



# Multi-criteria analysis for rapid vulnerability assessment of marine species to climate change

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## Abstract

The accelerating pace of climate-induced stress to global ecosystems threatens the sustainable management and conservation of biodiversity. To effectively respond, researchers and managers require rapid vulnerability assessment tools that can be readily implemented using diverse and existing knowledge sources. Here we demonstrate the application of multi-criteria analysis (MCA) for this purpose using a group of coastal-pelagic fishes from south-eastern Australia as a case-study. We show that MCA has the capacity to formally structure diverse knowledge sources, ranging from peer-reviewed information (which informed 29.2% of criteria among models) to expert knowledge (which informed 22.6% of criteria among models), to quantify the sensitivity of species to biophysical conditions. By integrating MCA models with spatial climate data over historical and future periods, we demonstrate the application of MCA for rapidly assessing the vulnerability of marine species to climate change. Spatial analyses revealed an apparent trend among case-study species towards increasing or stable vulnerability to projected climate change throughout the northern (i.e. equatorward) extent of the study domain and the emergence of climate refugia throughout southern (i.e. poleward) regions. Results from projections using the MCA method were consistent with past analyses of the redistribution of suitable habitat for coastal-pelagic fishes off eastern Australia under climate change. By demonstrating the value of MCA for rapidly assessing the vulnerability of marine species to climate change, we highlight the opportunity to develop user-friendly software infrastructures integrated with marine climate projection data to support the interdisciplinary application of this method.

**Keywords** Adaptation · Climate change · Habitat suitability · Multi-criteria analysis · Range shift

## 1 Introduction

Climate change is rapidly altering environmental conditions that have historically characterised natural systems (IPCC 2019), with subsequent biological responses ranging from species redistributions to altered food web dynamics (Du Pontavice et al. 2020; Gervais

et al. 2021; Pecl et al. 2017; Pinsky et al. 2019). For both marine and terrestrial systems, projections indicate that the rate and magnitude of these changes will continue to increase through the remainder of the twenty-first century (Johnson and Watson 2021; Reboita et al. 2022; Smith et al. 2022). These changes present considerable challenges for the conservation, harvest and sustainable management of biodiversity (Bonebrake et al. 2018). Assessments of the contemporary and future vulnerability of species to climate change are a necessary precursor to the development of adaptation strategies capable of minimising negative impacts and capitalising on emerging opportunities (Champion et al. 2022; Hare et al. 2016; Hobday et al. 2016a; McClure et al. 2023).

Climate change vulnerability assessments of species often require considerable time to develop (e.g. multiple years for a single species) and rely on the availability of specific datasets and specialist analytical expertise to parametrise (Pacifiçi et al. 2015). These factors mean that species responses to climate change may outpace the production and delivery of vulnerability assessments and thus the ability to implement early adaptation interventions. Assessment methodologies capable of rapidly integrating available, and potentially disparate, sources of information are required to enhance the capacity of stakeholders to understand and respond to the emerging effects of climate change (Cochrane et al. 2019; Pecl et al. 2014b).

Multi-criteria analysis (MCA) is a methodological framework developed to integrate the effects of multiple criteria on a specified outcome. MCA has been widely applied to waste disposal (Merkhofer et al. 1997), real estate evaluation (Kettani et al. 1998), decommissioning of obsolete marine infrastructure (Fowler et al. 2014), forestry (Kangas and Kangas 2005) and fisheries management (Mardle and Pascoe 1999). Given that MCA provides a structured framework capable of integrating diverse criteria and exiting data sources in focus group settings, it also presents a valuable approach for rapidly assessing vulnerability to climate change. However, MCA remains underutilised for assessing the vulnerability of species to climate change, particularly within marine systems where the rate and magnitude of climate-driven species responses are exceeding those occurring within terrestrial systems (Poloczanska et al. 2013).

MCA for species climate change vulnerability assessment identifies and includes criteria (i.e. variables) that influence species environmental sensitivities (e.g. ocean temperature and seawater chemistry). These criteria are subsequently partitioned into categories by defining a climate suitability step function (e.g. ocean temperature may be partitioned into bins ranging from 14.01 to 16°C, 16.01 to 18°C, and so on) to reflect the influence of each criterion on the response of the species being assessed (e.g. environmental habitat suitability and species abundance). Importantly, MCA can be informed by varied data sources, ranging from peer-reviewed literature to unpublished data. Expert knowledge (which includes indigenous knowledge) can also be drawn upon to adjust information inputs or to fill knowledge gaps that limit alternative climate change vulnerability assessment approaches. Expert knowledge is also crucial for weighting the relative importance of each criterion to the overarching response being assessed. The resulting MCA structure (or 'MCA model') can then be integrated with historical data or future climate projections (i.e. the environmental exposure component) to produce spatial assessments (Feizizadeh and Kienberger 2017; Store and Kangas 2001) of the vulnerability of species to climate change.

Here we demonstrate the value of MCA for rapidly assessing the vulnerability of marine species to climate change using diverse knowledge sources. To do so, we apply the approach to five harvested coastal-pelagic fishes from south-eastern Australia. This region is a climate change hotspot where ocean warming is occurring non-linearly at a rate that is between 2 and 4 times faster than the global average (Hobday and Pecl 2014;

Malan et al. 2021; Pecl et al. 2014a). Within this context, we specifically (1) categorise and quantify the diversity of knowledge sources utilised in case-study MCA models, (2) apply MCA to project changes to habitat suitability for each study species under future climate change within five marine bioregions off south-eastern Australia and (3) determine marine bioregions associated with the greatest projected climate-driven changes to environmental habitat suitability for each species. By doing so, we demonstrate the utility of MCA as a decision-support tool for climate adaptation planning in marine systems.

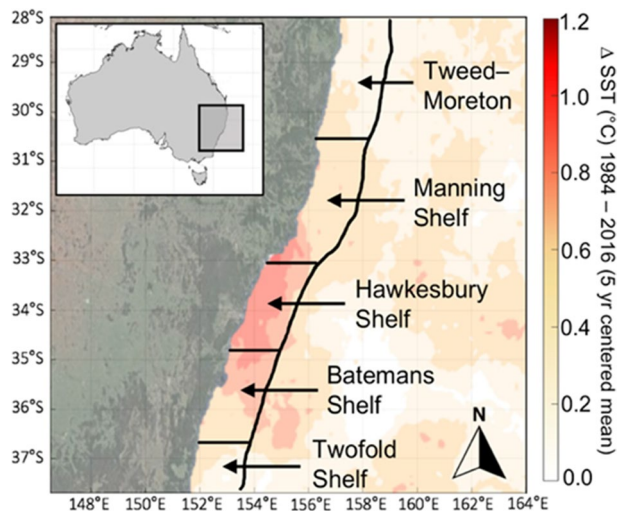
## 2 Methods

### 2.1 Case-study species and spatial extent

Here we apply MCA to undertake a rapid climate change vulnerability assessment for yellowtail kingfish (*Seriola lalandi*; ‘kingfish’), Australian bonito (*Sarda australis*; ‘bonito’), Australian spotted mackerel (*Scomberomorus munroi*; ‘spotted mackerel’), narrow-barred Spanish mackerel (*Scomberomorus commerson*; ‘Spanish mackerel’) and common dolphinfish (*Coryphaena hippurus*; ‘dolphinfish’). The distributions of these species are closely linked with dynamic oceanographic variables (Brodie et al. 2015) and are undergoing poleward range extensions off eastern Australia in response to climate change (Champion et al. 2021; Champion et al. 2018).

The study extent encompassed five marine bioregions that collectively extend over ~1000 km of south-eastern Australia’s coastal and continental shelf environments (Fig. 1; 28.2–38.1°S). The bioregional spatial units analysed here follow the Australian bioregionalisation framework (Interim Marine and Coastal Regionalisation for Australia Technical Group 1998) and include Tweed–Moreton, Manning Shelf, Hawkesbury Shelf, Batemans Shelf and Twofold Shelf bioregions.

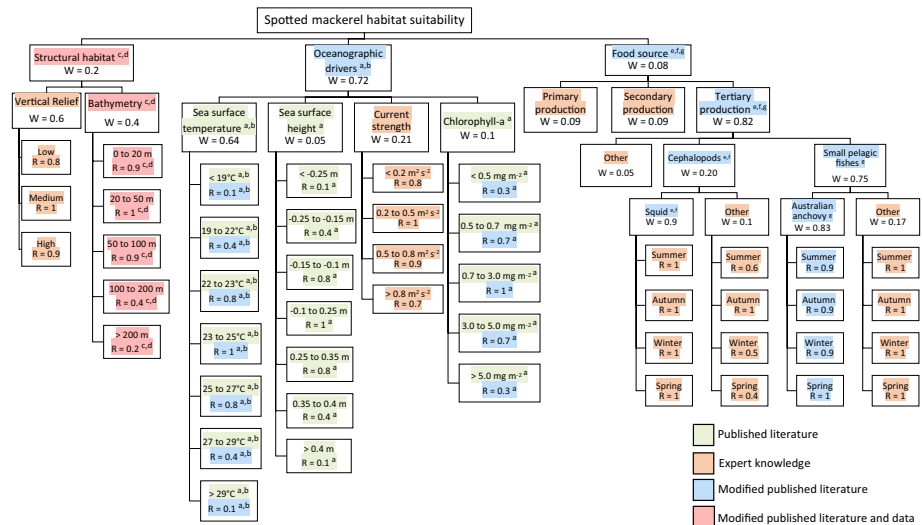
**Fig. 1** Spatial extent of the study region depicting the south-east Australian marine bioregions used to assess for climate-driven changes to habitat suitability for the study species. The study region is overlaid with the change in mean summer sea surface temperature from 1982 to 2018 based on 5-year means centred on 1984 and 2016 (see Table 2 for the source of historical SST data). N.B. Marine bioregions have been extended offshore in this figure to aid visual interpretation



### 2.2 Multi-criteria analysis

MCA models were developed to quantify an index of habitat suitability ranging between 0 (unsuitable) and 1 (optimal) for each species. These models are structured as flexible hierarchical decision trees that can accommodate varied biophysical factors that influence species habitat suitability (e.g. Fig. 2). Model structures for each species were developed in focus group workshops, where species experts utilised available sources of information on the factors contributing to habitat suitability for each species, in conjunction with their own expert knowledge, to develop models. Experts contributing to MCAs consisted of ecologists and fisheries scientists who are either currently researching or have previously researched the focal species in the study region. Experts had access to current and historical data on stock monitoring conducted by NSW DPI Fisheries, including distributional information on catch. Prior to convening focus group workshops, a literature review was undertaken to collate information on known biophysical drivers of habitat suitability for each species. This information was collated in data sheets (Online Resource 1) that were supplied to species experts to further support decision-making during focus group workshops.

Primary criteria directly contributing to species habitat suitability were initially identified and further divided into second and tertiary variable groupings where necessary (e.g. Fig. 2), with primary criteria common among models being ‘structural habitat’, ‘oceanographic drivers’ and ‘food source’. For example, oceanographic drivers of habitat suitability were commonly represented by three key variables known to regulate the distributions of coastal-pelagic fishes (Hobday and Hartog 2014), including sea surface



**Fig. 2** Full MCA hierarchical model developed for spotted mackerel (*Scomberomorus munroi*). Colours denote the knowledge sources that justify the inclusion of variables, their ratings and binned categories in the model structure. We note that this MCA is parametrised using four of the potential five knowledge source categories considered. Superscripts refer to the literature and data that support the model structure, where Champion et al. (2021)<sup>a</sup>, Begg et al. (1997)<sup>b</sup>, NSW DPI<sup>c</sup>, Ward and Rogers (2003)<sup>d</sup>, Jackson and Pecl (2003)<sup>e</sup>, Pecl et al. (2004)<sup>f</sup> and Begg and Hopper (1997)<sup>g</sup>. R, ratings; W, weightings

temperature, current velocity and sea surface height. At the base of each model structure, variables influencing habitat suitability (e.g. sea surface temperature) were partitioned into bins that collectively encompass the range of environmental conditions currently experienced by each species throughout their distributions and conditions likely to be experienced under future climate change. Ratings ranging between 0 (unsuitable) and 1 (optimal) were assigned by species experts to binned categories to reflect their suitability for each study species. For example, thermal habitat suitability for spotted mackerel is known to peak between 23 and 25°C (Champion and Coleman 2021); therefore, this binned category of sea surface temperature was assigned a rating of 1, whereas sea surface temperatures < 19°C and > 29°C were assigned ratings of 0.1 to reflect the relatively poor suitability of these conditions for spotted mackerel (Fig. 2).

Sources of information used to justify the inclusion of variables within MCA models, their partitioning into categorial bins and the assignment of ratings to bins were explicitly included within model structures (e.g. Fig. 2). Five categories were used to classify sources of input information; ‘published literature’ (i.e. peer-reviewed studies, books and reports), ‘data exploration’ (i.e. unpublished data analysis or data exploration), ‘expert knowledge’ (i.e. knowledge from species experts not formally captured in published literature), ‘modified published literature’ (i.e. information from published sources that was modified using knowledge from species experts) and ‘modified published literature and data’ (i.e. information from published sources and unpublished data analysis that was modified using knowledge from species experts). The modification of published literature and/or data by species experts reflects the adjustment of information from alternative spatial domains or species closely related to those assessed here (see Online Resource 1).

Once model structures were established and ratings describing the suitability of each variable for the study species were applied, weightings that reflect the relative contributions of each criterion to species habitat suitability were calculated. The criteria weighting process reflects that some variables have a relatively greater influence on habitat suitability than others. We applied the analytic hierarchy process (AHP) developed by Saaty (1987) to compare criteria and evaluate their relative contributions to habitat suitability for each study species. AHP assigns weights to each criterion through pairwise assessments that determine the criteria that have the greatest influence on habitat suitability and to what extent. This process was undertaken using the AHP intensity ranking framework applied by Romeijn et al. (2016) (Table 1), where comparisons between criteria using this framework were made according to the consensus opinion of experts, informed by available sources of information and their own knowledge, during focus groups.

Intensity rankings were placed into a pairwise comparison matrix (Saaty 1987) and normalised by dividing each value in the matrix column by the sum of that column.

**Table 1** Pairwise comparison importance scores used to quantify criteria weightings, adopted from Romeijn et al. (2016)

Intensity rating	Definition
1	Criterion <i>X</i> is of equal importance to criterion <i>Y</i>
3	Criterion <i>X</i> is slightly more influential than criterion <i>Y</i>
5	Criterion <i>X</i> is more influential than criterion <i>Y</i>
7	Criterion <i>X</i> is much more influential than criterion <i>Y</i>
9	Criterion <i>X</i> is extremely more influential than criterion <i>Y</i>

Weights for each criterion were then calculated by taking the mean of each matrix row, which are absolute values ranging between 0 and 1 that add up to 1 when summed across one criteria level.

Given a key objective of our analysis was to produce spatial predictions of species habitat suitability, models including variables for which spatial data layers are not available over historical or future projection periods were reduced to contain only variables associated with available spatial data. This was done by removing variables that could not be spatially estimated (e.g. food sources over historical and future projection periods and chlorophyll-*a* concentration in seawater over the future projection period) and recalculating weightings using the original intensity rankings derived from pairwise comparisons between only the retained variables. Full models containing all variables originally included in models for each species and reduced (i.e. finalised) models used to create spatial predictions of habitat suitability are presented in Online Resource 2. Habitat suitability maps were generated using raster reclassification to transform environmental data within each grid cell according to the defined ratings parameters associated with each variable, followed by weighted linear combination analysis to sum model variables according to their assigned weightings.

### 2.3 Historical spatial analysis

Finalised models were used to create historical spatial predictions of species habitat suitability at a seasonal temporal resolution over the 20-year period encompassing 1993–2012 using data sourced from the Copernicus Marine Environment Monitoring Service and the General Bathymetric Chart of the Oceans (Table 2). The temporal extent of historical spatial analyses was determined by the lack of available sea surface height and current strength data prior to 1993 and recommendations (e.g. Darbyshire et al. 2022) that climate impact analyses standardise the length of historical baseline and future projections periods (herein we use 20-year historical and future periods). Seasonal spatial predictions were averaged over the historical period to provide a baseline from which to examine the direction and magnitude of climate-driven changes to species habitat suitability.

Historical spatial predictions were also used to assess the accuracy of finalised MCA models. This involved a three-step model validation process. Firstly, a qualitative assessment was undertaken by asking species experts involved in focus group workshops whether the predicted seasonal distributions of habitat suitability accurately aligned with their understanding of the realised seasonal distribution of each study species. Secondly, an assessment of MCA model accuracy was undertaken by comparing habitat suitability values predicted at known occurrence locations of each study species with habitat suitability values predicted at a randomly generated sample of pseudo-absences. To do so, a sample of 100 species occurrence records over the historical analysis period were extracted for each season from the New South Wales Department of Primary Industries gamefish tagging database (NSW DPI 2019). This government administered citizen science database contains a large set of occurrence records for numerous coastal-pelagic fishes, representing a valuable resource for comparing predicted and realised species distributions. Finally, we utilised the Bhattacharyya coefficient (Aherne et al. 1998) to quantify the similarity between the frequency distributions of habitat suitability values predicted at known species occurrences and at randomly sampled points throughout the study area. The Bhattacharyya coefficient is a valuable metric for this analysis (e.g. Johnson and Watson 2021) as it measures the degree of overlap between two frequency distributions on a scale ranging between 0 and 1, where a value of 1 indicates that the two distributions are identical (i.e.,

**Table 2** Descriptions of criteria data sources used to create historical spatial predictions of species habitat suitability using finalised MCA models. CMEMS denotes the Copernicus Marine Environment Monitoring Service (<https://marine.copernicus.eu>) and GEBCO denotes the General Bathymetric Chart of the Oceans (<https://www.gebco.net>). N.B. historical ocean data were regridded to a common 0.05° resolution when making spatial predictions to match the resolution of downscaled future projection data

Criteria	Description	Spatial resolution	Units
Sea surface temperature	Daily global sea surface temperature reprocessed (level 4) from Operational SST and Ice Analysis system downloaded from CMEMS (product #010_011)	0.05°	°C
Sea surface height	Daily gridded sea surface height (level 4) from the Sea Level Thematic Assembly Centre downloaded from CMEMS (product #008_047)	0.25°	m
Current strength	Daily eddy kinetic energy computed from zonal and meridional velocity components from the Sea Level Thematic Assembly Centre downloaded from CMEMS (product #008_047)	0.25°	m <sup>2</sup> s <sup>-2</sup>
Bathymetry	Seafloor depth from the GEBCO (GEBCO_2020) global bathymetric dataset	0.004°	m
Vertical relief	Index of seascape vertical relief, derived from the GEBCO (GEBCO_2020) global bathymetric dataset calculated as: $\text{Vertical relief} = \frac{SD_{\text{net}}}{\text{Median}_{\text{extent}}} \times 100$ Where $SD_{\text{pixel}}$ is the standard deviation of groups of pixels bilinearly interpolated from a gridded resolution of 0.004° (i.e. the native resolution of the GEBCO_2020 dataset) to 0.05° (i.e. the common resolution of variables used to create spatial predictions), and $\text{Median}_{\text{extent}}$ is the median bathymetric value calculated nearshore of the continental shelf-break throughout the study extent	0.004°	Unitless



the MCA could not differentiate between known occurrences and pseudo-absences), while a value of 0 indicates that the two distributions have no overlap (i.e., complete discrimination between known occurrences and pseudo-absences). Therefore, smaller coefficients are indicative of higher model accuracy. For further validation, we replicated this process across two 10-year historical periods (1993–2002 and 2003–2012) to ensure that model accuracy was comparable between periods. This was undertaken because a fundamental objective of our study was to utilise MCA to project habitat suitability for a future period; therefore, Bhattacharyya coefficients that are consistently low across multiple validation periods provide additional evidence of model accuracy.

## 2.4 Future spatial projections

Future spatial projections were centred on a 2050-future (2040–2059 period) as this horizon provides sufficient lead-time for strategic long-term climate adaptation planning in marine systems (Hobday et al. 2016b). Climate data required to support future projections of species habitat suitability were obtained from five global climate models (GCMs) forced under RCP4.5 and 8.5 emissions scenarios from the Coupled Model Intercomparison Project (CMIP5; Table 3).

The coarse spatial resolution of GCM data ( $\sim 1^\circ$ ) challenges its utility for projecting species responses to climate change (Drenkard et al. 2021). Therefore, we applied the delta ‘change-factor’ method (e.g. Morley et al. 2018; Navarro-Racines et al. 2020; von Hammerstein et al. 2022) to downscale sea surface temperature, sea surface height and eddy kinetic energy data to a common  $0.05^\circ$  spatial resolution throughout study region. Delta downscaling was selected as it has proven utility for providing high-resolution mean climate conditions over decadal time periods for climate impact studies (Navarro-Racines et al. 2020). Furthermore, the addition of delta values to observed data incorporates an element of model bias correction since the high-resolution observed data contains empirical information on small-scale variations that are factored into the final product (Pourmokhtarian et al. 2016).

The delta downscaling process involved (1) remapping the curvilinear source GCM data to a global  $1^\circ$  rectilinear grid using the second-order conservative algorithm (remapcon2) in Climate Data Operators (Schulzweida 2021), (2) infilling missing data adjacent to the continental coast for datasets describing zonal (U) and meridional (V) flows using thin plated splines interpolation in R (R Core Team 2022), (3) calculating the difference

**Table 3** Details of GCMs (CMIP5) downscaled ( $0.05^\circ$ ) to support projections of species habitat suitability off south-eastern Australia. Variables downscaled from each model include sea surface temperature, sea surface height and eddy kinetic energy [derived from zonal (U) and meridional (V) flows] under RCP4.5 and 8.5 emissions scenarios

Model	Institution	Native ocean resolution ( $^\circ$ )
ACCESS1.0	CSIRO-BOM, Australia	1.0×1.0
CNRM-CM5	CNRM-CERFACS, France	1.0×0.8
GFDL-ESM2M	NOAA, GFDL, USA	1.0×1.0
HadGEM2-CC	MOHC, UK	1.0×1.0
MIROC5	JAMSTEC, Japan	1.6×1.4



(i.e. delta value) between seasonally aggregated data for the period 2040–2059 and a modelled historical baseline period encompassing 1993–2012 for each variable, GCM and RCP scenario, (4) disaggregating delta value matrices from their native model resolution ( $\sim 1^\circ$ ) to the finer resolution of observed ocean data (i.e.  $0.05^\circ$ ) using bilinear interpolation and (5) adding delta values to an observed seasonal climatology for each variable that encompassed the period 1993–2012 (Table 2). This method produced seasonally-explicit future ocean data downscaled to a common  $0.05^\circ$  resolution for the period 2040–2059 required to facilitate projections of species habitat suitability under climate change.

Future projections of seasonal habitat suitability were created by calculating mean habitat suitability within each grid cell over the 20-year future projection period (2040–2059) for each GCM, then taking the median of all GCMs to estimate the overall future habitat suitability for each study species. Future projections of seasonal habitat suitability for each species were subtracted from historical spatial predictions to quantify change between 2002- and 2050-centred periods. This process also enabled a spatial assessment of confidence in projected changes throughout the study extent by comparing levels change with variability among habitat suitability projections created using different GCMs. We utilised a categorical (i.e. high, medium and low) confidence scale derived from the ratio between change in habitat suitability from historical to future periods and the standard deviation (SD) of future habitat suitability values calculated among GCMs. For example, high levels of projected change in habitat suitability that are consistent among GCMs (therefore associated with low SD) are associated with high confidence, while levels of projected change that are similar to or exceeded by their associated SD among GCMs are associated with low to moderate confidence. Specifically, a change/SD ratio between 0 and  $<1$  is classed as low confidence, between 1 and  $<2$  is classed as moderate confidence and  $>2$  is classed as high confidence. Instances where both the change and SD are 0 (i.e. a ratio of 0) are also classed as high confidence.

Spatial calculation of historical and future habitat suitability from climate data using finalised MCA models was implemented in R (R Core Team 2022). Calculations were performed using the *raster*, *terra*, *sp* and *rgeos* R packages (Bivand et al. 2017; Hijmans et al. 2015; Hijmans et al. 2022; Pebesma and Bivand 2005) and figures were produced using the *ggplot2* and *rasterVis* packages (Lamigueiro and Hijmans 2022; Wickham et al. 2016).

## 3 Results

### 3.1 MCA models

Of the primary criteria included in MCA models, ‘oceanographic drivers’ were consistently associated with the greatest relative importance to habitat suitability for all species. For example, weightings applied to oceanographic drivers of habitat suitability ranged between 0.72 and 0.80 among full models, whereas weightings for structural habitat and food sources both ranged between 0.08 and 0.20. Sea surface temperature was consistently associated with the highest weighting values among oceanographic drivers of habitat suitability for each study species (0.63–0.70).

Of the criteria included in full models for all study species (e.g. Fig. 2; Online Resource 2), on average 34.2% of these were justified using ‘modified published literature’, 29.2% were justified using ‘published literature’ and 22.6% were justified using ‘expert

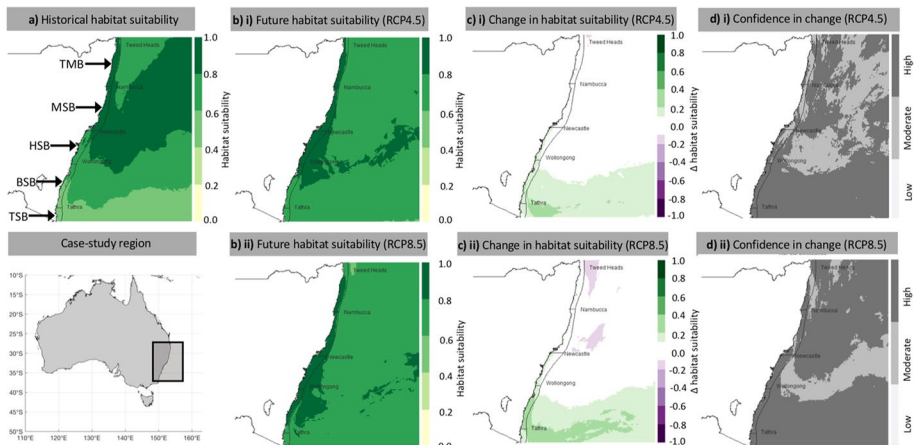
knowledge’, whereas ‘modified published literature and data’ (9.2%) and ‘data exploration’ (4.8%) were relied on to justify the inclusion of relatively fewer criteria within models.

### 3.2 Spatial analyses

Projected change in habitat suitability between historical and future periods revealed a trend towards increasing suitability for some species with southern (i.e. poleward) bioregions and declining suitability within northern (i.e. equatorward) bioregions (Fig. 3; Table 4). For example, habitat suitability is projected to increase between historical and future periods for all study species in at least one season of the year within the Batemans Shelf and Twofold Shelf bioregions (Fig. 3). However, projected increases in species habitat suitability within these bioregions remain minimal (i.e. change of between 0.1 and 0.2 units) to moderate (i.e. change of between 0.2 and 0.4 units). Within northern bioregions (i.e. Tweed-Moreton and Manning Shelf), minimal negative change to habitat suitability is projected for dolphinfish, bonito and kingfish during the warmer summer and autumn periods (Table 4).

Despite some evidence for latitudinal trends in projected change to habitat suitability, their direction and magnitude generally varied among species and bioregions (Table 4). For example, minimal negative change to habitat suitability for bonito and dolphinfish during summer is projected for the northernmost Tweed-Moreton bioregion, while negligible change (i.e. change of < 0.1 units) was apparent for Spanish and spotted mackerel within this season and bioregion.

MCA models consistently predicted higher habitat suitability in locations where species are known to have occurred relative to values corresponding to randomly distributed locations throughout the study extent (Fig. 4). Bhattacharyya coefficients evaluating the



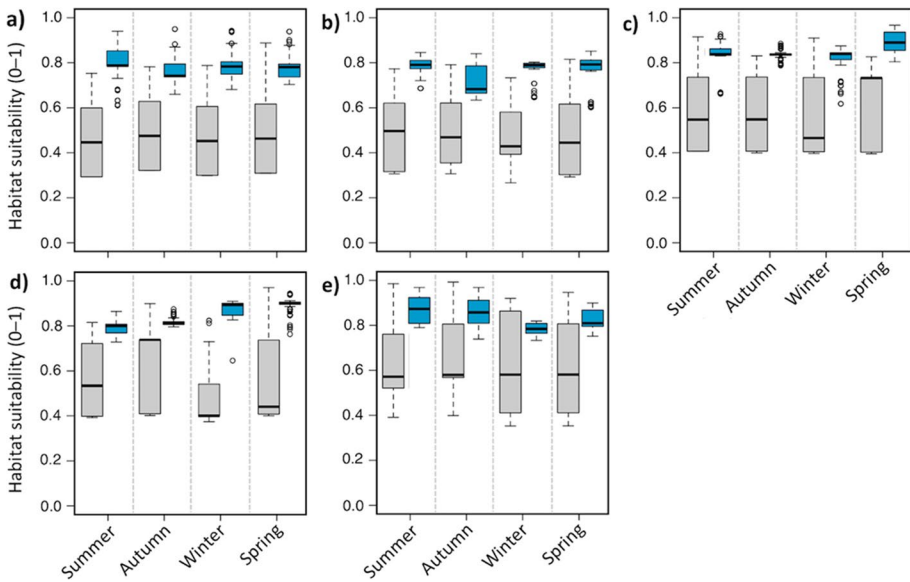
**Fig. 3** Projected summer (DJF) habitat suitability for spotted mackerel (*Scomberomorus munroi*) throughout the study extent: **a** mean historical habitat suitability (1993–2012), **b** future habitat suitability [i.e. median of five GCMs (2040–2059)] under (i) RCP4.5 and (ii) RCP8.5, **c** change in habitat suitability between future and historical periods under (i) RCP4.5 and (ii) RCP8.5 and **d** confidence in change in habitat suitability under (i) RCP4.5 and (ii) RCP8.5. Study bioregions are annotated in the top-left panel, which include the Tweed-Moreton (TMB), Manning Shelf (MSB), Hawkesbury Shelf (HSB), Batemans Shelf (BSB) and Twofold Shelf (TFB) bioregions

**Table 4** Summary of projected seasonal changes to species habitat suitability between historical (1993–2012) and future (2040–2059) periods within study bioregions. Symbols denote the direction and magnitude of change in habitat suitability, where ↑ indicates a projected increase, ↓ indicates a projected decrease and ● indicates negligible projected change ( $\Delta < 0.1$  units). One symbol indicates that change is minimal (e.g. †;  $\Delta 0.1$ – $0.2$  units) and two symbols indicate that change is moderate (e.g. †‡;  $\Delta 0.2$ – $0.4$  units). Summer = DJF, autumn = MAM, winter = JJA, spring = SON

Bioregion	Summer	Autumn	Winter	Spring
Tweed-Moreton	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ↓ (RCPs 4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ↓ (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ↓ (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: † (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: † (RCP4.5 and 8.5).  <i>Dolphinfish</i>: † (RCP4.5 and 8.5).</p>
Manning Shelf	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ↓ (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5) ↓ (RCP8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ↓ (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5). † (RCP8.5).  <i>Spanish mackerel</i>: † (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: † (RCP4.5 and 8.5).</p>
Hawkesbury Shelf	<p><i>Kingfish</i>: ↓ (RCP4.5 and 8.5).  <i>Bonito</i>: ↓ (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: † (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: †‡ (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5) ↓ (RCP8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: † (RCP4.5 and 8.5).  <i>Bonito</i>: † (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: † (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: † (RCP4.5 and 8.5).</p>

**Table 4** (continued)

Bioregion	Summer	Autumn	Winter	Spring
Bateman's Shelf	<p><i>Kingfish</i>: ● (RCP4.5), ↑ (RCP8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5)  <i>Spanish mackerel</i>: ↑ (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ↑ (RCP4.5), ↑↑ (RCP8.5).  <i>Dolphinfish</i>: ● (RCP4.5), ↑ (RCP8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5), ↑ (RCP8.5).  <i>Spotted mackerel</i>: ↑↑ (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ↑ (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ↑ (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ↑ (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ↑ (RCP4.5 and 8.5).  <i>Bonito</i>: ↑ (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5), ↑ (RCP8.5).  <i>Spotted mackerel</i>: ↑ (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ↑ (RCP4.5 and 8.5).</p>
Twofold Shelf	<p><i>Kingfish</i>: ↑ (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ↑ (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ↑ (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5), ↑ (RCP8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ● (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).</p>	<p><i>Kingfish</i>: ↑ (RCP4.5 and 8.5).  <i>Bonito</i>: ● (RCP4.5 and 8.5).  <i>Spanish mackerel</i>: ● (RCP4.5 and 8.5).  <i>Spotted mackerel</i>: ● (RCP4.5 and 8.5).  <i>Dolphinfish</i>: ● (RCP4.5 and 8.5).</p>

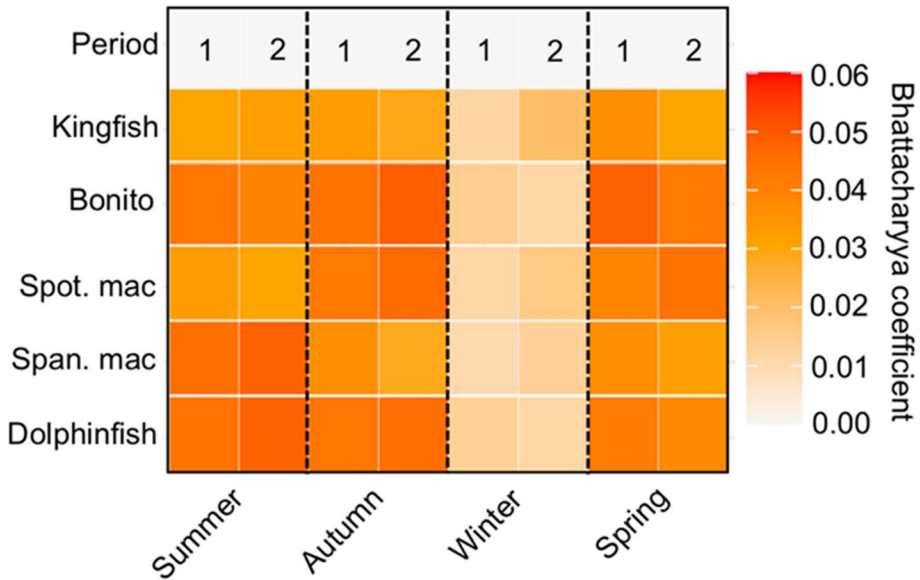


**Fig. 4** Boxplots showing the distribution of seasonally-explicit (southern hemisphere) habitat suitability values predicted at known locations of species occurrence ( $n = 100$ ; blue data) and at a set of pseudo-absences randomly distributed throughout the study extent ( $n = 100$ ; grey data). Habitat suitability predictions at occurrence and pseudo-absence locations were produced using the finalised MCA models for **a** kingfish (*Seriola lalandi*), **b** bonito (*Sarda australis*), **c** spotted mackerel (*Scomberomorus munroi*), **d** Spanish mackerel (*Scomberomorus commerson*) and **e** dolphinfish (*Coryphaena hippurus*). The historical period analysed encompasses 1993–2012

similarly between habitat suitability values corresponding to known species occurrences and pseudo-absence data were  $< 0.1$  for all species and seasons (Fig. 5). This result was consistent between both historical time periods analysed (Fig. 5). Focus group experts also agreed that the historical spatial distribution of predicted habitat suitability aligned with their understanding of the realised seasonal distribution of each study species.

## 4 Discussion

To respond to the increasing rate and magnitude of climate-driven changes within natural systems, researchers and managers require rapid vulnerability assessment methodologies that can be readily implemented using existing knowledge. Here we demonstrate the application of multi-criteria analysis (MCA) for this purpose using a group of coastal-pelagic fishes off south-eastern Australia as a case study. We show that MCA has the capacity to formally structure diverse knowledge sources, ranging from peer-reviewed information to expert knowledge, to inform the sensitivity of species to biophysical ocean conditions. By integrating MCA models with spatial environmental data over historical and future periods, we further demonstrate the application of MCA for quantifying changes to species habitat suitability under climate change. This approach facilitates an assessment of the relative vulnerability of species to climate change



**Fig. 5** Bhattacharyya coefficients evaluating the degree of overlap between the distributions of habitat suitability values predicted at known species occurrence locations and at a sample of pseudo-absences randomly distributed throughout the study extent. Results are presented for two historical periods, where period 1 encompasses 1993–2002 and period 2 encompasses 2003–2012. A sample of 50 occurrences and 50 pseudo-absences were assessed for each species within each period. Bhattacharyya coefficients range between 0 and 1 and smaller values are indicative of greater dissimilarity

within defined spatial domains, where species projected to experience relatively greater declines in habitat suitability are associated with higher vulnerability.

Coupling our MCA models with spatial climate projection data facilitated analysis of the likely vulnerability of species to future climate change. Here we utilised a 2050-centred future period to produce results that are associated with sufficient lead-time for strategic climate adaptation planning. However, MCA may be applied to assess species climate vulnerability at lead-times ranging from seasonal (i.e. weeks to months) to end-of-century scales and can therefore support both short- and long-term decision-making (Hobday et al. 2016b). Short-term decisions that MCA models could support include the timing and location of quota managed fishing and the deployment fish aggregation devices, while long-term decisions may include the design of marine protected areas.

We utilised MCA to assess for changes in species habitat suitability given the broad application of this response within studies using correlative species distribution models (SDM) to project climate change impacts (Melo-Merino et al. 2020). Importantly, results from projections using the MCA method applied here are consistent with analyses undertaken using correlative SDM showing that the distribution of suitable habitat for coastal-pelagic fishes off eastern Australia is seasonally dynamic (Brodie et al. 2015) and undergoing a poleward expansion in response to climate change (Champion et al. 2022; Hobday 2010; Robinson et al. 2015). It is reasonable to expect projections of habitat suitability made using SDM and MCA should produce results that are generally consistent, provided both models are associated with good predictive skill. However, it should not be assumed that projections from both approaches are directly comparable

even if they contain common predictor variables (e.g. environment-only factors). This is because the MCA approach incorporates flexibility for modifying species responses to variables using a diversity of knowledge sources, whereas projections using correlative SDM are commonly driven by statistical relationships between species occurrence data and prevailing environmental conditions (Elith and Leathwick 2009). For example, the ‘oceanographic drivers’ component of our analyses was informed by ‘published literature’ (including results from environment-only SDM), and also ‘modified published literature’ and ‘expert knowledge’ (e.g. Figure 2; Online Resources 2), whereas these responses within an environment-only SDM would be informed solely by correlative relationships. The ability to incorporate modified data sources into MCA is likely to be advantageous when occurrence data available for training correlative SDM are not representative of species’ realised distributions or are spatiotemporally biased.

MCA for rapid climate change vulnerability assessments have the advantage of being readily adapted to assess diverse responses (e.g. abundance and condition). For example, MCA models may be developed to assess the vulnerability of various life history characteristics (e.g. growth or fecundity) to climate change. Doing so would involve specifically parametrising model criteria to reflect the optimal biophysical conditions required to support the overarching response being assessed. This flexibility also provides opportunities for the development of demographically-explicit MCA models that capture variation in a species response to environmental conditions across different life stages (Brook et al. 2009). For marine species associated with high commercial or conservation value, it may be pragmatic to develop multiple MCA models that evaluate climate vulnerability for different life stages and life history characteristics to identify life cycle components that are most vulnerable to climate change. Furthermore, MCA does not require practitioners to have expertise in quantitative modelling approaches for climate impact assessments (e.g. SDM). This model trait has the potential to facilitate broad uptake of MCA for climate vulnerability assessments within management and policy spheres.

Over the past decade, a considerable number of climate change vulnerability assessments have been undertaken for marine species using a method developed by the United States National Oceanic and Atmospheric Administration (NOAA CVA method; Giddens et al. 2022; Hare et al. 2016; McClure et al. 2023; Spencer et al. 2019). This method, like MCA, integrates the exposure and sensitivity of species to climate change to evaluate vulnerability and can be informed by diverse sources of information, including expert knowledge. However, the NOAA CVA evaluates species sensitivity to environmental change using a trait-based framework (Spencer et al. 2019), whereas MCA is more related to correlative vulnerability assessments (Foden et al. 2019). Subsequently, the NOAA CVA approach has the advantage of producing a single assessment of species vulnerability encompassing species multiple life-history stages (e.g. Hare et al. 2016). This trait-based approach necessitates that both exposure and sensitivity components of the analysis are estimated categorically (i.e. high, medium and low), ultimately producing a categorical assessment of climate vulnerability (e.g. McClure et al. 2023). In contrast, the MCA method applied here has the advantage of producing estimates of vulnerability (herein change in habitat suitability) on a continuous response scale that can be spatially projected, with associated variation, throughout a study domain. This ability to project species vulnerability indices spatially is crucial for identifying climate refugia for species (e.g. Davis et al. 2021), particularly when future climate data have been downscaled to finer spatial resolutions, as demonstrated in this study.



## 5 Conclusion

Given the accelerating pace of climate-induced stress to global marine ecosystems (Henson et al. 2017), there is a growing need to operationalise rapid vulnerability assessment tools to facilitate their widespread application to marine species by researchers and managers. Software infrastructures incorporating accessible graphical user interfaces that enable rapid vulnerability assessments for marine species can support this need, particularly when these are applied ‘live’ in focus group settings that elicit expert knowledge. Packages developed in the R statistical computing environment for applying MCA are available (e.g. the *MCD*A package; Bigaret et al. 2017); however, considerable work remains to integrate these with marine spatial data layers to facilitate future projections. A key challenge to achieving this goal is access to application-ready future climate projection data for marine systems at spatial and temporal resolutions that are appropriate for large numbers of species across discrete geographies.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s10584-023-03577-2>.

**Author contribution** CC, JL, JP and MAC contributed to study conception and design. CC, DOC, AMF, FJ and HTS participated in focus group workshops. CC and JP finalised MCA models. CC and JL undertook spatial data analysis. The first draft of the manuscript was written by CC and all authors revised this version of the manuscript. All authors read and approved the final manuscript.

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**Data availability** Data underpinning the MCA models developed in this study are provided in Online Resources 1 and 2. Spatial environmental data used to create model projections are available via the resources detailed in Table 1 and online via the coupled model intercomparison project (CMIP5; <https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip5>).

## Declarations

**Competing interests** The authors declare no competing interests.

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