Predicting the Distribution of Golden Kelp Across the Great Southern Reef Under Future Climate Scenarios

Emily Clout[1,+,*], **India Phillips**[1,+,**], **and Jaida Damstra**[1,+,***]

[1]The University of Sydney, Sydney, Australia
[+]these authors contributed equally to this work
[*]SID: 550537322
[**]SID: 550344638
[***]SID: 530562076

ABSTRACT

Ecklonia radiata is a foundation species of kelp across Australia's Great Southern Reef (GSR). Highly sensitive to changes in the marine environment, they face a significant threat from climate change. This study aimed to predict the distribution of *Ecklonia radiata* across the GSR under present-day conditions (2010-2020), as well as future conditions (2040-2050 and 2090-2100) in three climate scenarios (SSP1, SSP2 and SSP3). A Generalised Linear Model (GLM), MaxEnt model and Random Forest (RF) model were used to predict habitat suitability, using the environmental variables identified as most influential: maximal sea surface temperature, mean nitrate concentration, mean salinity, mean pH and minimal sea water velocity. The GLM and MaxEnt model predicted that under the best-case scenario (SSP1), by 2040-2050, the range of suitable habitat will have contracted by over 96%. Although habitat suitability largely recovers by 2090-2100 under SSP1, it is unlikely that *Ecklonia radiata* will be able to repopulate the GSR without intervention. Under the middle-of-the road (SSP2) and worst case (SSP3) climate scenarios, 96-100% of suitable habitat is predicted to be lost by 2040-2050, and 99.7-100% by 2090-2100. Our findings emphasise the need for adaptive management strategies to prevent the extinction of *Ecklonia radiata* across the GSR.

Introduction

Kelp are seaweeds in the order *Laminariales*, found on shallow rocky seabeds across an estimated 22% of coastlines worldwide[1]. They provide vital ecosystem services, forming the basis of food webs and providing habitat for diverse marine life, while also benefiting humans through carbon sequestration, coastal protection and as a food source[2,3]. *Ecklonia radiata*, commonly referred to as Golden Kelp, is a foundation species and the most abundant kelp across Australia's Great Southern Reef (GSR)[4,5].

Kelp requires specific environmental conditions; their growth is influenced by a range of variables including ocean temperature, current strength, salinity, pH, light availability, nutrient concentrations and bathymetry[2,5–7]. *Ecklonia radiata* specifically experiences growth stress above 18.5°C and needs to grow on rocky substrates at a maximum depth of 40-50m[5]. High nutrient concentrations are also important for growth; but excessive levels are implicated in eutrophication and can have a negative effect on kelp survival[8–10].

However, these variables are projected to significantly change under future climate scenarios described by the Shared Socioeconomic Pathways (SSPs)[11]. Critically, the SSPs describe how the global climate is likely to change under different scenarios of social, economic and environmental development[11]. SSP1-1.9, for example, represents a pathway in which the world is focused on sustainable and equitable development[11]. Environmental conditions under this scenario are expected to get slightly worse by 2040-2050, before starting to return to baseline conditions in 2090-2100. SSP2-4.5 describes a moderate emissions scenario, with uneven progress towards social and sustainability goals[11]. This is considered the most likely scenario if global development follows historical trends, and reflects a gradual worsening of environmental conditions[12]. SSP3-7.0 depicts a world that prioritises energy and resource security - leading to high emissions and high regional conflict[11]. Previous studies have modelled *Ecklonia Radiata* distribution under the Representative Concentration Pathways - an earlier framework for climate projections - but not yet for the updated the SSPs.

Global climate change therefore is a significant threat to kelp. Changing ocean conditions are predicted to shift and contract the regions in which Kelp can be sustained[2]. Furthermore, these changes will increase competition and predation from more resilient species such as turf algae and sea urchins, which threaten potential for recovery[13]. The GSR is particularly vulnerable, with some areas warming at a rate two times the global average[14]. As an important feature of Southern Australia's coastal ecosystems, understanding how *Ecklonia radiata* will be impacted in this region is critical for effective conservation and management.

Our aims with this research are to determine which environmental variables are most important for predicting the distribution of *Ecklonia radiata* across the Great Southern Reef, and to predict the future distribution of *Ecklonia radiata* for the periods 2040-2050 and 2090-2100, under three climate scenarios (SSP1, SSP2 and SSP3). To do so we tested and compared the current and future predictions of three models: a Generalised Linear Model (GLM), Maxent model and Random Forest (RF) model. We hypothesise that range contraction will occur under all scenarios in 2040-2050, but will be greatest under SSP3 and smallest under SSP1. For SSP2 and SSP3, we expect that greater range contraction will occur at 2090-2100 compared to 2040-2050. Under SSP1, however, the range of suitable habitat is predicted to expand back towards present-day levels in 2090-2100 - following the improvement in environmental conditions at this time point. All environmental variables discussed are expected to contribute to the models.

Results

0.1 Environmental Variables

Figure 1 shows the pairwise Pearson correlations among the environmental variables, based on data from 2010-2020. High correlations ($|r| > 0.7$) were observed among all three temperature variables. Of these, the long-term maximal temperature (*thetao-ltmax*) was considered to be the most ecologically relevant for *Ecklonia radiata*, as it is able to capture the effects of extreme warming events - which are known to have a greater direct impact on kelp survival than average and minimum conditions[15–17]. It was therefore retained for modelling, while the mean (*thetao-mean*) and long-term minimal (*thetao-ltmin*) temperatures were discarded. Mean dissolved oxygen (*o2-mean*) and the long-term maximal phytoplankton concentration (*phyc-ltmax*) were also found to be highly correlated with each other and all temperature variables. They were therefore both removed. Finally, the two nutrient variables - mean nitrogen (*no3-mean*) and phosphate (*po4-mean*) concentrations - were highly correlated with each other. Since nitrogen is known to have a greater impact on kelp growth than other nutrients[18], it was retained for modelling while the phosphate variable was excluded.

After dredging the GLM with the remaining variables, the model with the lowest AICc value was found to exclude the long-term minimal phytoplankton concentration (*phyc-ltmin*) and the long-term maximal sea water speed (*sws-ltmax*). This indicates that these variables had little explanatory power. The variables selected for use in the final models therefore only included the long-term maximal temperature (*thetao-ltmax*), long-term minimal sea water speed (*sws-ltmin*), mean nitrate concentration (*no3-mean*), mean salinity (*so-mean*), and mean pH (*ph-mean*).

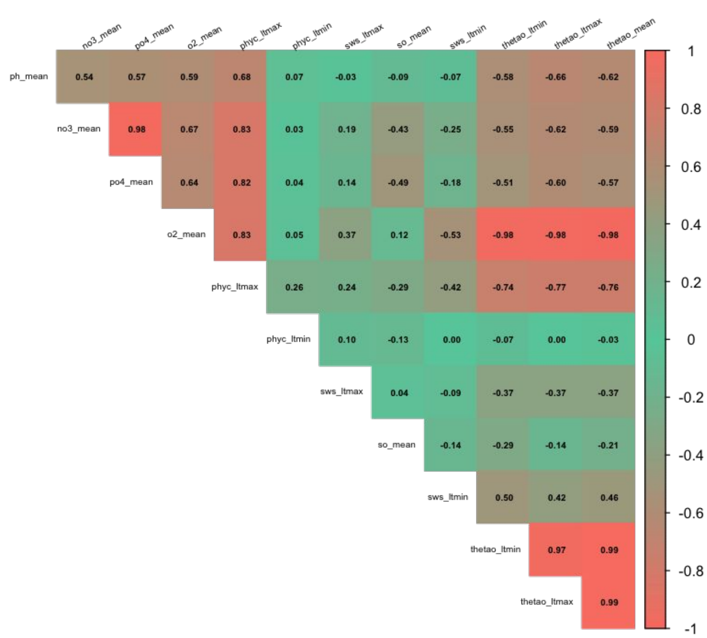

Figure 1. Pearson correlation matrix showing pairwise correlations between environmental predictor variables.

Figure 2 shows the environmental response curves that were generated for each model. Across all models, the probability of *Ecklonia radiata* occurrence generally increased as mean nitrate concentrations and pH values increased, up until 4 mmol/m3 and 8.10 respectively. Beyond these points, MaxEnt and RF models predicted a drop in habitat suitability, while the GLM probabilities continued increasing.

The GLM also predicted the probability of *Ecklonia radiata* occurrence to increase as mean salinity and long-term minimal sea water speed increased. However, the MaxEnt and RF response curves for these variables were more complex. Both these models predicted habitat suitability to increase with sea water speed until 0.2 m/s, after which probability values were relatively consistent. Habitat suitability levels were similar across most values of mean salinity in the MaxEnt model, though the lowest probability values did occur at lower mean salinity levels. In contrast to both the GLM and MaxEnt, the RF model predicted the probability of occurrence to be greatest at lower salinity levels.

The GLM also predicted the likelihood of *Ecklonia radiata* presence to decrease as long-term maximal temperature increased. The MaxEnt and RF models, however, both predicted habitat suitability to increase as the long-term maximal temperature increased, until 25°C. They then predicted a rapid drop in the probability of occurrence at higher maximal temperatures.

As shown in Table 1, all environmental variables included in the GLM contributed significantly to explaining the distribution of *Ecklonia radiata* ($p < 0.001$). Similarly, variable importance measures from the RF model indicated that all environmental predictors strongly contributed to the model - with mean decreases in accuracy ranging between 26.21 and 38.53, and mean decreases in the gini value ranging between 54.66 and 177.79.

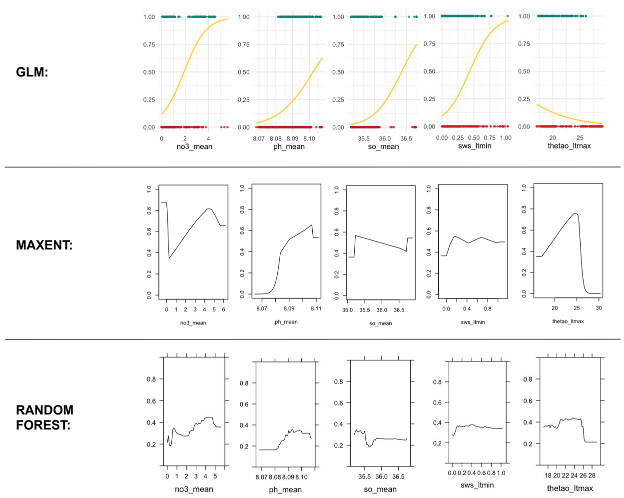

Figure 2. Response curves of environmental predictors for GLM, MaxEnt and RF models. X-axis shows the value of each environmental variable, and the y-axis shows the predicted probability of *Ecklonia radiata* occurrence.

Predictor Variable	GLM p-value	RF Mean Decreae Accuracy	RF Mean Decrease Gini
no3-mean	<0.01	38.5	177.8
thetao-ltmax	<0.01	26.2	109.8
so-mean	<0.01	33.0	97.6
ph-mean	<0.01	28.6	97.0
sws-ltmin	<0.01	27.2	54.7

Table 1. Table showing the significance and importance of environmental variables across the GLM and RF models.

0.2 Model Performance

Receiver operating characteristic (ROC) curves were generated for each model, with corresponding area under the ROC curve (AUC) values. All three models showed high predictive accuracy - the RF model achieved the greatest AUC with a value of 0.983; MaxEnt achieved 0.931; and the GLM achieved 0.900.

0.3 Projections

Figure 3 shows the range of suitable habitat for *Ecklonia radiata*, modelled by the GLM, for 2010-2020, 2040-2050 and 2090-2100 under each SSP scenario. The presence threshold, represented by the black line across each map, generally moves south with each SSP over time - except for under SSP1. This presence threshold was calculated to be 0.45. The present day predictions (2010-2020) show the probability of Kelp presence in the northern coasts of Australia as very low, increasing into southern waters. Along the coast of the GSR, there is a mixture of low to medium probability, and the southeastern coast has the highest probability for kelp presence. For SSP1, habitat range decreases between the 2010 and 2040 decades by 96.0%, but improves by 2090-2100 to only show a 7.3% loss compared to present-day conditions. For SSP2, greater range contraction occurs by 2040-50 with a 96.7% loss, reaching 99.9% by 2090-2100. SSP3 displays the greatest loss, with 97.0% of suitable habitat predicted to be lost by 2040-50, and 100% by 2090-2100.

Figure 4 shows the predicted presence of *Ecklonia radiata* (where probability values are above the presence threshold) in areas with depths less than 50 m, as modelled by the GLM. In 2010-2020, and for SSP1 at 2090-2100, kelp is modelled to be present across a large area of the GSR. For all other scenarios except SSP3 at 2090-2100 (in which there is no suitable habitat for kelp), the only area predicted to be suitable for kelp is shown off the coast of Port Augusta in South Australia.

The Maxent predictions of suitable habitat at each time point and scenario can be seen in Figure 5. Maxent predicts suitable habitat will not be present north or south of the GSR for 2010-2020, with the highest probability of Kelp presence on the western coast to south western coast of Australia. The presence threshold (calculated as 0.28) and minimum bathymetry required for *Ecklonia radiata* occurence is limiting suitable habitat to near the coasts of mainland Australia and Tasmania. There is slightly greater range contraction at each SSP and time period than for the GLM, excluding 2090-2100 for SSP1. 100% loss is predicted across SSP2 and SSP3 for both future time points. Under SSP1, 98.5% of suitable habitat is predicted to be lost at 2040-50, but the habitat range increases to show only a 6% loss in 2090-2100 compared to present-day conditions.

Figure 6 shows the Maxent-modelled presence of suitable habitat with depths less than 50 m. Under present-day conditions (2010-2020), Maxent predicts kelp to occur along the southwest coast, the central GSR, around Tasmania and up the southeast coast. Predictions for 2040-2050 under SSP1 show kelp as being present in the same region off the Coast of Port Augusta as the GLM had predicted, and for 2090-2100 shows an even greater range across Tasmania and the southwestern coast. For each other scenario *Ecklonia radiata* is not present.

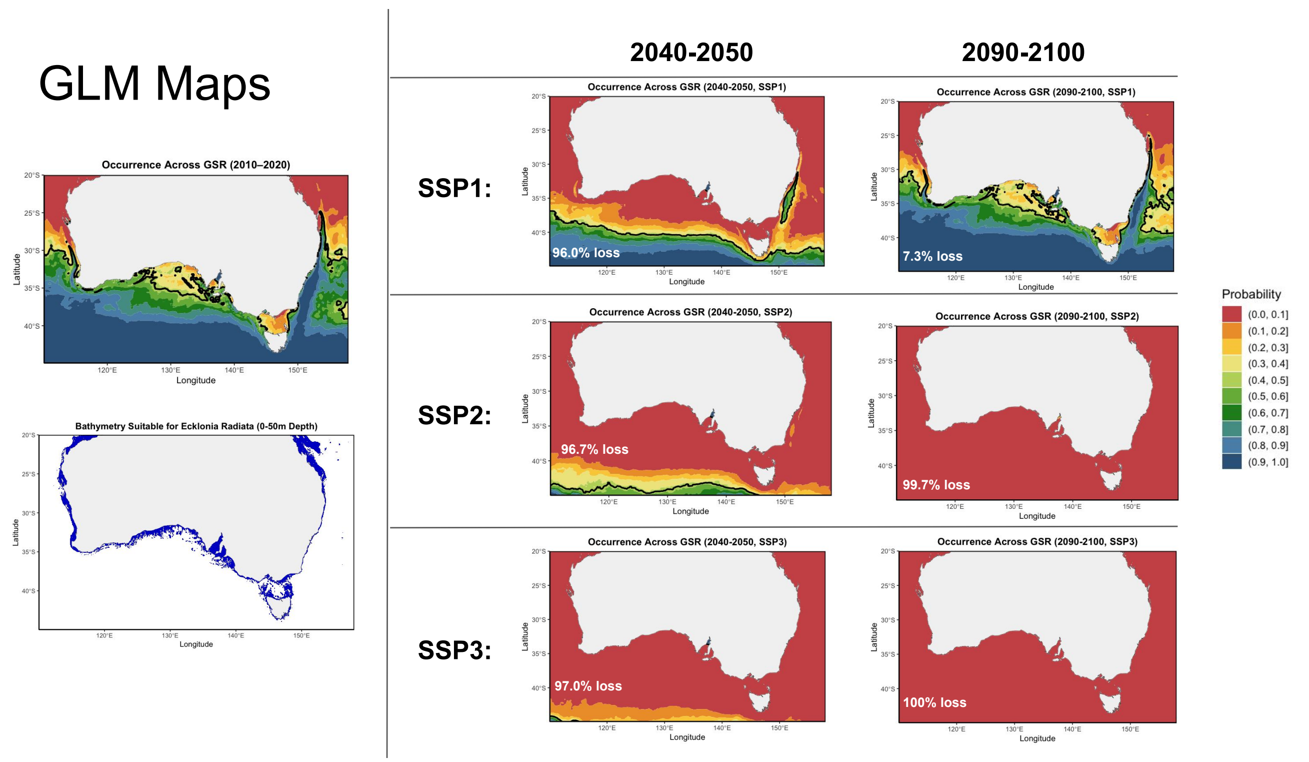

Figure 3. GLM predictions showing the probability of suitable habitat across the GSR in present-day conditions (2010-2020), and future conditions (2040-2050 and 2090-2100) under SSP1, SSP2 and SSP3. The black contour lines indicate the presence threshold (0.45), above which habitat is considered suitable. These maps should be interpreted alongside the bathymetry map (bottom left corner), which highlights areas with depths less than 50 m - the depth suitable for *Ecklonia radiata*.

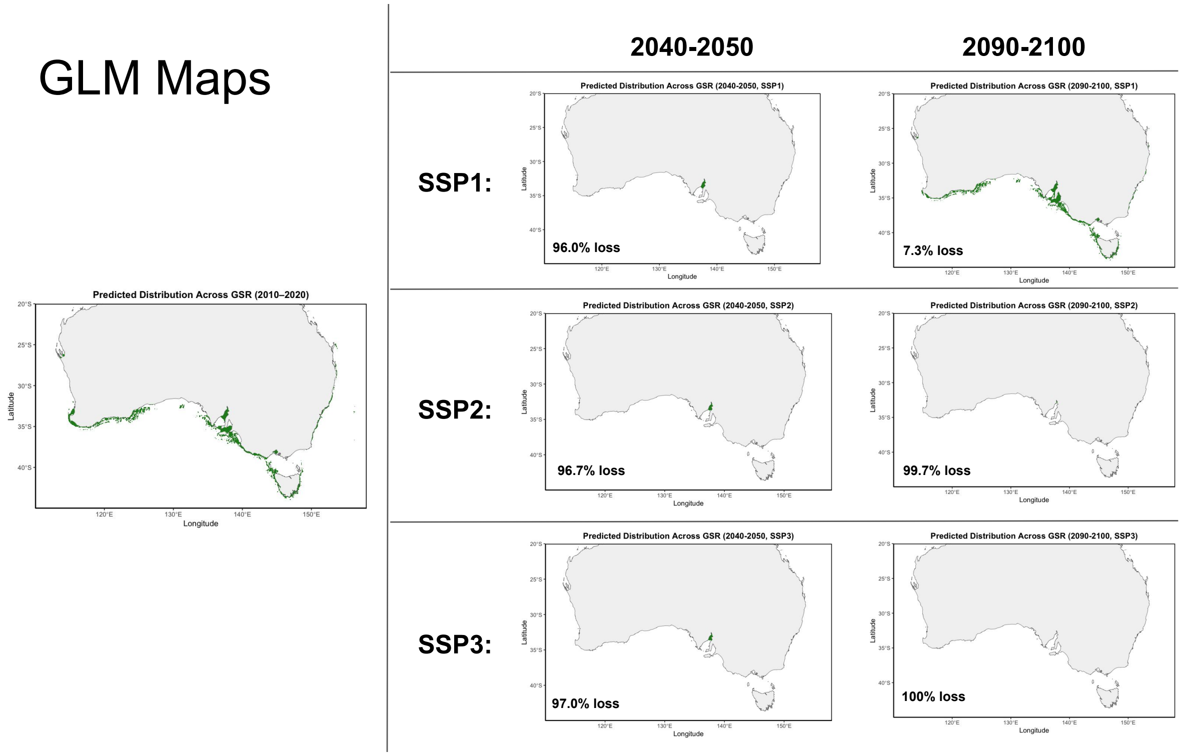

Figure 4. GLM predictions of suitable habitat for *Ecklonia radiata* across the GSR, highlighting areas with probabilities above the presence threshold (0.45) and within depths less than 50 m under present-day (2010-2020) and future conditions (2040-2050 and 2090-2100) for SSP1, SSP2 and SSP3.

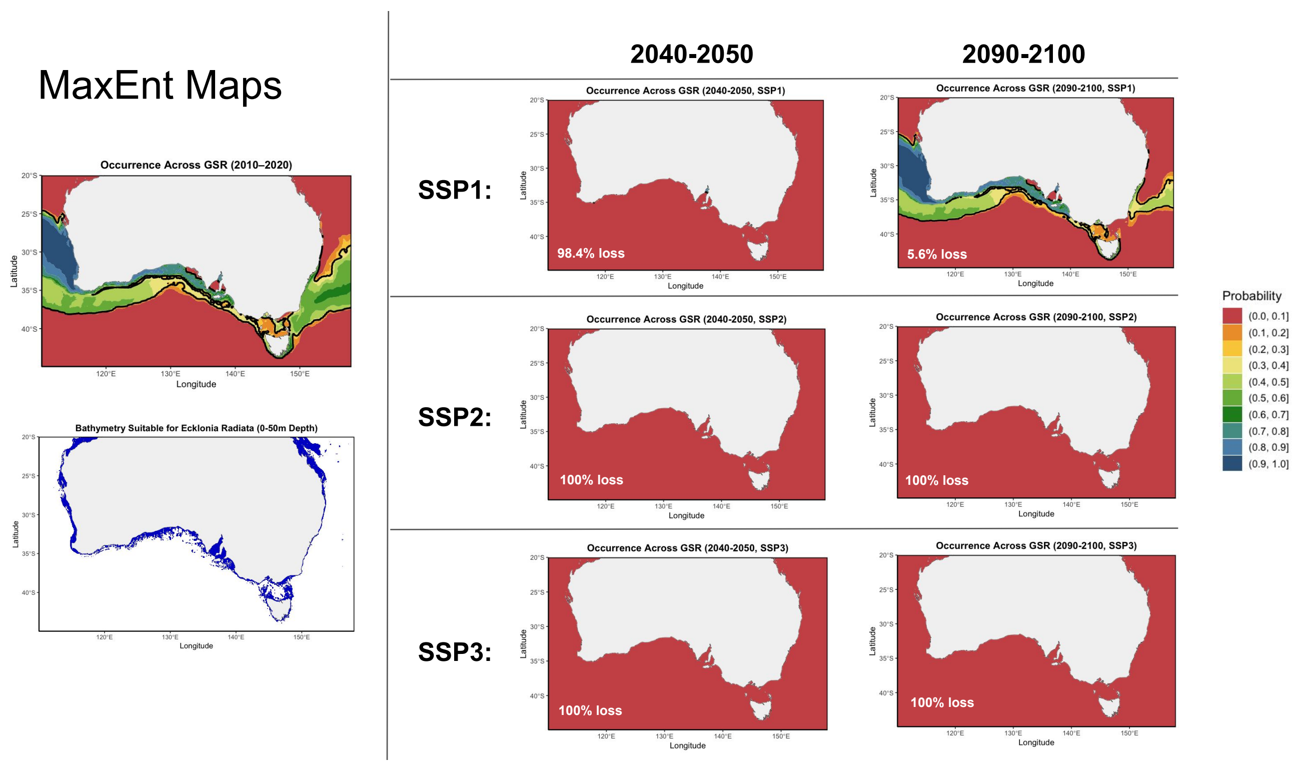

Figure 5. MaxEnt predictions of suitable habitat across the GSR in present-day conditions (2010-2020), as well as future conditions (2040-2050 and 2090-2100) under SSP1, SSP2 and SSP3. The black contour lines indicate the presence threshold (0.28), above which habitat is considered suitable. These maps should be interpreted alongside the bathymetry map (bottom left corner), which highlights areas with depths less than 50 m - the depth suitable for *Ecklonia radiata*.

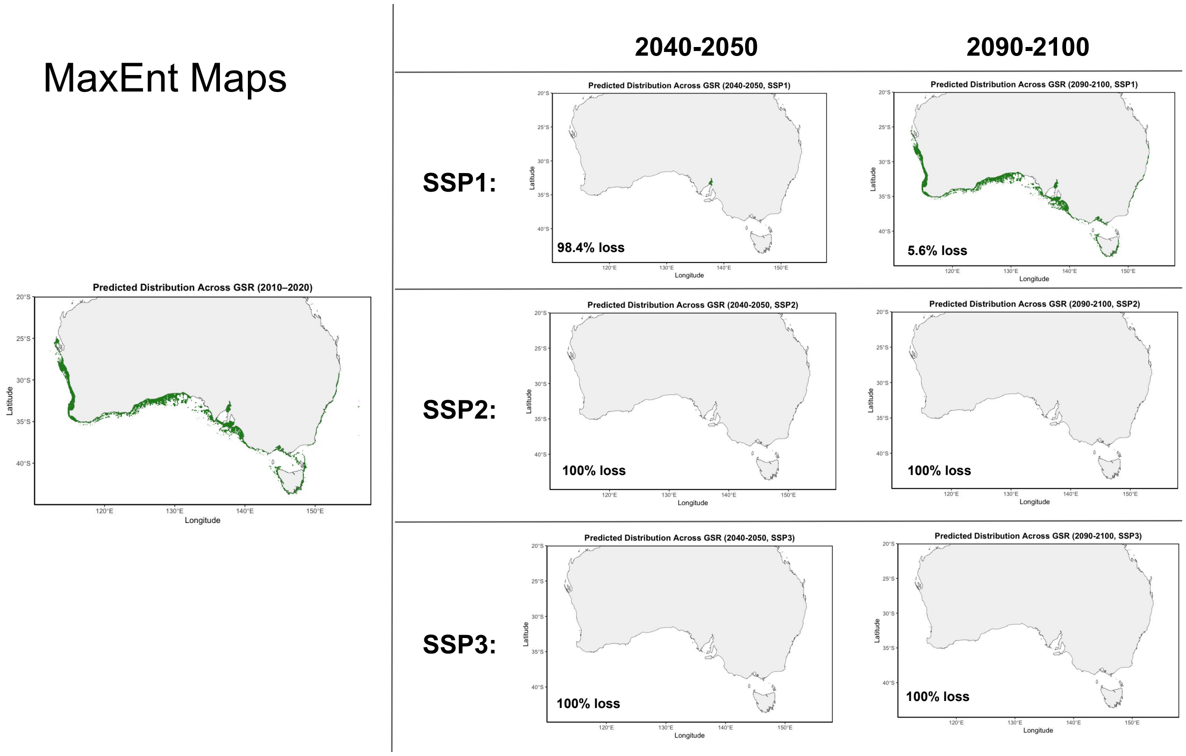

Figure 6. MaxEnt predictions of suitable habitat for *Ecklonia radiata* across the GSR, highlighting areas with probabilities above the presence threshold (0.28) and within depths less than 50 m under present-day (2010-2020) and future conditions (2040-2050 and 2090-2100) for SSP1, SSP2 and SSP3.

Our RF model predicted a similar pattern to the GLM for areas of suitable habitat from 2010-2020, with the most northern coasts unsuitable for kelp growth. Areas with a high probability of suitability were small, including a southern portion of the east coast and the east coast of Tasmania, with variable areas of middle to low probability across the rest of the southern Australian ocean. Present day distributions were very similar to Maxent, favouring the west over the east coast. The predicted areas of suitable habitat and distributions for each SSP at 2040-50 and 2090-2100 were abnormally high, and were deemed ecologically irrelevant for interpretation due to issues extrapolating the data.

Discussion

One of the environmental variables identified as a key driver of *Ecklonia radiata* distribution was the maximum sea surface temperature, which is consistent with the species' preference for cooler waters[19]. The response curves indicated that suitability declines once temperatures exceed the species' upper thermal tolerance. Ecologically, this reflects the known temperature limits of *Ecklonia radiata*[19], where short-term marine heatwaves can cause tissue damage and mortality[20], and prolonged warming can impair growth, reproduction, and resilience[21,22,23]. These results are consistent with observed declines in kelp populations across Australia, which have been widely attributed to ocean warming driven by climate change[24].

The other variables identified as key drivers of *Ecklonia radiata*'s distribution in the final model also align with ecological expectations. Kelp occurrence increased with rising nitrate concentration before declining at higher levels, reflecting the species' nutrient requirements[23] but also the negative effects of excessive enrichment and eutrophication[10]. Sea water velocity was positively associated with kelp presence, consistent with the role of currents in delivering nutrients[25]. Increasing salinity also corresponded with greater *Ecklonia radiata* presence, as reduced salinity from freshwater inputs is known to stress or limit kelp[26]. Finally, lower pH values were associated with reduced kelp suitability, consistent with the impacts of ocean acidification reported in the literature, in which more acidic conditions can indirectly affect kelp through increased disease susceptibility[27] and competition from opportunistic turf algae[28].

All three models produced useful predictions for present day distributions, however the GLM and Maxent were better suited to generating future predictions than the RF. The GLM produced a more conservative and spatially fragmented current prediction of kelp distribution compared to MaxEnt, which captured smoother and more continuous patterns of suitability along the coastline, reflecting more ecologically realistic spatial variation. The RF model predicted a much broader area of suitable habitat than observed, achieving high accuracy on the training data but likely reflecting overfitting and therefore a tendency to assign moderate suitability across large environmental ranges[29]. Although model performance for present-day predictions was strong across all three approaches, the RF projections under future climate scenarios were unrealistic, predicting high suitability across all years and SSPs. This aligns with the known issue that RF models perform poorly when extrapolating beyond the environmental conditions available in the training data, limiting its reliability for forecasting under changing climates[30].

Both the GLM and MaxEnt models projected extensive habitat loss across all SSPs by 2040 (95-100%), reflecting the strong influence of rising ocean temperatures and other variables on the distribution of *Ecklonia radiata*. However, unlike SSP2 and SSP3, conditions under SSP1 improved by 2090, consistent with the recovery of environmental conditions to less extreme values in this scenario[11].

Under SSP2 and SSP3, no suitable habitat is predicted to remain along the Australian coastline, with significant consequences for biodiversity, fisheries, and coastal livelihoods[2,3] . Although suitable habitat re-emerges under SSP1 by 2090, natural recovery is unlikely, as the complete loss of kelp by 2040 would remove the local source populations required for recolonisation[23]. Without surviving populations to provide propagules, kelp cannot re-establish even if conditions improve[23]. Additionally, degraded ecosystem states, such as urchin barrens or turf-dominated algae, may persist due to ecological hysteresis, in which feedbacks reinforce these alternative stable states and hinder a return to kelp dominance[13].

Regardless of the future climate trajectory, our predictions demonstrate that active intervention will be required to restore or sustain kelp populations, and provide insights into which areas of the ocean this should be implemented[31]. Restoration and conservation initiatives should target nearshore environments where kelp is already present or where suitable habitat currently exists (figs. 4-7) , as these regions are best positioned to continue providing ecosystem services[31]. Efforts should also prioritise lower latitude areas, which are least likely to be impacted by future climate change (figure 3). However, to reduce the chance of *Ecklonia radiata's* extinction by the 2040s (fig. 7), assisted gene flow and selective genetic manipulation could be used to expand the species' thermal tolerance, which could enhance its capacity to persist under warming ocean conditions[32].

Nearshore restoration should be also complemented by the development of offshore aquaculture[33]. Kelp aquaculture can be established in deeper offshore waters, as farmed kelp does not require rocky substrate for attachment[34], and provides additional advantages such as food production, livestock feed and carbon sequestration[33]. Under the SSP1 scenario, aquaculture could be instrumental in providing the genetic material needed to restore suitable habitat in 2090[31]. In contrast, under SSP2 and SSP3, it may be the only viable method for sustaining *Ecklonia radiata* populations in the Oceania region. This approach should be prioritised south of Tasmania, where proximity to projected suitable habitat (figures 4-7) and access to established infrastructure in and around Hobart make aquaculture operations most practical.

This study is subject to several limitations that may influence model accuracy and interpretation. Firstly, the observation data are spatially biased[35], with most presence points concentrated along the more accessible regions of Australia's east coast. This limits representation of the species' full environmental range and may reduce the model's ability to generalise across the broader Great Southern Reef. Secondly, due to computational processing and storage constraints the environmental data needed to be of relatively low resolution, leading us to use BioOracle data (0.05°). These same limitations also prevented the inclusion of benthic substrate data, which would have provided an important mask for delineating suitable habitat. Finally, the models considered only abiotic factors and did not account for key biotic interactions, particularly sea urchin grazing pressure, which is driving the widespread formation of urchin barrens along the east coast of Australia[36].

Methods

0.4 Environmental Data

Environmental data were obtained from Bio-ORACLE v3.0 - a global dataset of marine environmental layers with a spatial resolution of 0.05° (approximately 5 km at the equator) and a temporal resolution of 10-year intervals[37]. Data on sea surface conditions were downloaded across the Great Southern Reef for the 2010-2020 decade (to represent present-day conditions); as well as the 2040-2050 and 2090-2100 decades under SSP1-1.9, SSP2-4.5 and SSP3-7.0.

As already discussed, the SSPs describe how the global climate is likely to change under different scenarios of social, economic and environmental development[11]. Data on future environmental conditions under SSP1, SSP2 and SSP3 were downloaded to reflect best-case, most likely, and worst-case emissions scenarios, respectively. Data on future environmental conditions under SSP4 and SSP5 were not used to create our models. This is because SSP4 describes a pathway with emissions that are higher than SSP1 but lower than SSP3[11] - making it neither the "best-case" scenario, or the most likely "middle-of-the-road" scenario. Furthermore, the highest emissions scenario described by SSP5 is considered to be very unlikely, leading us to select SSP3 as a realistic worst case scenario[11,12,38].

The environmental variables extracted from Bio-ORACLE were those considered to be most relevant to the ecology and distribution of *Ecklonia radiata*. This included three temperature variables (the long-term maximal, long-term minimal and mean sea surface temperatures) - since prolonged periods of exposure to non-optimal temperatures is known to impact the survival and reproduction of kelp[15–17]. Mean concentrations of nitrate and phosphate were also considered. These macronutrients are important for kelp growth; but excessive levels are implicated in eutrophication and can have a negative effect on kelp survival[8–10]. In addition to this, data was downloaded for primary productivity variables (long-term maximal and minimal phytoplankton concentrations), to serve as indicators of light availability and nutrient levels[7]; as well as three chemical variables (mean salinity, pH and dissolved oxygen concentration) expected to have either direct or indirect effects on kelp function and distribution[2]. Finally, variables related to current strength were extracted (long-term maximal and minimal sea water speed). These are important to consider, as changes in current strength can alter kelp dispersal dynamics[6].

A pairwise Pearson correlation matrix was created using data from 2010-2020 to examine multicollinearity among the environmental variables. Variables with a Pearson correlation coefficient above 0.7 ($|r| > 0.7$) were identified as being highly correlated. When this occurred, the variable considered to be more ecologically meaningful, based on previous research, was kept for modelling, while the other was removed. This step is essential in preventing overfitting of species disribution models, especially GLMs.

Data on the minimum bathymetry of each 0.05° grid cell was also downloaded from Bio-ORACLE v3.0 under present-day conditions. *Ecklonia radiata* is known to occur at maximum depths of 50 m[5]. A 50 m depth mask was therefore created, to restrict predictions from the models to areas where *Ecklonia radiata* can realistically occur.

0.5 Observations Data

Presence-only data on the distribution of *Ecklonia radiata* were downloaded from two publicly available sources: the Integrated Marine Observing System (IMOS) National Reef Monitoring Network Sub-Facility - Benthic Cover Data[39]; and the Global Biodiversity Information Facility (GBIF)[40].

The IMOS dataset collates in-situ survey data collected by various contributors through the Australian Temperate Reef Collaboration (ATRC) since 1992[39]. Surveys are carried out by skilled divers who record the benthic species present in 50 x 50 cm quadrats along 200 m transect lines, spaced 10 m apart, at shallow reef sites across Australia[39]. The GBIF dataset integrates species occurrence data from a wider range of sources, including citizen science programs and other research initiatives[40].

For the current study, both datasets were filtered to only include observations of *Ecklonia radiata* across Australia between 2010 and 2020. This provided records of *Ecklonia radiata* at 640 unique locations. 272 of these presence points originated from the IMOS dataset, while 368 were sourced from the GBIF dataset.

0.6 Presence-Background Points and Sample Extent

Figure 7 shows the distribution of the 640 presence points across the Great Southern Reef. Examining this map, it is clear that observations of *Ecklonia radiata* are concentrated on the southeast coast of Australia. On the south and west coasts, there are very few occurrence records outside of capital cities. This is likely due to sampling bias - because people are more densely populated along Australia's southeastern coastline[41], more citizen scientists can contribute data to GBIF in this region. Research on kelp forests around Australia is also typically concentrated in this area[39,40]. The lack of presence points along the southern and western coastlines is likely because data has not been collected in these regions, rather than because *Ecklonia radiata* is genuinely absent. This biased distribution of presence data can reduce the accuracy of species distribution models - especially those that use randomly generated pseudo-absence points, as they assume that kelp is absent from these unsampled areas.

To address this bias, the original map of observational data was cropped to the longitude that includes 80% of presence points on its eastern side - 144°E. This new geographic extent is shown in Figure 7 . In doing so, the total number of presence points available to create the species distribution models was reduced from 640 to 512.

This area was then expanded to an extent suitable for sampling background points. The maximum longitude and minimum latitude were increased to 155°E and 45°S respectively, and the maximum latitude was decreased to 20°S to capture areas without presence points. Importantly, the minimum longitude of the sample extent remained at the previously cropped 144°E boundary, to avoid generating background points in areas where presence points had been removed. The 50m bathymetry mask was then applied to the map, and 1,000 background points were randomly generated across the masked sample extent. A map of presence and background points across the final sample extent can be seen in Figure 7 .

A dataframe of presence and background points was then created, and the 2010-2020 environmental data corresponding to each point was extracted. Initially, there were 222 presence points (43%) with no environmental data matching their coordinates. Most of these presence points occurred right on the coastline, indicating that the coarse resolution of the Bio-ORACLE data was not capturing these locations. To address this, environmental data was extracted for each of these presence points from the nearest neighbouring grid cell with available data within a 10 km range. Only one presence point was left that did not have data associated with it after this. The nearest neighbour of this point was more than 10 km away, and unlikely to be representative of local environmental conditions at the presence point. This point was therefore removed from the dataframe, leaving a final 511 presence points to create the model.

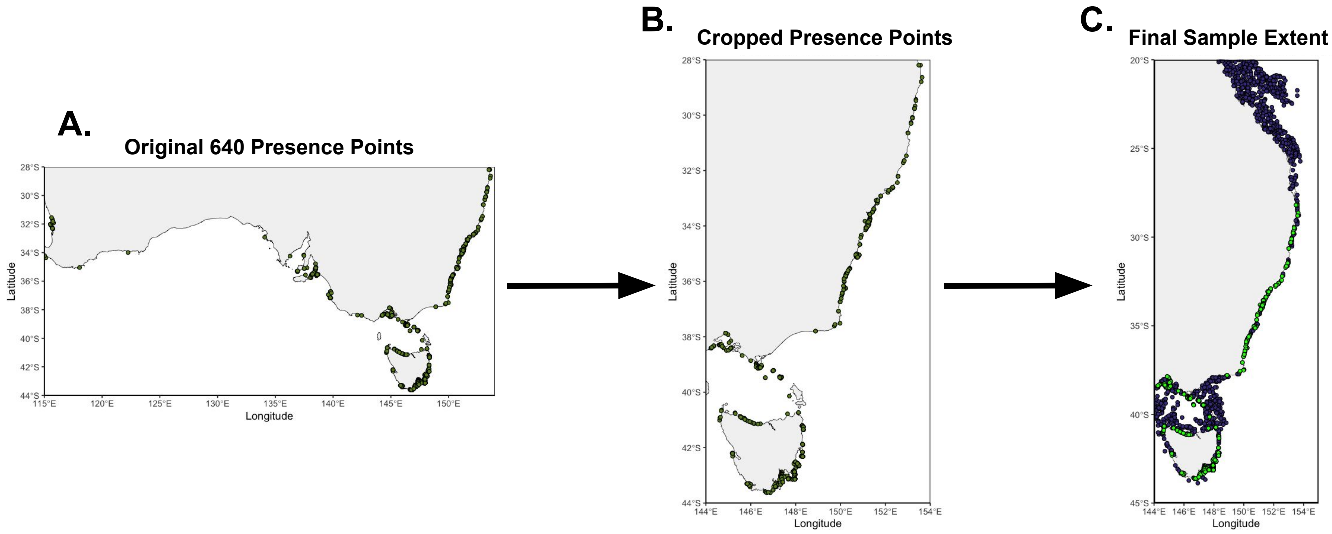

Figure 7. Maps showing the distribution of: (A) all 640 presence points obtained from the IMOS and GBIF datasets across the original geographic extent; (B) the extent of the 80% east-most presence points; and (C) the final 512 presence points (green) and 1,000 background points (purple) across the sample extent.

0.7 Model Building

Three models were developed to model the distribution of *Ecklonia Radiata* across the sample extent: a GLM, a MaxEnt, and a RF model. All models were developed in R using Jupyter, with presence-background data randomly split into 80% for training and 20% for testing the models.

The GLM was developed first. GLMs are statistical modelling methods that work with presence and pseudo-absence data to estimate where a species is likely to occur. Background points in our training dataframe were therefore applied as pseudo-absence points to create the GLM. The GLM was then dredged to test all possible combinations of environmental variables, with models compared using the Akaike Information Criterion (AIC). The model with the lowest AIC value was identified as the most parsimonious - that is, the most explanatory model with the least environmental variables - and was ran as the final GLM. Importantly, GLMs make predictions by modelling linear relationships between environmental variables and species presence. This often makes them simpler to interpret than other models, but they can miss complex non-linear relationships. They are also more sensitive to overfitting than other models - though, this has been limited by selecting the most parsimonious model.

The MaxEnt and RF models were then built using the same set of environmental variables in the final GLM. This allowed for direct comparisons between the three models and limited overfitting by excluding redundant variables. MaxEnt models often perform better for presence-only data than other models - which is what was used in the current study. This is because it compares environmental conditions at presence points with background points to determine the most uniform distribution possible across the sample extent - without assuming the species is absent at background points. This machine learning technique also has the benefit of being able to capture complex non-linear relationships between variables.

RF models, like MaxEnt, are also a machine learning methods and can capture non-linear relationships. Like in GLMs, however, they assume the species is absent at background points. They typically have high predictive accuracy when environmental conditions are within the range of the training data, but struggle to extrapolate into novel environmental conditions. For this reason, the RF model is likely to be most useful at determining whether the environmental variables selected for use in the final GLM and MaxEnt models are appropriate.

All models generate a value for the probability of occurrence within each 0.05° grid cell on the map. To clearly map suitable and unsuitable habitat, presence threshold values for each model were calculated as the probability with the greatest sensitivity and specificity when detecting *Ecklonia radiata* occurrence.

0.8 Model Evaluation

Response curves were generated for each model to examine how the predicted distribution of *Ecklonia radiata* varied with each environmental variable. These curves were then compared to determine how models aligned with previous research on the ecology of *Ecklonia radiata.A* Receiver Operating Characteristic (ROC) curve was also generated for each model using the testing dataset, and the Area Under the Curve (AUC) was calculated. This provided insight into how accurately each model predicted the the location of presence and absence points.

0.9 Projected Habitat Suitability

A geographic extent slightly larger than the size of the GSR was generated (110°E to 158°E longitude, 20°S to 45°S latitude). Each model was then used to predict habitat suitability across this entire extent for present-day conditions (2010-2020), as well as conditions in 2040-2050 and 2090-2100 under SSP1, SSP2 and SSP3. Maps of predicted habitat suitability were generated for each model and each scenario, and the percentage of predicted habitat loss compared to present-day conditions (2010-2020) was calculated for 2040-2050 and 2090-2100 under each SSP. Outputs from models were compared and examined for inconsistencies.

References

1. Jayathilake, D. R. M. & Costello, M. J. A modelled global distribution of the kelp biome. *Biol. Conserv.* **252**, 108815, DOI: https://doi.org/10.1016/j.biocon.2020.108815 (2020).
2. Harley, C. D. G. *et al.* Effects of climate change on global seaweed communities. *J. Phycol.* **48**, 1064–1078, DOI: https://doi.org/10.1111/j.1529-8817.2012.01224.x (2012). https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1529-8817.2012.01224.x.
3. Eger, A. M. *et al.* The value of ecosystem services in global marine kelp forests. *Nat. Commun.* **14**, 1894, DOI: 10.1038/s41467-023-37385-0 (2023).
4. Allcock, A. L. *Oceanography and Marine Biology: An annual review. Volume 57.* Oceanography and Marine Biology - An Annual Review (Taylor & Francis, Erscheinungsort nicht ermittelbar, 2019).
5. Marzinelli, E. M. *et al.* Large-Scale Geographic Variation in Distribution and Abundance of Australian Deep-Water Kelp Forests. *PLOS ONE* **10**, 1–21, DOI: 10.1371/journal.pone.0118390 (2015). Publisher: Public Library of Science.
6. Coleman, M. A. *et al.* Variation in the strength of continental boundary currents determines continent-wide connectivity in kelp. *J. Ecol.* **99**, 1026–1032 (2011).
7. Martínez, B. *et al.* Distribution models predict large contractions of habitat-forming seaweeds in response to ocean warming. *Divers. Distributions* **24**, 1350–1366 (2018).
8. Akinnawo, S. O. Eutrophication: Causes, consequences, physical, chemical and biological techniques for mitigation strategies. *Environ. Challenges* **12** (2023).
9. Gonzalez-Aragon, R. M. M. L. C. T. F. I. V. J. A. . B. B. R., D. A species distribution model of the giant kelp macrocystis pyrifera: Worldwide changes and a focus on the southeast pacific. *Ecol. Evol.* **14** (2024).
10. Mason, . B. C. O., J. M. Vulnerability of kelp, ecklonia radiata, to persistent nitrogen pollution and coastal darkening. *Mar. Biol.* **171**, DOI: 10.1007/s00227-024-04545-9 (2024).
11. O'Neill, B. C. *et al.* The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob. Environ. Chang.* **42**, 169–180, DOI: https://doi.org/10.1016/j.gloenvcha.2015.01.004 (2017).
12. Burgess, B. S. L. L. R. E. F. A. B. C. M., M. G. Climate change scenarios in fisheries and aquatic conservation research. *ICES J. Mar. Sci.* **80**, 1163–1178, DOI: 10.1093/icesjms/fsad045 (2023).
13. Filbee-Dexter, K. & Wernberg, T. Rise of Turfs: A New Battlefront for Globally Declining Kelp Forests. *BioScience* **68**, 64–76, DOI: 10.1093/biosci/bix147 (2018). _eprint: https://academic.oup.com/bioscience/article-pdf/68/2/64/23813986/bix147.pdf.
14. Bureau of Meteorology. State of the climate. (2024).
15. Bartsch, V. J. P. C., I. & Hanelt, D. Prevailing sea surface temperatures inhibit summer reproduction of the kelp laminaria digitata at helgoland (north sea). *J. Phycol.* **49**, 1061–1073 (2013).
16. Simonson, M. A., E.J. & Scheibling, R. Kelp in hot water: effects of warming seawater temperature on kelp quality as a food source and settlement substrate. *Mar. Ecol. Prog. Ser.* **537**, 105–119 (2015).
17. Alsuwaiyan, V. S. F.-D. K. C. M. C. M., N.A. & Wernberg, T. Genotypic variation in response to extreme events may facilitate kelp adaptation under future climates. *Mar. Ecol. Prog. Ser.* **672**, 111–121 (2021).
18. Roleda, . H.-C. L., M. Y. .
19. Schwoerbel, J. *et al.* Thermal performance curves identify seasonal and site-specific variation in the development of ecklonia radiata (phaeophyceae) gametophytes and sporophytes. *J. Phycol.* **60**, 83–101 (2024).

20. Wernberg, T. *et al.* An extreme climatic event alters marine ecosystem structure in a global biodiversity hotspot. *Nat. Clim. Chang.* **3**, 78–82 (2013).

21. Alsuwaiyan, N. A. *et al.* Genotypic variation in response to extreme events may facilitate kelp adaptation under future climates. *Mar. Ecol. Prog. Ser.* **672**, 111–121 (2021).

22. Britton, D. *et al.* Cool-edge populations of the kelp ecklonia radiata under global ocean change scenarios: strong sensitivity to ocean warming but little effect of ocean acidification. *Proc. Royal Soc. B* **291**, 20232253 (2024).

23. Wernberg, T. *et al.* Biology and ecology of the globally significant kelp ecklonia radiata. *Oceanogr. marine biology* (2019).

24. Wernberg, T. *et al.* Climate-driven regime shift of a temperate marine ecosystem. *Science* **353**, 169–172 (2016).

25. Jackson, G. A. & Winant, C. D. Effect of a kelp forest on coastal currents. *Cont. Shelf Res.* **2**, 75–80 (1983).

26. Davis, T. *et al.* Extreme flooding and reduced salinity causes mass mortality of nearshore kelp forests. *Estuarine, Coast. Shelf Sci.* **275**, 107960 (2022).

27. Qiu, Z. *et al.* Future climate change is predicted to affect the microbiome and condition of habitat-forming kelp. *Proc. Royal Soc. B* **286**, 20181887 (2019).

28. Connell, S. D., Kroeker, K. J., Fabricius, K. E., Kline, D. I. & Russell, B. D. The other ocean acidification problem: Co2 as a resource among competitors for ecosystem dominance. *Philos. Transactions Royal Soc. B: Biol. Sci.* **368**, 20120442 (2013).

29. Barreñada, L., Dhiman, P., Timmerman, D., Boulesteix, A.-L. & Van Calster, B. Understanding overfitting in random forest for probability estimation: a visualization and simulation study. *Diagn. Progn. Res.* **8**, 14 (2024).

30. Santini, L., Benítez-López, A., Maiorano, L., Čengić, M. & Huijbregts, M. A. Assessing the reliability of species distribution projections in climate change research. *Divers. Distributions* **27**, 1035–1050 (2021).

31. Eger, A. M. *et al.* Global kelp forest restoration: past lessons, present status, and future directions. *Biol. Rev.* **97**, 1449–1475 (2022).

32. Harden, M. *et al.* Heat stress analysis suggests a genetic basis for tolerance in macrocystis pyrifera across developmental stages. *Commun. Biol.* **7**, 1147 (2024).

33. Grebe, G. S., Byron, C. J., Gelais, A. S., Kotowicz, D. M. & Olson, T. K. An ecosystem approach to kelp aquaculture in the americas and europe. *Aquac. Reports* **15**, 100215 (2019).

34. Buschmann, A. H. *et al.* Seaweed production: overview of the global state of exploitation, farming and emerging research activity. *Eur. J. Phycol.* **52**, 391–406 (2017).

35. Idris, S. H., Mat Jalaluddin, N. S. & Chang, L. W. Ethical and legal implications of gene editing in plant breeding: a systematic literature review. *J. Zhejiang Univ. B* **24**, 1093–1105 (2023).

36. Przeslawski, R. *et al.* A review of urchin barrens and the longspined sea urchin (centrostephanus rodgersii) in new south wales, australia. *Mar. Freshw. Res.* **76**, NULL–NULL (2025).

37. Assis, F. B. S.-S. V. S. L. G. L. F. E. L. F. V. B. T. L. S. E. V. H. D. C. O., J. Bio-oracle v3.0. pushing marine data layers to the cmip6 earth system models of climate change research. *Glob. Ecol. Biogeogr.* DOI: 10.1111/geb.13813 (2024).

38. Hausfather, . P. G. P., Z. Emissions – the 'business as usual' story is misleading. *Nature* **577**, 618–620, DOI: 10.1038/d41586-020-00177-3 (2020).

39. System, I. M. O. Imos - national reef monitoring network sub-facility - benthic cover data (in situ surveys). (2025).

40. GBIF.org. Gbif occurrence download. (2025).

41. Australia, A. D. A. Abs australian population grid 2024. (2025).

Acknowledgements

We are grateful to Tristan Salles for his advice on this project and guidance on our models.

Authors contribution statement

J.D., E.C. and I.P. contributed equally to this project.

Additional Information

The Github repository associated with this report can be accessed `here.`

Data

Data used for this report can be accessed by the following links:
imos data: `here.`
gbif data: `here.`
Bio-ORACLE: `here.`