012). Wind velocities in each direction were taken as the 90th percentile wind speeds from weather stations nearest to each estuary (maximum distance 34 km) using data obtained from the Australian Bureau of Meteorology (<http://www.bom.gov.au> accessed 27 November 2015). Fetch was calculated using the Waves2012 toolbox in ArcGIS 10 (Rohweder et al. 2012), based on the US Army Corps of Engineers Shore Protection Manual procedure (USACE 1984). Port Stephens was the only embayment where the estuary entrance allowed substantial swell ingress, and ocean swell heights within the estuary were calculated using a two-dimensional hydrodynamic model of the estuary generated in the wave propagation simulation software ARTEMIS (Hervouet 2000). Data on storm-driven swells from 2000–2011 were obtained from the Manly Hydraulics Laboratory (<http://new.mhl.nsw.gov.au> accessed 10/12/15) and analysed to determine peak wave heights and swell periods for directions where significant swells were capable of entering the estuary (i.e. 90°, height = 3.39 m, period = 7.8–13.8 s; 135°, height = 3.68 m, period = 7.5–10.9 s), with these data applied at the ARTEMIS model offshore boundaries.

2.3 Relative environmental suitability model development

Relative environmental suitability models use species presence data to define ecological niches in terms of preferred and absolute presence ranges for explanatory variables (here *Light*, *Current*, *Waves*) (Kaschner et al. 2006). Probabilities of seagrass presence in RES models were calculated at each point using trapezoidal envelopes, which defined species-specific preferred and absolute presence ranges for explanatory variables, for data from Port Stephens using methods based on Kaschner et al. (2006). Probability of species presence for an explanatory variable (P_v) was defined as $P_v = 1$ for variables in the preferred range, $P_v = 0$ for values outside the absolute range, and linearly interpolating for values between preferred and absolute ranges (Figure 2). Absolute range limits were defined by the minimum and maximum values for variables where species were present in the training data. Preferred range limits were defined using species percentile occurrence levels, as per Ready et al. (2010), but with limits defined to maximise model precision (Kappa), rather than using fixed 10th and 90th lower and upper percentile limits (Ready et al. 2010). Limits to maximise Kappa were calculated for data from Port Stephens by examining all possible combinations of percentile limits (from 0–100th percentile, in 1% increments), for all explanatory variables (Supplementary Table S1). The overall probability of seagrass presence in RES models (P_{RES}) was computed by multiplying presence probabilities across all variables at each point ($P_{RES} = P_{Light} \times P_{Current} \times P_{Waves}$) with seagrass presence defined by $P_{RES} = 1.0$. Points where $0.0 < P_{RES} < 1.0$, while not used in prediction of seagrass presence, provided indications of areas where seagrasses could potentially occur under sub-optimal conditions. Models developed using training data from Port Stephens were tested by predicting seagrass presence/absence for the other four estuaries examined (external validation), with the accuracy and precision of predictions assessed using known distribution maps for seagrass species.

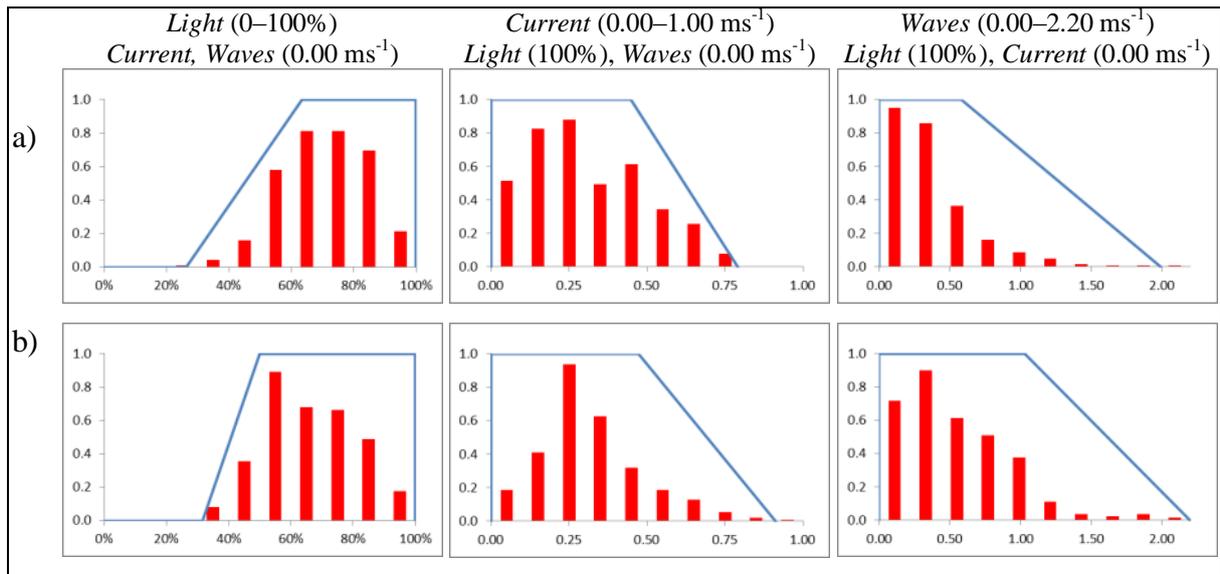


Figure 2: Relative Environmental Suitability (RES) envelopes (solid blue lines) defining probability of seagrass species presence (P_v) for explanatory variables of; % photosynthetic available radiation at the seabed (*Light*), tidal velocity (*Current*), and wave orbital velocity at seabed (*Waves*) for (a) *Posidonia australis* and (b) *Zostera muelleri*. Envelopes and curves based on presence data (red bars) from Port Stephens.

2.4 Modelling effects of climate change induced sea level rise and increased turbidity

The impacts of climate change induced sea level rises on seagrass distributions were simulated in study estuaries for projected rises to 2050 (0.25 m) and 2100 (0.74 m) (Intergovernmental Panel on Climate Change trajectories RCP 8.5) (Church et al. 2013) by increasing water depths in calculations for the explanatory variables *Light* and *Waves*. In addition, the impact on seagrass distributions of future increases in turbidity were examined by modelling nominal reductions in Secchi depth of 10–50% in each estuary, with substantial turbidity increases predicted due to increased frequency and severity of storms and floods (Waycott et al. 2007; Björk et al. 2008). For future scenarios, areas of seagrass loss were defined as those which currently support seagrass but for which future conditions preclude seagrass presence. Changes to sea levels and turbidity were considered separately as detailed projections of turbidity increases under climate change were not available for the estuaries examined. The effects of climate change on wind velocities, storm waves, and currents were not examined as the magnitude of changes to these factors could not be quantified, due to the high degree of uncertainty that currently exists in attributing global climate change effects to weather patterns at a regional scale (Bindoff et al. 2013).

3. Results

3.1 RES model performance

Relative environmental suitability models provided a high level of discrimination for seagrass presence/absence for the internal validation at Port Stephens, with >82% of points correctly classified and Kappa values exceeding 0.32 (Table 2). Generally, RES models accurately predicted seagrass distributions, although they over-predicted seagrass presence in northern and eastern sections of the estuary (Figure 3).

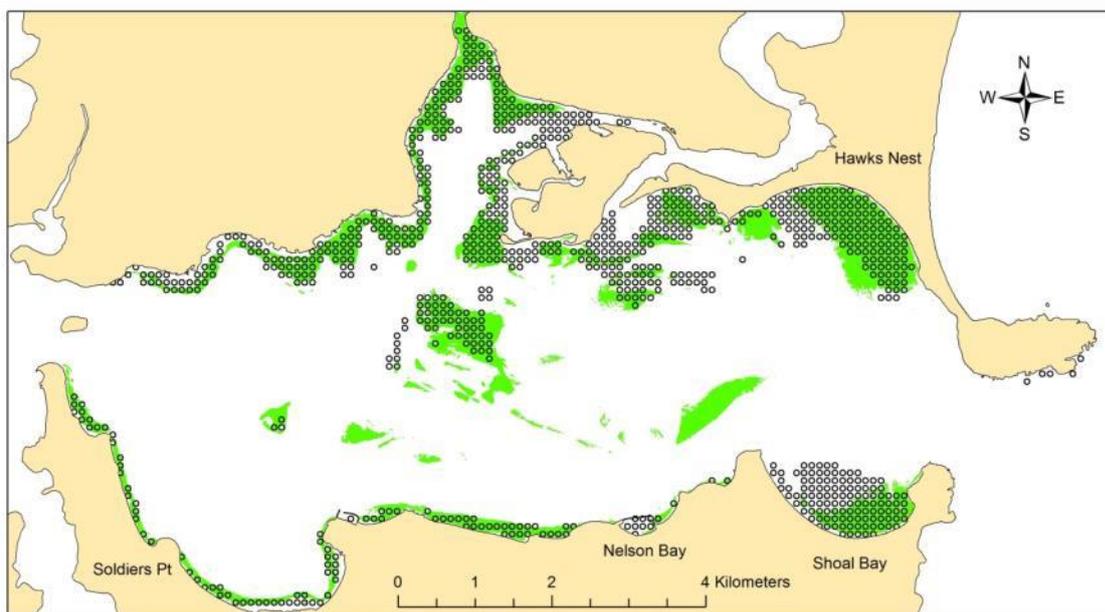


Figure 3: Distribution of seagrass in Port Stephens from aerial photography (green shading) and predicted seagrass presence (circles) for relative environmental suitability model built using training data from the Port Stephens estuary.

An average RES accuracy of $67.2 \pm 4.1\%$, and precision (Kappa) of 0.261 ± 0.082 , was achieved for estuaries outside Port Stephens (external validation) (Table 2). However, RES models tended to overestimate the extent of shallow seagrass beds (Figure 4). Precision was low for *P. australis* in Wallis Lake (Kappa = 0.05) and for *Z. muelleri* in Merimbula Lake (Kappa = 0.07), as many of the points predicted to be occupied by these species were already taken by the dominant seagrass species (i.e. *Z. muelleri* in Wallis Lake and *P. australis* in Merimbula Lake) leading to a high proportion of false presences (Table 2). An examination of RES model envelopes for *P. australis* and *Z. muelleri* found that there were considerable

overlaps in the preferred ranges for these species, in terms of their light requirements and tolerances to waves and currents (Table S1). Overlaps in species envelopes thus confounded the ability to distinguish between species in SDMs, and indicating that there is potential for competition for space between seagrass species.

Table 2: Overall model accuracy (%), model precision (Kappa statistic), true presence (%), and false presence (%) at study sites for relative environmental suitability models. (a) *Posidonia australis* presence, (b) *Zostera muelleri* subsp. *capricorni* presence

	Site	Overall accuracy	Kappa statistic	True presence	False presence
a)	Port Stephens	91.5	0.41	49.6	5.1
	Wallis Lake	67.2	0.05	62.5	32.7
	Merimbula Lake	68.6	0.19	43.8	23.8
	Pambula Lake	70.9	0.35	90.9	32.9
b)	Port Stephens	85.1	0.39	73.9	13.8
	Wallis Lake	70.0	0.41	84.8	37.7
	Lake Illawarra	85.3	0.64	94.0	17.3
	Merimbula Lake	53.0	0.07	66.7	48.6
	Pambula Lake	55.1	0.12	84.8	47.9

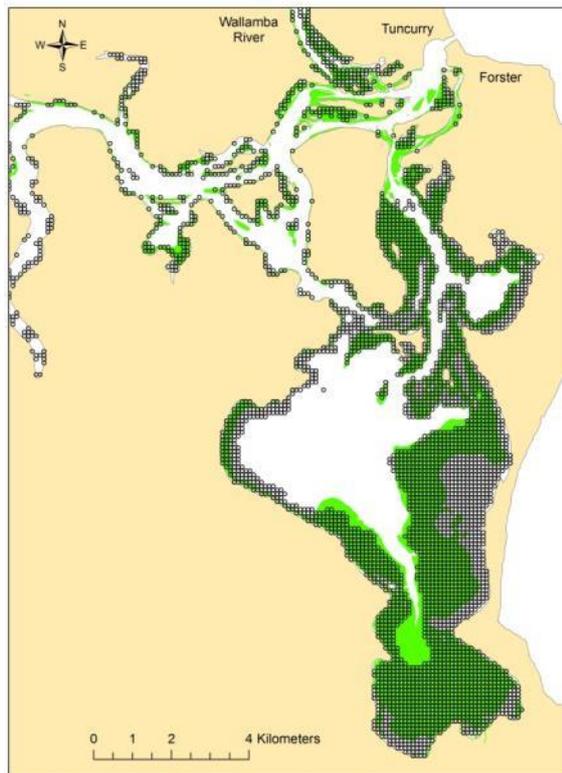


Figure 4: Distribution of seagrass in Wallis Lake from aerial photography (green shading) and predicted seagrass presence (circles) for relative environmental suitability model built using training data from the Port Stephens estuary.

3.2 Predicted seagrass losses due to sea level rise and increased turbidity

Substantial losses of existing seagrass cover were predicted for both sea level rise and increased turbidity, with losses varying between species and among estuaries (Table 3). Calculated losses did not account for seagrass gains from colonisation of shallow areas, due to a lack of detailed elevation data for intertidal areas and because, in many areas, it was not possible to distinguish gains from false presences in shallow areas (e.g. Figure 4). The greatest losses for sea level rise, for *P. australis* and *Z. muelleri*, were predicted to occur in Wallis Lake, with extensive shifts (~1500 m) predicted to occur by 2100 at the deeper boundary of the *Z. muelleri* beds at the southern end of the lake. Losses due to increased turbidity (i.e. 10–50% reductions in Secchi depth) were also predicted to be greatest in Wallis Lake with a 50% reduction in Secchi depth resulting in 53% loss of *P. australis* and 54% loss of *Z. muelleri* (Figure 5). Across all estuaries, it was predicted that sea level rise and increased turbidity would cause seagrass losses in deeper areas, while seagrasses were predicted to be unaffected, or have the potential to expand in shallow areas resulting in net

shoreward shifts in seagrass beds (Figure 5). The greatest impacts of sea level rise and turbidity occurred in flat or gently sloping areas covered by turbid water where small increases in water depth or turbidity resulted in substantial reductions in light availability over extensive areas. In contrast, sea level rise and increased turbidity were predicted to have minimal impact on seagrasses in shallow areas with low turbidity, such as in Merimbula Lake, as these areas were predicted to receive sufficient light even when sea levels or turbidity increased. When averaged across all estuaries, seagrass losses were predicted to increase approximately linearly with increased turbidity (i.e. for 10–50% reductions in Secchi depth), with *P. australis* showing greater sensitivity to increased turbidity than *Z. muelleri* (Figure 6).

Table 3: Predicted losses for existing seagrass areas in study estuaries for projected sea level rises in 2050 (+0.25 m) and 2100 (+0.74 m), and for reductions in Secchi depth (-50%). Results for relative environmental suitability (RES) models, for *Zostera muelleri* and *Posidonia australis*, built using training data from Port Stephens

Estuary	<i>Z. muelleri</i> loss in 2050	<i>P. australis</i> loss in 2050	<i>Z. muelleri</i> loss in 2100	<i>P. australis</i> loss in 2100	<i>Z. muelleri</i> loss for Secchi (-50%)	<i>P. australis</i> loss for Secchi (-50%)
Port Stephens	-4%	-9%	-13%	-21%	-40%	-41%
Wallis Lake	-8%	-11%	-32%	-44%	-54%	-53%
Lake Illawarra	0%	n/a	-13%	n/a	-18%	n/a
Merimbula Lake	0%	0%	0%	-3%	0%	-10%
Pambula Lake	-6%	-4%	-6%	-11%	-9%	-16%

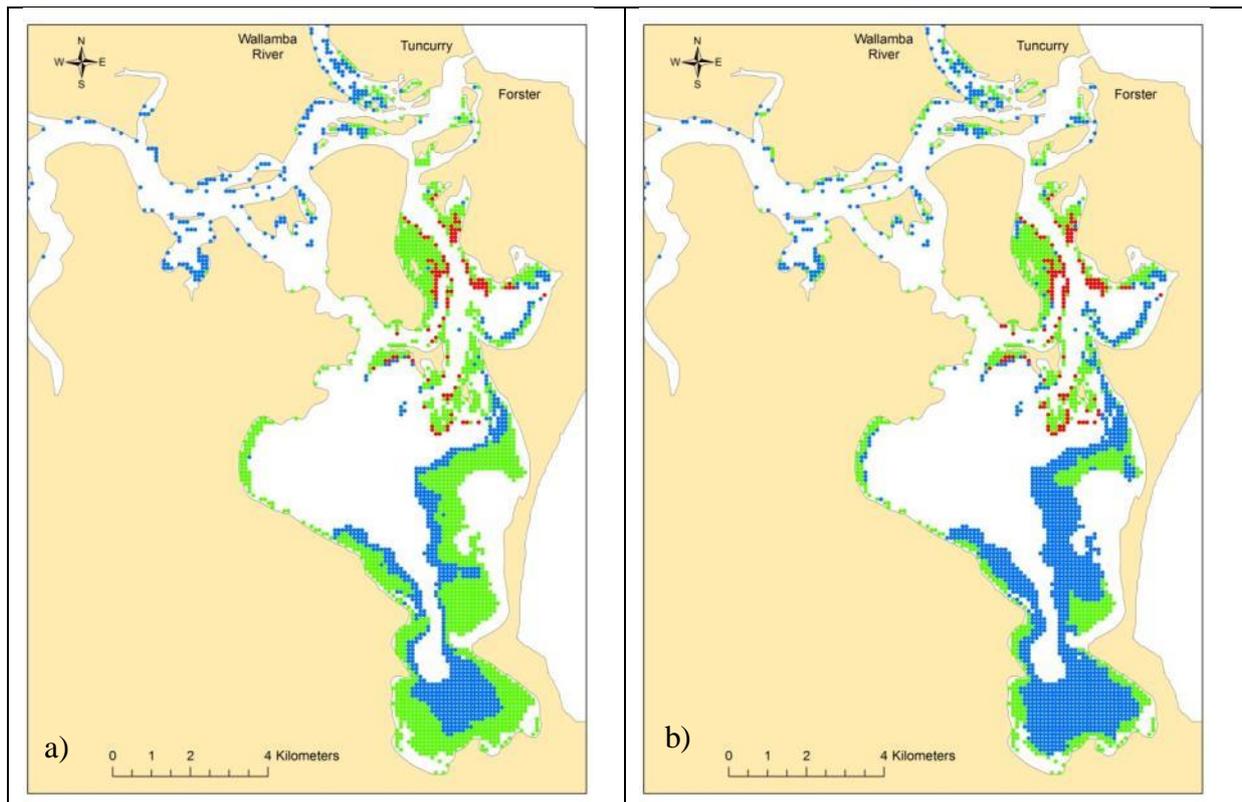


Figure 5: Predicted seagrass losses in Wallis Lake for a) a sea level rise in 2100 of 0.74 m, b) 50% reduction in Secchi depth. Results based on a relative environmental suitability model built using training data from the Port Stephens estuary. Red = *Posidonia australis* losses, blue = *Zostera muelleri* losses, green = seagrass unchanged.

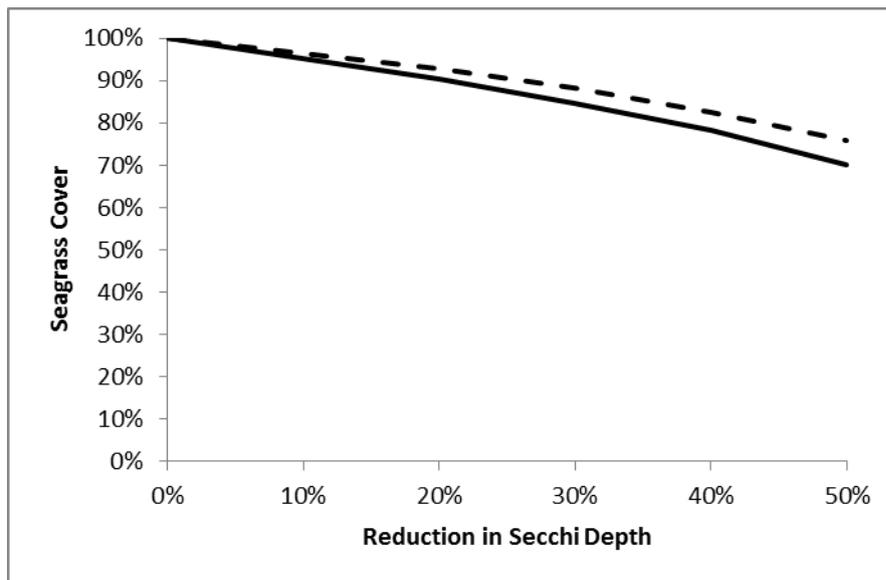


Figure 6: Predicted effect of changes in Secchi depth on seagrass distributions averaged across all study sites. Results based on relative environmental suitability models built using training data from the Port Stephens estuary. Solid Line = *Posidonia australis*, dashed line = *Zostera muelleri*.

4. Discussion

The main environmental variables directly influencing seagrass distributions in well mixed estuarine systems are light availability (Duarte et al. 2007), waves (Infantes et al. 2009) and, to a lesser extent, currents (Fonseca and Bell 1998). This study clearly identified that each of these variables has a significant influence on seagrass distributions in the Port Stephens estuary, and that RES models developed using these variables at this location, could be reliably applied to other estuaries over a broad section of the NSW coast.

Seagrass SDMs with broad applicability provide powerful tools for management and conservation planning. These models should be based on established relationships between seagrasses and their environment (Fonseca and Bell 1998), and allow prediction of environmental effects on seagrass distributions across a range of estuarine systems (Grech and Coles 2010). Relative environmental suitability envelopes simulate ecological niches of target species for explanatory variables (Kaschner et al. 2006) and we found that linkages between the preferred ranges for explanatory variables in RES models and species

distributions were easily understood, supporting the contention by Ready et al. (2010) that RES models are easily interpretable, and are therefore useful in conservation planning.

As RES envelopes are representative of ecological niches, any overlap in envelopes among species indicates that they may compete for resources. Here we found that RES envelopes for *P. australis* and *Z. muelleri* substantially overlapped in terms of requirements for light and in their resistance to waves and currents. This indicated that *P. australis* and *Z. muelleri* may compete for space, a conclusion supported by the presence of mixed beds of *P. australis* and *Z. muelleri* in some parts of most of the estuaries examined. *Posidonia australis* was observed to dominate some mixed beds with its longer, broader leaves and dense growth (pers. obs.); however, *Z. muelleri* was found to dominate the shallow edges of beds where there was greater wave exposure and possible emersion during low spring tides. The dominance of *Z. muelleri* at the fringes of seagrass beds indicates that this species either has a higher tolerance to wave exposure than *P. australis*, or that *Z. muelleri* recovered more quickly in areas subjected to disturbances from waves. Disturbances from storms and floods occur frequently on the east Australian coast and have been linked to substantial losses of seagrass through wave damage (Preen et al. 1995) and increased turbidity (Campbell and McKenzie 2004). Following disturbances, many seagrass species, especially large slow-growing species such as *P. australis*, are very slow to recover, with recovery sometimes taking decades (Cambridge 1975; Kendrick et al. 2002). In comparison, *Z. muelleri* often recovers relatively quickly following disturbance (Campbell and McKenzie 2004) and is therefore likely to dominate areas where seagrass beds are frequently disturbed, and is also more likely to initially colonise areas submerged by climate change induced sea level rise.

Previous studies examining anticipated distribution changes in seagrasses in response to global climate change have identified that sea level rise may cause shoreward shifts in seagrass beds (Short and Neckles 1999; Björk et al. 2008). Our modelling supports this conclusion, with shoreward shifts in seagrass distributions predicted in most study estuaries under the sea level rise scenarios examined. Sea level rise was found to have an effect on all of the explanatory variables examined in the study, and to influence seagrass distributions through changes to light availability and wave impacts, with both of these variables declining with increasing depth. Loss of seagrass was predicted in deeper areas due to reduced light availability, with these losses being offset by increased cover in shallow areas due to reduced wave impacts and the availability of new areas for colonisation.

The future impact of shifts in seagrass beds on overall seagrass cover depends primarily on the hypsometry of estuaries (i.e. land elevation relative to sea level), which controls the ratio of area lost to area gained by seagrasses (Carr et al. 2011), as well as the rate at which seagrasses can colonise newly submerged areas (Waycott et al. 2007). Losses can potentially be reduced where sediment accretion keeps pace with sea level rises, with seagrasses shown to increase net sediment accretion (Bos et al. 2007). Nonetheless, losses will be aggravated where shoreline defences are installed to prevent coastal erosion and these defences inhibit the shoreward migration of seagrass beds (Waycott et al. 2007). In addition, losses will be intensified in locations where climate change causes an increase in average turbidity through increased storm activity and floods, or where turbidity increases due to anthropogenic effects. In general, SDMs such as those developed in this study, provide valuable tools for managers to evaluate the complex interactions between sea level rise, turbidity, hypsometry, sediment accretion, and shoreline modifications, allowing assessment of the combined impact of these factors on the shoreward migration of seagrass beds and on total cover of seagrass species.

5. Conclusions

This study demonstrates the power of SDMs for predicting seagrass distributions and distributional changes. RES modelling, in particular, was able to accurately predict seagrass distributions for dominant species in the estuaries examined. SDMs can play a valuable role in predicting the future of seagrass beds under climate change, identifying locations where seagrass losses may occur as well as target areas for monitoring, and providing managers with knowledge of resilient locations where high levels of protection are warranted to ensure long-term preservation of seagrasses. In addition, models provide a tool to assist with identification of areas where conditions are suitable for seagrass rehabilitation, thereby contributing important information for restoration projects, enabling them to address the ongoing seagrass losses that are occurring within many estuarine systems.

6. Acknowledgements

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Tidal data and storm history wave data for the NSW coast was sourced from the Manly Hydraulics Laboratory (<http://www.mhl.nsw.gov.au> accessed 10 December 2015). Hydrodynamic modelling was conducted using TELEMAC-2D and ARTEMIS freeware from the TELEMAC-MASCARET Consortium. Hydrographic survey data was obtained from the NSW Office of Environment and Heritage (<http://www.environment.nsw.gov.au> accessed 30 December 2015).

References

- Abal E, Dennison W (1996) Seagrass depth range and water quality in southern Moreton Bay, Queensland, Australia. *Marine and Freshwater Research* 47: 763-771. <http://dx.doi.org/10.1071/MF9960763>
- Anthony K, Ridd PV, Orpin AR, Larcombe P, Lough J (2004) Temporal variation of light availability in coastal benthic habitats: Effects of clouds, turbidity, and tides. *Limnology and Oceanography* 49: 2201-2211.
- Barbier EB, Hacker SD, Kennedy C, Koch EW, Stier AC, Silliman BR (2011) The value of estuarine and coastal ecosystem services. *Ecological Monographs* 81: 169-193.
- Bindoff NL, Stott PA, AchutaRao M, Allen MR, Gillett N, Gutzler D, Hansingo K, Hegerl G, Hu Y, Jain S (2013) Detection and attribution of climate change: from global to regional. *Climate Change 2013 The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK, pp 867-952
- Björk M, Short F, Mcleod E, Beer S (2008) *Managing seagrasses for resilience to climate change*. IUCN, Gland, Switzerland
- Bos AR, Bouma TJ, de Kort GL, van Katwijk MM (2007) Ecosystem engineering by annual intertidal seagrass beds: sediment accretion and modification. *Estuarine, Coastal and Shelf Science* 74: 344-348.
- Bridges K, Phillips R, Young P (1982) Patterns of some seagrass distribution in the Torres Strait, Queensland. *Marine and Freshwater Research* 33: 273-283.
- Cambridge M (1975) Seagrasses of south-western Australia with special reference to the ecology of *Posidonia australis* Hook f. in a polluted environment. *Aquatic Botany* 1: 149-161.
- Campbell SJ, McKenzie LJ (2004) Flood related loss and recovery of intertidal seagrass meadows in southern Queensland, Australia. *Estuarine, Coastal and Shelf Science* 60: 477-490. <http://dx.doi.org/10.1016/j.ecss.2004.02.007>
- Carr JA, D'Odorico P, McGlathery KJ, Wiberg PL (2011) Modeling the effects of climate change on eelgrass stability and resilience: future scenarios and leading indicators of collapse. *Marine Ecology Progress Series* 448: 289-301.
- Carruthers T, Dennison W, Longstaff B, Waycott M, Abal E, McKenzie L, Long W (2002) Seagrass habitats of northeast Australia: models of key processes and controls. *Bulletin of Marine Science* 71: 1153-1169.
- Church JA, Clark PU, Cazenave A, Gregory JM, Jevrejeva S, Levermann A, Merrifield M, Milne G, Nerem R, Nunn P (2013) Sea level change. *Climate Change 2013 The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK, pp 1137-1216

- Creese RG, Glasby TM, West G, Gallen C (2009) Mapping the habitats of NSW estuaries. Industry & Investment NSW, New South Wales, Australia
- Davis T, Gallen C, Laird R, Harasti D (2015) Mapping sub-tidal habitats in the Eastern Port of Port Stephens. NSW Department of Primary Industries, New South Wales, Australia
- Davis T, Harasti D, Smith S (2016) Developing a habitat classification typology for subtidal habitats in a temperate estuary in New South Wales, Australia. *Marine and Freshwater Research*. <http://dx.doi.org/10.1071/MF15123>
- Downie A-L, von Numers M, Boström C (2013) Influence of model selection on the predicted distribution of the seagrass *Zostera marina*. *Estuarine, Coastal and Shelf Science* 121: 8-19.
- DPWS (1998) Port Stephens tidal data collection September 1993. NSW Department of Public Works and Services, Manly Hydraulics Laboratory, New South Wales, Australia
- Duarte CM (2002) The future of seagrass meadows. *Environmental Conservation* 29: 192-206.
- Duarte CM, Marbà N, Krause-Jensen D, Sánchez-Camacho M (2007) Testing the predictive power of seagrass depth limit models. *Estuaries and Coasts* 30: 652-656.
- Dulvy NK, Sadovy Y, Reynolds JD (2003) Extinction vulnerability in marine populations. *Fish and Fisheries* 4: 25-64.
- Elgin (2014a) Merimbula Lake: Environmental monitoring in coastal lakes and lagoons of Bega Valley Shire Council region 2012-2013. Elgin Associates Pty Ltd, Bega, Australia
- Elgin (2014b) Pambula Lake: Environmental monitoring in coastal lakes and lagoons of Bega Valley Shire Council region 2010-2013. Elgin Associates Pty Ltd, Bega, Australia
- Emanuel KA (2013) Downscaling CMIP5 climate models shows increased tropical cyclone activity over the 21st century. *Proceedings of the National Academy of Sciences* 110: 12219-12224.
- Fonseca M, Whitfield PE, Kelly NM, Bell SS (2002) Modeling seagrass landscape pattern and associated ecological attributes. *Ecological Applications* 12: 218-237.
- Fonseca MS, Bell SS (1998) Influence of physical setting on seagrass landscapes near Beaufort, North Carolina, USA. *Marine Ecology-Progress Series* 171: 109-121.
- Grech A, Coles R (2010) An ecosystem - scale predictive model of coastal seagrass distribution. *Aquatic Conservation: Marine and Freshwater Ecosystems* 20: 437-444.
- Greve T, Krause-Jensen D (2005) Predictive modelling of eelgrass (*Zostera marina*) depth limits. *Marine Biology* 146: 849-858.
- Guisan A, Thuiller W (2005) Predicting species distribution: offering more than simple habitat models. *Ecology Letters* 8: 993-1009.
- Guisan A, Zimmermann NE (2000) Predictive habitat distribution models in ecology. *Ecological Modelling* 135: 147-186.
- Harasti D (2016) Declining seahorse populations linked to loss of essential marine habitats. *Marine Ecology Progress Series* 546: 173-181.
- Hoegh-Guldberg O, Bruno JF (2010) The impact of climate change on the world's marine ecosystems. *Science* 328: 1523-1528.
- Holmes RW (1970) The Secchi disk in turbid coastal waters. *Limnology and Oceanography* 15: 688-694.
- Infantes E, Terrados J, Orfila A, Cañellas B, Álvarez-Ellacuría A (2009) Wave energy and the upper depth limit distribution of *Posidonia oceanica*. *Botanica Marina* 52: 419-427.

- Jiang A, Ranasinghe R, Cowell P, Savioli J (2011) Tidal asymmetry of a shallow, well-mixed estuary and the implications on net sediment transport: A numerical modelling study. *Australian Journal of Civil Engineering* 9: 1-18.
- Kaschner K, Watson R, Trites A, Pauly D (2006) Mapping world-wide distributions of marine mammal species using a relative environmental suitability (RES) model. *Marine Ecology Progress Series* 316: 2-3.
- Kelly NM, Fonseca M, Whitfield P (2001) Predictive mapping for management and conservation of seagrass beds in North Carolina. *Aquatic Conservation: Marine and Freshwater Ecosystems* 11: 437-451.
- Kendrick GA, Aylward MJ, Hegge BJ, Cambridge ML, Hillman K, Wyllie A, Lord DA (2002) Changes in seagrass coverage in Cockburn Sound, Western Australia between 1967 and 1999. *Aquatic Botany* 73: 75-87.
- Lathrop RG, Styles RM, Seitzinger SP, Bognar JA (2001) Use of GIS mapping and modeling approaches to examine the spatial distribution of seagrasses in Barnegat Bay, New Jersey. *Estuaries* 24: 904-916.
- Lotze HK, Lenihan HS, Bourque BJ, Bradbury RH, Cooke RG, Kay MC, Kidwell SM, Kirby MX, Peterson CH, Jackson JB (2006) Depletion, degradation, and recovery potential of estuaries and coastal seas. *Science* 312: 1806-1809.
- Nearmap (2014) <https://au.nearmap.com/>, accessed 8/10/2014
- Nelson RC (1994) Depth limited design wave heights in very flat regions. *Coastal Engineering* 23: 43-59. [http://dx.doi.org/10.1016/0378-3839\(94\)90014-0](http://dx.doi.org/10.1016/0378-3839(94)90014-0)
- OzCoasts (2015) Geoscience Australia. <http://www.ozcoasts.gov.au/>, accessed 5/12/2015
- Poulos D, Gallen C, Davis T, Booth D, Harasti D (2015) Distribution and spatial modelling of a soft coral habitat in the Port Stephens-Great Lakes Marine Park: implications for management. *Marine and Freshwater Research* 67: 256-265. <http://dx.doi.org/10.1071/MF14059>
- Preen A, Long WL, Coles R (1995) Flood and cyclone related loss, and partial recovery, of more than 1000 km² of seagrass in Hervey Bay, Queensland, Australia. *Aquatic Botany* 52: 3-17.
- Ready J, Kaschner K, South AB, Eastwood PD, Rees T, Rius J, Agbayani E, Kullander S, Froese R (2010) Predicting the distributions of marine organisms at the global scale. *Ecological Modelling* 221: 467-478.
- Rohweder J, Rogala J, Johnson B, Anderson D, Clark S, Chamberlin F, Potter D, Runyon K (2012) Application of wind fetch and wave models for habitat rehabilitation and enhancement projects—2012 update. US Army Corps of Engineers, St. Paul, Minnesota, USA
- Short FT, Neckles HA (1999) The effects of global climate change on seagrasses. *Aquatic Botany* 63: 169-196.
- Stewart M, Fairfull S (2007) Primefact 629: Seagrasses. Department of Primary Industries, New South Wales
- Stuart-Smith RD, Edgar GJ, Stuart-Smith JF, Barrett NS, Fowles AE, Hill NA, Cooper AT, Myers AP, Oh ES, Pocklington JB (2015) Loss of native rocky reef biodiversity in Australian metropolitan embayments. *Marine Pollution Bulletin* 95: 324-332.
- Van der Heide T, Peeters E, Hermus D, Van Katwijk M, Roelofs J, Smolders A (2009) Predicting habitat suitability in temperate seagrass ecosystems. *Limnology and Oceanography* 54: 2018-2024.
- Waycott M, Collier C, McMahon K, Ralph P, McKenzie L, Udy J, Grech A (2007) Vulnerability of seagrasses in the Great Barrier Reef to climate change. Great Barrier Reef Marine Park Authority and Australian Greenhouse Office, Queensland

West G, Williams R, Authority NM, Wales NS (2008) A preliminary assessment of the historical, current and future cover of seagrass in the estuary of the Parramatta River. NSW Department of Primary Industries, New South Wales, Australia

Supplementary tables

Table S1: Relative Environmental Suitability (RES) envelope limits defining probability of seagrass species presence (P_v) for explanatory variables of: % photosynthetic available radiation at the seabed (*Light*); tidal velocity (*Current*); and wave orbital velocity at seabed (*Waves*). Limits calculated from seagrass presence data from the eastern bay of Port Stephens for *Posidonia australis* and *Zostera muelleri*. Probability of seagrass presence linearly interpolated for explanatory variables between preferred and absolute ranges

Seagrass	Preferred range percentile limit	Preferred range limit for variable ($P_v = 1$)	Absolute range limit for variable ($P_v = 0$)
<i>P. australis</i>	<i>Light</i> > 29 th	<i>Light</i> > 58.1%	<i>Light</i> < 24.0%
	<i>Current</i> < 76 th	<i>Current</i> < 0.447 ms ⁻¹	<i>Current</i> > 0.790 ms ⁻¹
	<i>Waves</i> < 84 th	<i>Waves</i> < 0.580 ms ⁻¹	<i>Waves</i> > 1.992 ms ⁻¹
<i>Z. muelleri</i>	<i>Light</i> > 11 th	<i>Light</i> > 48.7%	<i>Light</i> < 31.6%
	<i>Current</i> < 85 th	<i>Current</i> < 0.472 ms ⁻¹	<i>Current</i> > 0.911 ms ⁻¹
	<i>Waves</i> < 91 st	<i>Waves</i> < 1.031 ms ⁻¹	<i>Waves</i> > 2.199 ms ⁻¹