RESEARCH ARTICLE

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Citizen science aids the quantification of the distribution and prediction of present and future temporal variation in habitat suitability at species' range edges

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Abstract

Citizen science programs are effective methods to collect large volumes of data to assist researchers in monitoring ecological environments. As species shift their distributions globally due to climate change, the use of citizen science data to detect these shifts is increasing. Using targeted citizen science programs to collect data on these species could provide information on range edges to inform species distribution modelling. Currently, species distribution models (SDMs) often rely on large data repositories that may lack observations, and hence ability, to detect changes at the range edge. Here, we developed a SDM to compare traditional data repository observations with targeted citizen science data at the southern distribution limit of two recreationally important marine fish in Tasmania, Australia to investigate the potential change in spatial predictions at their range edge. The SDM using the targeted citizen science data in addition to traditional observation data improved the representation of species by 2.3 and 52.7% and increased the southern distribution of the species by 277 and 438 km, for snapper and King George whiting, respectively. Future (centred around 2050 under IPCC RCP 8.5) habitat suitability was predicted to increase more over the winter season, with implications for species overwintering and persistence of populations. The use of citizen science data allowed for the modelling of historical and future change for two range-extending species, an outcome possible due to the collaboration of two citizen science programs that collected observational data on the target species. Species range shifts will require ongoing monitoring and we have demonstrated that complimentary citizen science initiatives are effective in capturing occurrences of species at their range edge. Increasing collaboration between programs may further increase data collection efforts and provide the knowledge to create a hub for these data to be used more efficiently in the future.

Highlights

- Species distribution models (SDMs) are an important tool to describe and predict potential changes of areas of suitable habitat but may be less accurate at a species' range edge
- Using targeted citizen science initiatives can be an effective method to capture occurrence records at the poleward edge of a species' range
- Data from two targeted citizen science initiatives in Tasmania were used to improve the representation of two range extending marine species
- We compared SDMs using traditional data repository observations with the targeted citizen science initiatives to investigate the potential change in spatial predictions of habitat suitability for the two marine species
- We found models which included these targeted citizen science programs predicted higher mean suitability across all seasons in some regions around Tasmania, with the greatest change predicted in the winter season for both species

Keywords: *Chrysophrys auratus,* citizen science, delta downscaling, fisheries, ocean warming, range-shift, *Sillaginodes punctatus*, South-East Australia, species distribution model, species redistribution.

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Introduction

Citizen science initiatives present effective opportunities to gather a large quantity of data by involving members of the community and can provide many benefits to participants (Jordan et al. 2012, Den Broeder et al. 2017, Bremer et al. 2019). Improved observational effort achieved by engaging members of the public in ecological monitoring can increase the potential for long-term assessments of localised regions (e.g. Hepper 2003), capture the distribution or behaviour of a singular species across a broad spatial scale (Callaghan and Rowley 2020, Weaver et al. 2020), document the occurrence of rare species (Roberts et al. 2022), or record new species in novel habitats (e.g. the Range Extension Database and Mapping Project (Redmap); Stuart-Smith et al. 2018, Pecl et al. 2019b). The advent of new technologies (e.g. image and sound processing software, app-based platforms, etc.) have increased the potential for citizen scientists to effectively monitor their local environments and provide valuable data to scientists (Bonney et al. 2014, Aceves-Bueno et al. 2017, Roberts et al. 2022). However, the value of citizen science for ecological monitoring is dependent on initiatives having clear objectives and the inclusion of data validation steps to ensure information is reliable (Callaghan et al. 2019). For example, if objectives relate to determining species distributions, citizen science initiatives may seek to enhance the spatiotemporal coverage of species occurrence data, whereas initiatives aiming to monitor biodiversity may endeavour to frequently assess localised sites for changes through time (Callaghan et al. 2019). Given that citizen science participation is on the rise, collaboration across various initiatives holds the potential to maximise impact, increase data collection potential and social engagement with environmental initiatives (Bonney et al. 2014).

Incorporating citizen science in ecological monitoring projects often results in trade-offs (i.e. improved cost effectiveness of data collection versus reduced data quality; Callaghan et al. 2019), depending on design of the specific program. As with any kind of ecological sampling, potential biases associated with citizen science data collection should be considered within the sampling design, and addressed within program implementation (i.e. participant training, data validation by experts or image/sound software) and with appropriate statistical approaches (Dickinson et al. 2010). When properly trained, and with sound knowledge of the local environment, data gathered by citizen scientists can be equivalent to that of experts (Danielsen et al. 2014). However, given that citizen science datasets are a product of the efforts of multiple people, observer bias can affect their quality. Observer bias is known to depend on the quality of training (Fitzpatrick et al. 2009), how long citizen scientists have been involved with the program (i.e. "learner" or "first year" effects; Bas et al. 2008, Jiguet 2009, Schmeller et al. 2009) and age of observers (Delaney et al. 2008). Further, access to areas of interest often result in spatial and temporal variation in sampling effort (Dickinson et al. 2010). These spatial and temporal biases, which are often associated with easy to access locations or management exclusion zones (e.g. marine reserves, rehabilitation areas, no-take zones), or favourable times of the year (i.e. weekends, school holidays, periods of good weather, etc.), are a concern for questions requiring homogenous sampling through space and time (such as for species distribution modelling: Callaghan et al. 2019). Given these limitations, scientists seeking to analyse data produced by citizen science initiatives for the purpose of species distribution modelling must carefully select and apply appropriate methods (Table 1). For example, generalized linear or generalized additive mixed effects models (GLMMs and GAMMs) have proven to be useful tools for analysing citizen science data as the addition of a random effect (e.g. year, season, location) can absorb some of the spatial and temporal variation (i.e. clustering) commonly associated with citizen science data (Bird et al. 2014). Further, thinning data through space and time is an additional technique that has proven useful for reducing spatial and temporal autocorrelation among occurrence records sourced from citizen science datasets (Brodie et al. 2015, Champion et al. 2018).

As climate change is driving a global redistribution of species, understanding when and where species may be moving is a priority for ecologists and natural resource managers (Pecl et al. 2017). Collecting data on range extending species is difficult as this is largely dependent on which stage of the range extension pathway a species may be progressing through (i.e. between arrival, persistence and establishment: Bates et al. 2014), and thus often challenging. Given that the relative abundance of species at their range edges is typically lower than throughout their core distribution, critical information regarding species occurrence in range edge habitats is often poorly understood. Therefore, citizen science is an ideal tool for collecting data on species at their range edges (Robinson et al. 2015), as engaging with the local community markedly increases the potential to locate and record species in novel environments (Wang et al. 2018, Pecl et al. 2019b). In response to this need, the Range Extension Database and Mapping Project (Redmap: Pecl et al. 2019b) was established to encourage members of the Australian public to photograph and report species that they observe or catch that are new or unusual for that particular area along the coast. Photos submitted to Redmap are verified by one of ~80 experts around the country to ensure robust out of range observational data (Pecl et al. 2019b). Out of range observations linked to long-term change in climatic processes (e.g. ocean warming), are likely indicative of a range shift (rather than a random vagrant found out of range) and repeated observations in novel environments indicate a species may be at the initial "arrival" stage of their range extension (Bates et al. 2014, Pecl et al. 2019b). For example, yellowtail kingfish (*Seriola lalandi*) was identified 200 km southward of its previous known record using the Redmap platform, as was the first

Table 1. Steps to address data limitations of common occurrence-only citizen science data with varied objectives to develop robust species distribution models.

Step	Method
1. Selecting appropriate data to match to environmental covariates	While historical records of occurrence may date back to the 1800s, as records are matched to satellite-derived covariates, data is normally constrained to the 1980s—when satellite data became available.
2. Data thinning	To account for spatio-temporal autocorrelation among species occurrence records, only one occurrence is included from the same day and location, and all other occurrences from the same day can only be retained if they are greater than 0.05 km apart (Brodie et al. 2015, Champion et al. 2018).
3. Generation of pseudo-absences	For presence-only data sets, points are generated to estimate areas of species absence: pseudo-absences. A ratio of 10 pseudo-absences:1 occurrence, as recommended for regression type analyses of species distributions, throughout the temporal extent encompassed by species occurrence data (Barbet-Massin et al. 2012).
4. Assessment of spatial and temporal autocorrelation	Once data thinning steps are completed, and models are developed, spatial and temporal semi-variograms relevant to the scale of which the data are collected (i.e., usually within 100 kms, and within 30 days for recreational fishing studies) are visually assessed to determine the degree of spatial or temporal autocorrelation for data used in the model.
5. Assessment of collinearity among predictors	Collinearity among predictors is assessed by comparing variance inflation factors (VIF) which are used to detect the severity of multicollinearity in the ordinary least squares regression (Thompson et al. 2017).

record of amberjack (*S. dumerili*) in eastern Tasmania (Stuart-Smith et al. 2018). While Redmap has been successful in the initial identification of species at the range edge, it is a challenge however to sustain observer motivation when a species becomes more common place, and loses its novelty (Pecl et al. 2019b), which may underrepresent the abundance of that species at the range edge.

Species distribution models (SDM) have been used widely in ecology and conservation as a tool for exploring trends in species diversity (Graham et al. 2006) and predicting climate-driven species redistributions (Araújo et al. 2005, Thomas and Ohlemuller 2006, Elith et al. 2010). SDMs perform the latter by determining the preferred habitat of a given species, and then using projected future climate data to estimate the future location of preferred habitat for that species (Araújo et al. 2005, Elith et al. 2010). SDMs, otherwise coined as 'habitat suitability models' (Keith et al. 2008), achieve this by relating species data (e.g. abundance or occurrence data) to environmental variables to determine species' environmental habitat preferences, which can then be used to estimating a species' distribution (Elith et al. 2006, Barbet-Massin et al. 2012). The use of SDMs to predict climate-driven shifts in marine systems are increasing (see Robinson et al. 2015, Champion et al. 2018, Champion et al. 2019, Davis et al. 2021) and have accurately predicted the geographic distributions of species across a range of marine taxa, including fish (Guinotte et al. 2006), temperate corals (Tittensor et al. 2009), invertebrates (Bentlage et al. 2009) and macroalgae (Verbruggen et al. 2009). Citizen science data is valuable for the calibration of correlative SDMs because large datasets are often available that can be robustly combined through strategic removal of records (i.e. data thinning as described above), and assessments of data autocorrelation and collinearity of predictors (Table 1).

Due to disproportionate warming in Tasmania (Hobday and Pecl 2014), driven by the extension of the Eastern Australian Current, this region is a hotspot for marine species range extensions, having more records of species poleward of their historic distributions than anywhere else in Australia (Gervais et al. 2021). These shifts are either from waters adjacent to the Australian mainland into Tasmanian waters, or from the north of Tasmania into more southern areas. Range-shifting species include algae, ascidians, bivalves, gastropods, octopuses, starfish, sea urchins, crustaceans, sharks and rays, and fish (Pitt et al. 2010, Last et al. 2011, Robinson et al. 2011, Ramos et al. 2018, Gervais et al. 2021). The potential implications of range shifting species for resource management are important to consider, as many stakeholder groups are already starting to adapt autonomously to these changes (Pecl et al. 2019a).

In this study, we focus on two species: snapper (*Chrysophrys auratus*) and King George whiting (*Sillaginodes punctatus*), which are undergoing range extensions in and increasing in abundance in the Tasmanian region, providing new fishing opportunities for recreational and, to a lesser extent, commercial fishers (Last et al. 2011, Robinson et al. 2015, Wolfe et al. 2020). As the presence of these two species in Tasmania is now relatively well known, a targeted citizen science program that engaged with recreational anglers to document catches of these species was implemented in 2019. Here we draw on data from this citizen science initiative, in conjunction with data from the Redmap Australia, to quantify and predict the distributions for these species at their poleward range edges. We demonstrate the value of citizen science data recorded at the range edge by: (i) Quantifying the contribution of citizen science initiatives strategically operating at species range edges to improve our understanding of species distributions at their distributional limits, (ii) comparing spatial predictions of habitat suitability for snapper and King George whiting at their poleward range edges using SDMs that did and did not include data from targeted citizen science initiatives at the range edge, and (iii) using SDMs that incorporated data from the range edge to project future shifts in suitable habitat for snapper and King George whiting in an ocean warming hotspot under future climate change.

Materials & Methods

Quantifying the contribution of citizen science initiatives

Study extent

The spatial extent of our analysis ranges from 25 to 46°S and 134 to 154°E. Although snapper can occur further north of this latitudinal domain, we chose a cut off latitude at 25°S (i.e. Bundaberg), to generate a thermal preference curve relevant to the mid-southern limit of the range of snapper on the east coast. Furthermore, this domain was selected as it encompassed the south-eastern Australian ocean warming hotspot (Hobday and Pecl, 2014), which is warming at a rate between two to four times faster than the global average and driving a poleward redistribution of marine life in this region (Gervais et al. 2021).

Occurrence records from the range edge

Three unique sources of range edge species occurrence data were captured in this study and utilised in the development of species distributions models. These include:

Data from the range edge (1, 2 and 3)

1. Tassie Fish Frame Collection Program

The Tassie Fish Frame Collection (TFFC) Program was launched by the Institute for Marine and Antarctic Studies (IMAS) at the University of Tasmania in December 2019 with the aim of creating a recognisable and ongoing fish frame (i.e. a fish with the fillets removed) collection program for Tasmania. The program has provided a platform to engage with the Tasmanian recreational fishing community, and an opportunity for fishers to participate in citizen science through the donation of important biological samples and data, from fish waste which would otherwise be discarded (i.e. fish frames).

To enable the Tassie Fish Frame Collection Program to operate on a state-wide scale, a network of 16 drop-off points was established to provide strategic spatial coverage along most of coastal Tasmania. These drop-off points were predominately tackle stores, which provide a natural point for knowledge sharing and communication around fishing for the target species. IMAS staff members regularly liaised with the drop-off points to organise pick-up and transport of frozen fish frames to IMAS laboratories in Launceston and Hobart for processing. As these data were provided to researchers, there is high confidence in the data quality though this is also associated with a higher cost to obtain the data (advertising of the program, collecting the frames, identifying and processing the samples, etc.). Within the project sampling period (July 2019–July 2021) a total 718 fish frames were donated from across Tasmania, which included 264 snapper and 454 King George whiting. Prior to the official launch of the TFFC program, fish frames were occasionally donated by the recreational angling community to IMAS for research purposes, and as such an additional 669 King George whiting fish frames were included within this data set donated between 2016–2019 (until July). It was this initial success of engaging with the recreational fishing community which formed the basis to launch the official TTFC Program for targeted species around the state.

2. Range Extension Data Base and Mapping Project (Redmap)

Redmap (www.redmap.org.au, Pecl et al. 2019b) is an Australian citizen science initiative which encourages members of the public to photograph and report new or unusual species along the coast. These photographs are then identified or verified by a network of expert scientists, ensuring the quality of the reports. As such, it is a useful source of data particularly for range extending species (Robinson et al. 2015, Champion et al. 2018, Champion et al. 2019). Modelling species at their range edges requires data from these range limits, and therefore Redmap is an ideal data source because its objective is specifically to identify species outside of their historical distributions.

3. Fishery-independent sampling

Fishery independent sampling is a method by which researchers fish and sample the population, and can account for any biases associated with fishery-dependant sampling (i.e. size limits, seasonal closures, bag limits etc). Therefore, to account for spatial and temporal biases from citizen science sources in Tasmania, we also used occurrence records from fishery-independent sampling during the period of which the TFFC Program was launched (i.e. 2019–2021; Table S1). Sampling consisted of fishery independent research trips mainly targeting undersized fish (rod and line and seine nets). Due to the nature of this kind of sampling, the data is of high quality but is one of the most expensive collection methods.

Additional sources of occurrence data (4 and 5)

To ensure the core distributions of both study species were appropriately represented and species distribution models fitted to data from both core and range edge environments, data were also sourced from:

4. Atlas of Living Australia

Atlas of Living Australia (ALA, www.ala.org.au) is a comprehensive collection of occurrence records and biodiversity data, aggregated from natural history collections, government departments, researchers and university institutions, community groups and individuals Australia-wide. These data are numerous and free to use, however the quality of data may be variable, and cannot be confirmed by the data user.

5. Reef Life Survey

Reef Life Survey (RLS, reeflifesurvey.com, Edgar et al. 2020) is a non-profit citizen science program which use highly trained volunteer SCUBA divers to conduct standardized underwater visual surveys of rocky- and coral reefs worldwide and provide open-source occurrence and biodiversity data. Due to training received by those collecting the data, quality is high, but as it requires this training and processing of the data collected, is also an expensive data source.

When occurrence data from each aforementioned sources were combined, these records ranged from 1897–present. However, the temporal range of data was restricted to 1985–2021 to match the availability of satellite-derived environmental covariates. We then mapped these occurrences to determine the contribution (%) of each data source to the entire distribution of each species, accounting for all possible data, and the data only used by each species distribution model (required data thinning steps and model development explained in methods below).

Comparing spatial predictions of habitat suitability

Species Distribution Model Development

Spatial and temporal autocorrelation and data thinning

To account for spatio-temporal autocorrelation among species occurrence records that may be apparent within the combined set of species occurrences, only one occurrence was included from the same day and location, and all other occurrences from the same day were only retained if they were greater than 0.20° apart for snapper and 0.10° apart for King George whiting (Table 1; Brodie et al. 2015, Champion et al. 2018). These values were determined by the visual assessment of spatial and temporal semi-variograms (as described in Table 1). Once this was done, a total of 3662 snapper and 429 King George whiting records were available for model fitting and cross-validation (Fig. 1).

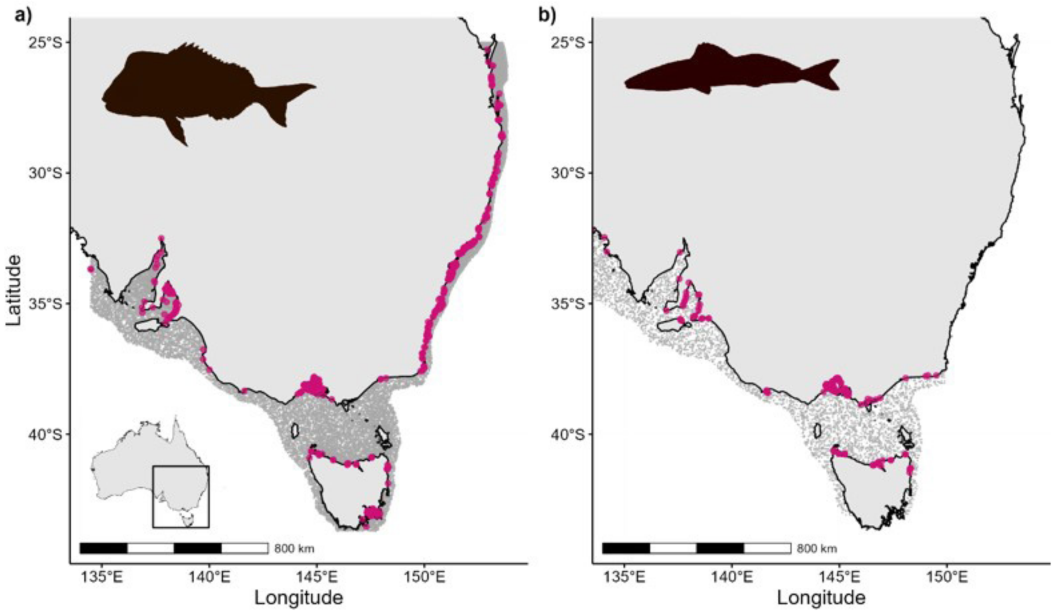

Figure 1. Presence (pink) and pseudo absence (grey) points used in optimal species distribution model for a) snapper (*Chrysophrys auratus*) and b) King George whiting (*Sillaginodes punctatus*).

Pseudo-absence generation

To characterise unsuitable environmental conditions for each study species, pseudo-absence points were randomly generated at a ratio of 10 pseudo-absences:1 occurrence, as recommended for regression type analyses of species distributions (Barbet-Massin et al. 2012), throughout the temporal extent encompassed by species occurrence data. Pseudo-absences were only generated nearshore of the 200 m isobath (the continental shelf break) and within the spatial envelope encompassed by species occurrence data to characterise environmental variation prevalent within, and not beyond, the known distributions of the study species. Combining occurrence and pseudo-absences data produced a binomial distributed response variable for statistical modelling (Barbet-Massin et al. 2012). Large sampling of pseudo-absence points for generating background data have been shown to have high explanatory power and predictive skill when assessing range shifts or animal movement across wide spatial scales (Hazen et al. 2021), and was therefore deemed appropriate as our study extent extended as far north as 25°S in Queensland (snapper) and 32°S in South Australia, and 37°S in New South Wales (King George whiting) (Fig. 1).

Environmental predictors

To predict the spatial distribution of suitable habitat for snapper and King George whiting, individual species distribution (i.e. habitat suitability) models for each species were developed. Specifically, sea surface temperature (SST), depth (m), and distance (m) to seagrass habitat (King George whiting only) were used as predictors of environmental habitat suitability (Table 2), which are known to be significant predictors of the distributions of both snapper and King George whiting throughout their southern Australian distributions (Jenkins et al. 2020). Satellite-derived sea surface temperature (SST) data was sourced from the Copernicus Marine Environment Monitoring Service (Table 2). Gridded bathymetry data measured from optical sensors was obtained from the General Bathymetric Chart of the Oceans (GEBCO Compilation Group 2020). Each presence and pseudo-absence point were matched to day- and location-specific values for SST and depth. Seagrass habitat data was sourced from Seamap Australia (Butler et al. 2017), and the distance to seagrass was calculated by measuring the distance of each presence and pseudo-absence point to the nearest seagrass polygon using the function *st_distance* in the “sf” package in R (version 1.0.2; Pebesma 2018).

Collinearity among predictors was assessed using variance inflation factors (VIF) that detect the severity of multicollinearity in the ordinary least squares regression (Thompson et al. 2017). VIFs for factors included in the optimal model were <1.09 for both snapper and King George whiting (Table S2), indicating a low degree of dependence between the focal predictor (i.e. SST, depth, distance to seagrass) versus the other predictors in the model (i.e. SST relative to depth and distance to seagrass, etc; Thompson et al. 2017), and would therefore have little effect on model performance (Zuur et al. 2007).

Species distribution modelling incorporating range edge occurrences

Individual generalised additive mixed models (GAMM) with a logit link function were developed for both snapper and King George whiting by

Table 2. Descriptions of explanatory covariates for model selection for habitat suitability models for snapper (*Chrysophrys auratus*) and King George whiting (*Sillaginodes punctatus*).

Predictor	Description	Source	Spatial Resolution	Units
SST	Daily global sea surface temperature reprocessed (level 4) from Operational SST and Ice Analysis system.	Copernicus Marine Monitoring Service (https://marine.copernicus.eu), product #010_011	0.05°	°C
Depth	Gridded bathymetry data measured by optical light sensor downloaded from the General Bathymetric Chart of the Oceans.	General Bathymetric Chart of the Oceans (GEBCO_2021 https://www.gebco.net/)	0.004°	m
Distance to Seagrass	Distance to seagrass was measured by measuring the distance of each point to the nearest seagrass polygon from the Seamap Australia dataset.	Seamap Australia (https://seamapaustralia.org/) Downloaded from: https://data.gov.au FINALPRODUCT_Seamap Aus)	0.004°	m
Year	Calendar year (random intercept term in mixed models).		-	-

relating the binomially distributed response variable (presence vs. pseudo-absence) to environmental predictors (Zuur et al. 2009). Due to the lack of consistent information of sampling effort in the Atlas of Living Australia database, Year was also included as a random effect in the model to account for intra-annual variability in sampling effort (Champion et al. 2018). Multiple models containing all reasonable combinations of model predictors were trialled and model selection was conducted by comparing Akaike Information Criterion (AIC) values (see Table S3 for full model selection). To avoid overfitting in the snapper GAMM, four knots were applied to the SST smoothing term to reflect ecological realism in the thermal habitat response of this species (i.e. a unimodal thermal performance curve: see Fig. S1).

Model evaluation

To ensure that removing occurrences from the same day and location, and occurrences within 0.20° and 0.10° and for snapper and King George whiting respectively, established spatiotemporal independence among occurrence records used to fit SDMs, spatial and temporal semi-variograms were used to relate semi-variance of points to the space (degrees) and time (days) separating each occurrence record (Figs. S2, S3). Cut-off distances were chosen to reflect the spatial and temporal limits where autocorrelation is likely to arise (i.e. at relatively close distances in space (i.e. < 100 km) and time (i.e. < 30 days). Semi-variograms were created by converting dates into Julian days to generate a cut off distance of 30 days to assess temporal autocorrelation and coordinates were used with a cut off distance of 111 kms (1.0°) to assess spatial autocorrelation.

To assess the predictive accuracy of the optimal models for each species, k-fold cross validations were used. This was done by randomly partitioning the full set of species occurrence and pseudo-absences into five subsets (k = 5) containing an equal amount of occurrence and pseudo-absences at a ratio of 10 pseudos:1 occurrence (Barbet-Massin et al. 2012, Brodie et al. 2015). Each model was then trained on each of four sets of subset data, and then tested against the 5th subset. Five folds were used as a conservative measure as partitioning data into a greater number of model fitting and testing folds would have compromised the predictive skill of the model being tested (Smith et al. 2017).

The area under the receiver operating characteristic curve (AUC) and the true skill statistic (TSS) were calculated to determine both model accuracy and predictive performance, as appropriate for statistical models used to predict spatial variation in species habitat suitability (Allouche et al. 2006, Brodie et al. 2015). Rates of true positive predictions (sensitivity) and false positive predictions (1 - specificity) were used to calculate the mean AUC (range 0–1, where a value of 0.5 indicates poor prediction i.e., similar to random, and values > 0.8 indicate good predictive accuracy; Araújo et al. 2005). The AUC is a useful metric to assess the accuracy of species distribution models as it can differentiate between suitable and unsuitable habitat without assuming a cut-off probability (Elith et al. 2006). The TSS was calculated as TSS = sensitivity + specificity – 1, and ranges between -1 to 1, where 0 indicates zero predictive skill. The optimal model for snapper had a mean AUC (*SD*) of 0.9559 (0.0005) and a mean TSS (*SD*) of 0.8443 (0.0026). The optimal model for King George whiting had a mean AUC (*SD*) of 0.9873 (0.0002) and a mean TSS (*SD*) of 0.9626 (0.0013).

Comparing the influence of citizen science observations from the range edge on spatial predictions of suitable habitat

To compare the influence of citizen science observations from the range edge on the spatial predictions of suitable habitat for snapper and King George whiting we developed similar GAMMs using only occurrence records from the ALA and RLS datasets. We then compared spatial predictions of suitable habitat of the aggregated historical period (i.e. 1998–2018) between models which included data from targeted citizen science initiatives at the range edge (i.e. the TFFC Program and Redmap, supplemented with the fishery independent data) and those that did not. Given our objective was to make spatial comparisons between models, we kept the optimal combination of covariates determined by AIC from models with the entire data set (as above). Generalised linear models were then developed per species to assess differences in future spatial projections of models including and excluding data collected from the programs at the range edge. These models also included season as a fixed factor, and a binomial error distribution (as data were bound between 0 and 1). We also calculated the absolute difference in forecasted habitat suitability between the models using each dataset by subtracting the grid cells each prediction raster per season:

$$\text{prediction\_raster}_{\text{alldata}} - \text{prediction\_raster}_{\text{norangeedge}}$$

Historical spatial predictions of suitable habitat used satellite-derived sea surface temperature (SST) data aggregated to an Austral seasonal temporal resolution (i.e. spring: September–November, summer: December–February, autumn: March–May, winter: June–August) over the 21-year period 1998–2018. Seasonal SST rasters were then stacked with depth and distance to seagrass (King George whiting) spatial data layers, as these predictors were assumed to be static, and bilinearly interpolated to a common resolution of 0.004°. This fine scale resolution was selected to ensure that the effects of nearshore variation in depth on species distributions were effectively represented within spatial predictions (Table 2). The predicted responses (i.e. relative probability of species occurrence) of each of the optimal models were then converted into a 'habitat suitability index' (following Champion et al. 2018). This was calculated by dividing all relative probability of occurrence predictions by the maximum relative probability predicted over the entire spatial domain duration of the study period. This was done because the relative probability of presence values are dependent on the ratio of occurrence to pseudo-absence data selected to fit the model (Pearce and Boyce 2006). The habitat suitability index therefore ranged between 0 (not suitable) and 1 (highly suitable).

Using SDMs to project future shifts

Analysis for changes to habitat suitability under future climate change

To project future changes in the poleward range edge distribution of snapper and King George whiting we used the SDM parameterised with range edge occurrence data.

i) Delta downscaling method for future climate change projections

To assess the potential shift and/or increase in habitat suitability under future projections, future environmental data were obtained by downscaling sea surface temperature to a common resolution from five CMIP5 climate models (Table S4) forced under the IPCC RCP 8.5 prediction scenario. This was done by applying the delta method to modelled environmental data (e.g. Morley et al. 2018, Navarro-Racines et al. 2020), which involves calculating the difference (i.e. delta value) between seasonally aggregated SST data for the period 2036–2065 (centred on 2050) and a modelled historical baseline period encompassing 1993–2006 for each CMIP5 model forced under the RCP 8.5 emissions scenario. Secondly, delta value matrices were bilinearly interpolated from their native model resolution (~1°) to the finer resolution of observed ocean data (i.e. 0.05°) and adding to a satellite-derived seasonal climatology that encompassed the period 1993–2006.

Observed SST data for the historical baseline period was sourced from the Copernicus Marine Environment Monitoring Service (sea surface temperature product #010_011). This procedure produced seasonally aggregated sea surface temperature, downscaled to a common 0.05° resolution from six CMIP5 models forced under RCP 8.5. This method was chosen as it has been shown to be robust to correct mean climate projections worldwide (Hawkins et al. 2013, Morley et al. 2018) and it has been useful in for providing downscaled mean climate conditions over shorter (i.e. decadal) time periods (Navarro-Racines et al. 2020).

A multi model average of the six CMIP5 climate models used to produce downscaled SST data was used to make future projections of habitat suitability of snapper and king George whiting. This model average was further interpolated to 0.004° to match the resolution of depth and distance to seagrass habitat (King George whiting only) predictors as they are assumed static. Future habitat projections created using these data were then compared to predictions created using observed environmental (i.e. SST) data for a 21-year period (averaged) of encompassing 1998–2018, as to compare two ~20-year averaged data sets centred on 2008 (hindcast) and 2050 (forecast).

Analysis for changes to habitat suitability under future climate change

In the interest of understanding the emerging fishery of snapper and King George whiting in Tasmania and the potential spatial variation in predicted suitable habitat in this region, we divided Tasmania into six regions. These include, i) North-West (NW), extending north of Temma (41°12'S, 144°38'E), and extending just east of Devonport (41°09'S, 146°28'E), ii) North-East-North (NEN) which includes the Tamar River the Furneaux Islands and contours the North East coast to Eddystone Point (40°59'S, 148°20'E), iii) North-East (NE) which extends south of Eddystone, to Bicheno (41°52'S, 148°18'E), iv) East (E) which extends south of Bicheno to the Southern tip of Maria Island (Latitude = 41°44'S), v) South-East (SE) which extends south of Maria Island and west to Recherche Bay (43°34'S, 146°53'E), and lastly vi) West (W) which includes most of the West Coast; west of Recherche Bay and south of Temma (Fig. 2). As seagrass habitat is not yet mapped for the Furneaux Islands, predicted habitat suitability for this region are not directly comparable with other regions, but assessing projected changes through time for this region remain robust.

High resolution proportional change between historical and future periods

To assess for changes in habitat suitability between historical (1998–2018) and future (2036–2065) time periods, we measured the proportional change within each 0.004° (416 m^2) grid cell within each region. This was done to account for the variation in habitat

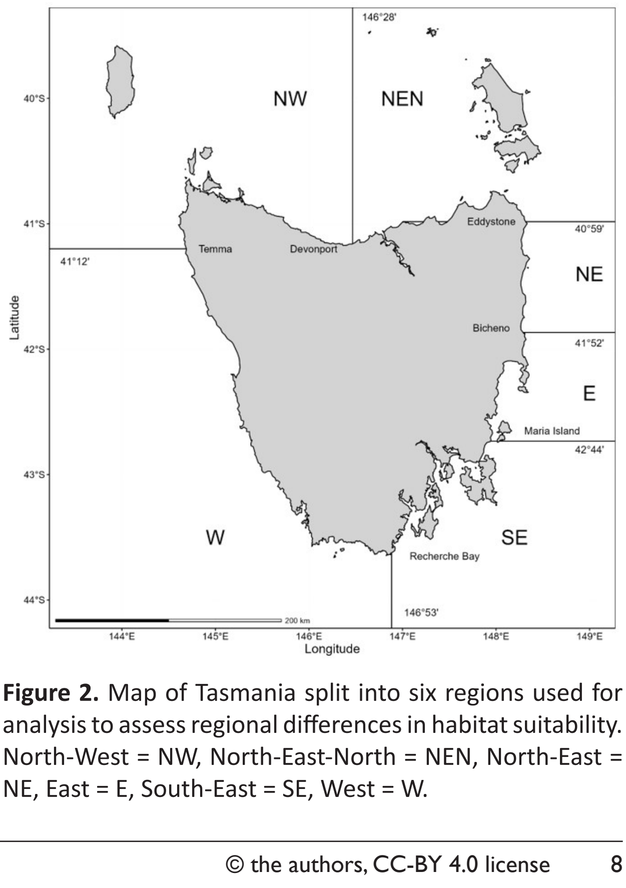

Figure 2. Map of Tasmania split into six regions used for analysis to assess regional differences in habitat suitability. North-West = NW, North-East-North = NEN, North-East = NE, East = E, South-East = SE, West = W.

suitability within each region. We calculated the proportional change by subtracting the grid cells of the hindcast raster from the forecast raster and dividing by grid cells of the hindcast raster and multiplying each value by 100.

$$\text{i.e. } \left(raster_{forecast} - raster_{hindcast}\right) / \ raster_{hindcast}) \times 100$$

Linear models were used to assess differences in this high-resolution proportional change between regions and season to inform the likely trajectory of future fishing opportunities for snapper and King George whiting in these regions. Region and season were used as fixed factors and a gaussian error distribution was used. Data was assessed for normality and homogeneity of variance by assessing residual and Q-Q plots.

Statistical Analyses

All statistical analyses were conducted using the R Environment (version 4.0.3; R Core Team 2021). Spatial thinning of occurrence records was conducted using the 'spThin' package (version 0.2.0; Aiello-Lammens et al. 2015), generalised additive mixed models were fitted using the 'gamm4' package (version 0.2.6; WoodScheipl 2020), k-fold cross-validation was conducted using the 'dismo' package (version 1.3.3; Hijmans et al. 2020), generalised linear and linear models were conducted using the 'lme4' package (version 1.1.27.1; Bates et al. 2015). Where differences between factors were detected in linear and generalised linear models, pairwise comparisons between factors and were conducted using the 'emmeans' package (version 1.6.3; Lenth 2021). Spatial analyses (i.e. model averaging of downscaled climate models forced under RCP 8.5, averaging of environmental data between 1998–2018, and conducting spatial predictions using best habitat suitability model) were conducted using the 'raster' package (version 3.4.13; Hijmans 2021). Maps and plots were made using 'raster', 'sf', and ggplot2 within the 'tidyverse' (version 1.3.1; Wickham et al. 2019) packages.

Results

Quantifying the contribution of citizen science initiatives

Data Sources

The combined contributions of the TFFC Program and Redmap citizen science data sources increased the volume of available data by 2.3% and extended the distributional coverage by 277.70 km poleward for snapper (Fig. 3a, b), and increased the volume of data by 52.7% and extended the distributional coverage by 437.90 km poleward for King George whiting (Fig. 3f, g). After spatial and temporal thinning of the data for model fitting (i.e. removing occurrences from the same day and location, and occurrences within 0.2° and 0.1° for snapper and King George whiting respectively), the proportion of available data for model fitting from the Tassie Fish Frame Collection program and Redmap was 2.8% and 37% for snapper and King George whiting respectively (Fig. 3c, h). However, within Tasmania alone, the Tassie Fish Frame Collection Program and Redmap comprised the majority of the data at 81% and 85.7% for snapper and King George whiting respectively before spatial and temporal thinning, and increased to 88% and 90% once thinned and available for model fitting (Fig. 3d, e, i, j).

Comparing spatial predictions of habitat suitability

Environmental habitat suitability models

The optimal models (based on AIC comparisons) for snapper and King George whiting environment habitat included sea surface temperature (SST: °C), distance to seagrass (m), and depth (m) (Table S3):

$$\text{Snapper: Response} \sim s(SST,\ k = 4) + s(depth) + (1|\,year)$$

$$\text{King George whiting: Response} \sim s(SST) + depth + distance\ to\ seagrass + (1|\,year)$$

where: Response is the relative probability of occurrence as a function SST, depth and distance to seagrass (King George whiting), 's' denotes a smoothing term.

The effect of SST on snapper occurrence was non-linear with a peak effect at approximately 20°C (Fig. 4a). Depth was also significantly non-linear but displayed a general positive effect at shallower depths (i.e. < -50m; Fig. 4b, Table 3).

The effect of SST on King George whiting occurrence was non-linear and peaked at approximately 18 °C (Fig. 4c, Table 3). Both depth and distance to seagrass were significant linear predictors of King George whiting occurrence, where the effect on King George whiting occurrence declined with increasing depth and distance to seagrass (Fig. 4d, e, Table 3).

Comparisons of spatial predictions of historical (1998 – 2018) habitat suitability between models including and excluding targeted citizen science at the range edge

i) *Snapper*

Historical spatial predictions differed between the two models using different datasets where mean future predicted habitat suitability of snapper across the Tasmanian domain ranged from 9–31% higher from the GAMM which included data from the TFFC Program and Redmap (Fig. 5a, Table 4). Historical spatial projections of habitat suitability (by grid cell) differed on average from 0.008 (± 0.01 *SD*) suitability units in the winter to 0.03 (± 0.03 *SD*) in the summer between the optimal GAMM which included all data, and the GAMM which excluded data from the programs at the range edge (Fig. 5), which accounts for an average proportional increase per grid cell ranging between 0.39 (± 0.24 *SD*) in the winter to 0.65 (± 0.27 *SD*) in the summer.

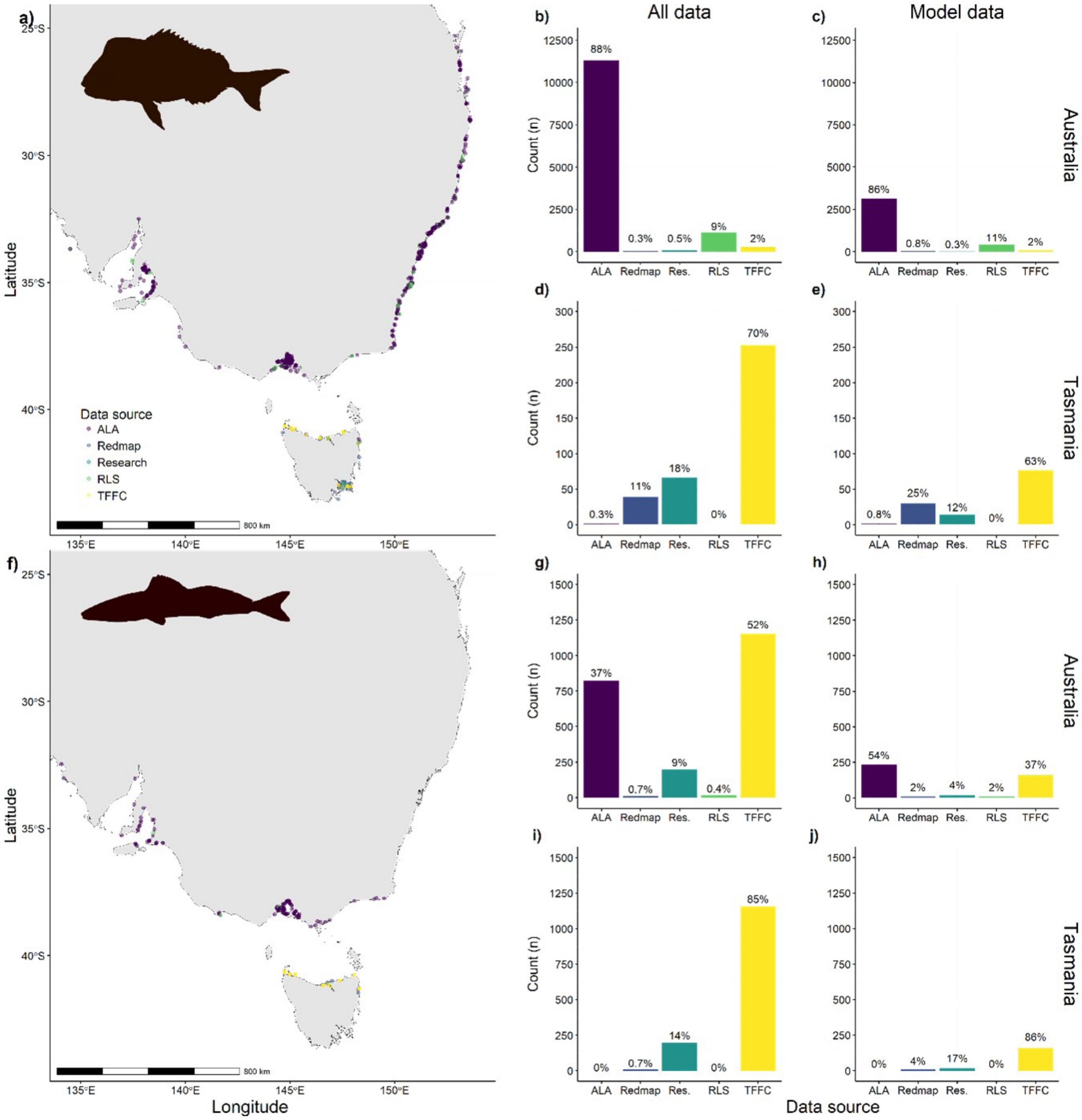

Figure 3. Spatial distribution of data sources for a) snapper (*Chrysophrys auratus*) and f) King George whiting (*Sillaginodes punctatus*), and data sources available for modelling (b, d, g, i) and used in species distribution model after data thinning steps (c, e, h, j) for snapper (upper panels) and King George whiting (lower panels). Note, "Res." Represents fishery independent sampling data.

ii) *King George whiting*

Historical spatial predictions differed between the two models using different datasets where mean future predicted habitat suitability of King George whiting across the Tasmanian domain ranged from 31–41% higher from the GAMM which included data from the Tassie Fish Frame Collection Program and Redmap (Table 4). Historical spatial projections of habitat suitability differed on average from 0.01 (± 0.03 *SD*) suitability units in the summer to 0.03 (± 0.04 *SD*) in the winter between the optimal GAMM which included all data, and the GAMM which excluded data from the programs at the range edge (Fig. 5b, Table 4), noting that most of the differences occurred on the East and SE coast (Fig. 5b, Table 4).

Using SDMs to project future shifts

i) *Snapper*

When using the SDM which included data from the TFFC Program, Redmap, and fishery independent sampling, the proportional change in habitat suitability of snapper was greatest in the winter throughout each region in Tasmania (when comparing seasonally

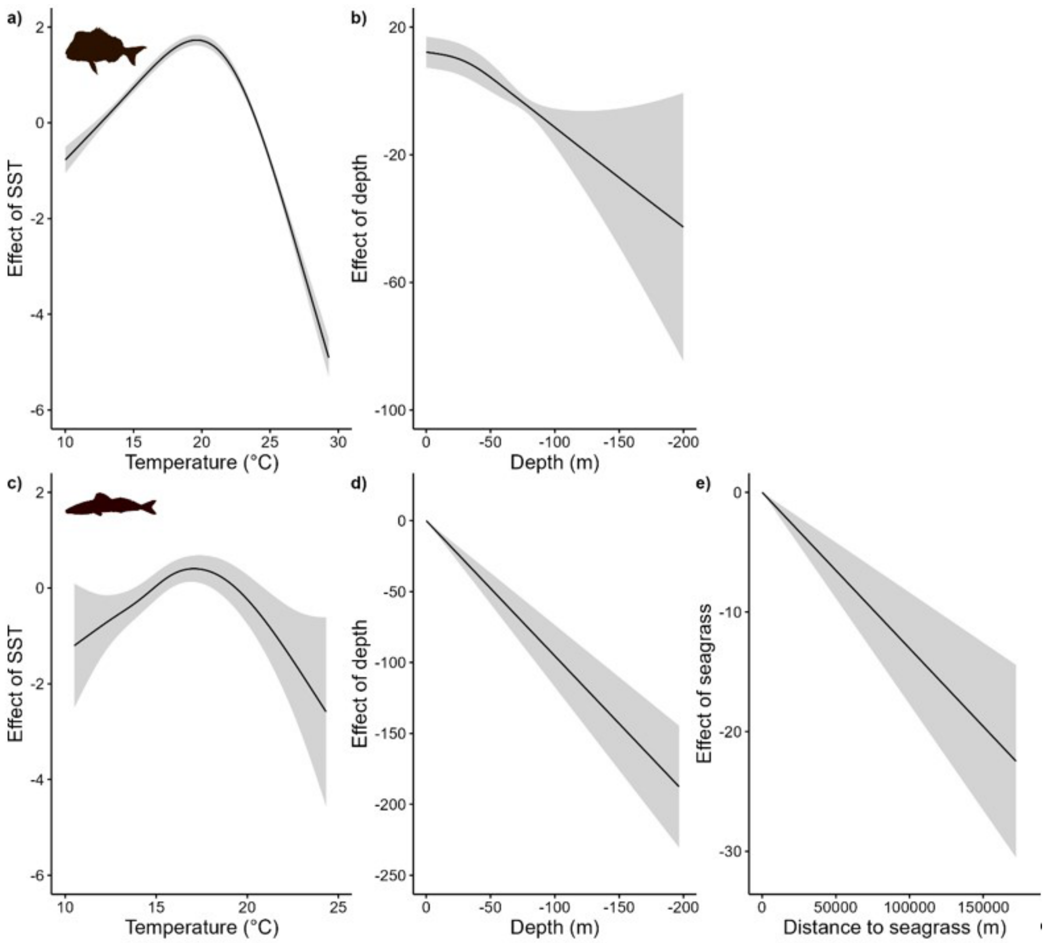

Figure 4. Partial effects of sea surface temperature (SST), depth and distance to seagrass on the fitted values of the optimal habitat suitability model for a–b) snapper (*Chrysophrys auratus*) and c–e) King George whiting (*Sillaginodes punctatus*) ± 95% confidence intervals (shaded in grey).

Table 3. Summary of results for the optimal model for suitable habitat of snapper (*Chrysophrys auratus*) and King George whiting (*Sillaginodes punctatus*). Smoothing terms are denoted by an 's'.

Species	Factor	Effective degrees of freedom (edf)	Coefficient estimate	*p*-value
Snapper	s(SST)	2.99	-1.81	<0.01*
	s(depth)	2.82	8.09	<0.01*
	$Year_{intercept}$	-	-14.45	<0.01*
King George whiting	s(SST)	2.46	-0.18	0.02*
	distance_Seagrass	-	-1.19 e^{-4}	<0.01*
	depth	-	0.92	<0.01*
	$Year_{intercept}$	-	2.0	<0.01*

aggregated environmental data averaged across 20 years: hindcasted (1998–2018), and forecasted (2036–2065) periods) within each grid cell (0.004° or 416 m^2)). The average percent increase (estimated marginal model mean ± *SE*) ranged from 126.33 (± 0.29) % in the NE region to 249.31 (± 0.06) % in the NEN region (Fig. 6a, Table S5). The greatest proportional increase in habitat suitability was 296.58% in the NEN region in the winter (Fig. 6a). There was also a small increase in suitability in the spring and summer seasons across all regions ranging from an increase of 35 (± 0.08)–60.89 (± 0.14) % in the spring (NW and SE

Table 4. Results of pairwise contrasts comparing future spatial predictions between models including (i.e. all data) and excluding targeted citizen science initiatives at the range edge by season for snapper and King George whiting. Results are on the response scale.

Species	Season	Contrast	Odds Ratio	*SE*	*df*	*Z* ratio	*p*
Snapper	Spring	All data / excl. range edge programs	1.17	0.02	Inf	7.81	<.001*
	Summer	All data / excl. range edge programs	1.31	0.02	Inf	16.84	<.001*
	Autumn	All data / excl. range edge programs	1.25	0.02	Inf	12.53	<.001*
	Winter	All data / excl. range edge programs	1.09	0.02	Inf	4.35	<.001*
King George whiting	Spring	All data / excl. range edge programs	1.39	0.04	Inf	9.78	<.001*
	Summer	All data / excl. range edge programs	1.31	0.04	Inf	9.27	<.001*
	Autumn	All data / excl. range edge programs	1.32	0.04	Inf	9.34	<.001*
	Winter	All data / excl. range edge programs	1.41	0.04	Inf	9.87	<.001*

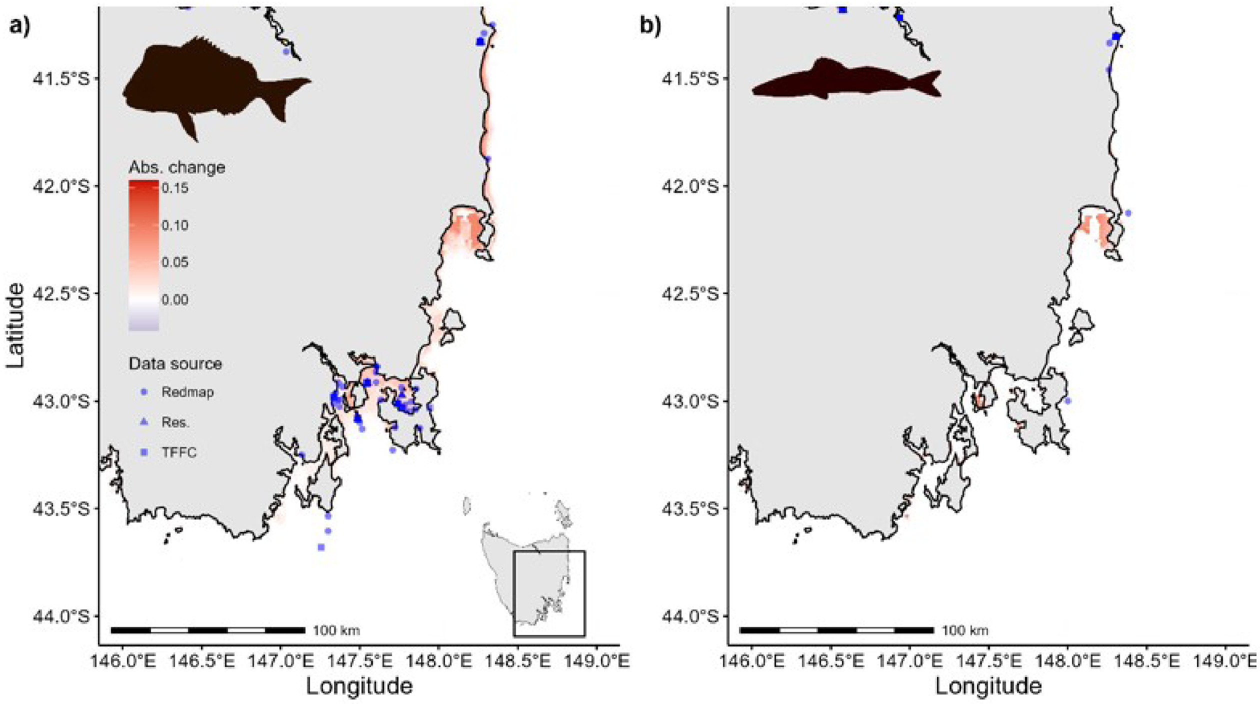

Figure 5. Differences between spatial projections (absolute change) of historical habitat suitability (1998 – 2018) during the summer season for a) snapper (*Chrysophrys auratus*) and b) King George whiting (*Sillaginodes punctatus*) between models using the entire data set, and models which excluded data from the Tassie Fish Frame Collection Program, Redmap, and fishery independent sampling (Res.) at the range edge (i.e. the south-east coast of Tasmania). Points are occurrence records. *NB This figure is a high resolution snap-shot at the range edge, during one season. For all comparisons across all of Tasmania please see Supplemental Information (Fig. S4).

regions respectively) and 21.01 (± 0.06)–40.27 (± 0.13) % in the summer (NEN and SE regions respectively: Fig. 6a). Proportional change remained low and consistent in the autumn across all regions.

ii) *King George whiting*

Proportional change in habitat suitability of King George whiting within each grid cell (0.004°/416 m^2), when comparing seasonally aggregated environmental data averaged across 20 years: hindcasted (1998–2018) and forecasted (2036–2065) periods was greatest in the winter throughout each region. The average percent increase (estimated marginal model mean ± *SE*) ranged from 54.9 (0.51) % in the East, to 132% in the North-East North (NEN: Fig. 6b). The greatest predicted future proportional increase in habitat suitability was 189% in the SE in the winter (Fig. 6b). There was also increased variance in the proportional change within each region during the winter due to some grid cells increasing in suitability while others remained unchanged (Fig. 6b, Table S6). There was also an increase in suitability in the spring across all

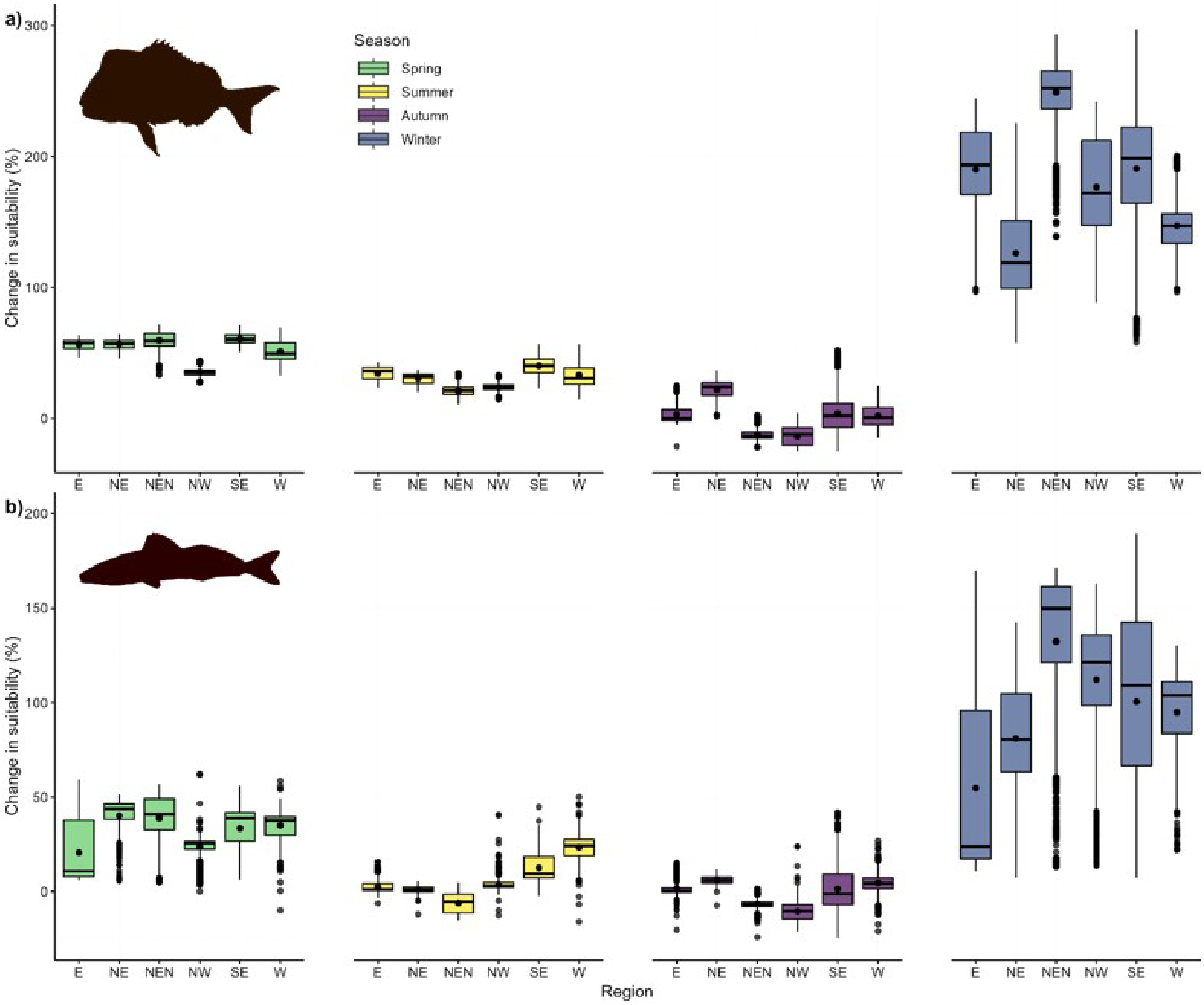

Figure 6. Proportional change (%) in predicted habitat suitability of each grid cell (i.e. 416 m^2 area) within six regions of Tasmania, comparing seasonally aggregated environmental data averaged across 20 years: hindcasted (1998–2018), and forecasted (2036–2065) periods, predicting oceanographic suitable habitat of a) snapper (*Chrysophrys auratus*) and b) King George whiting (*Sillaginodes punctatus*). Boxplots show the median and inner quantiles, points are means ± *SE*. Note the *y*-axis between species differs.

regions ranging from 20.66 (± 0.50) % in the East to 40.22 (± 0.90) % in the North-East (Fig. 6b). Change remained low and consistent in the summer and autumn (Fig. 6b, Table S6).

Discussion

Here, we highlight the value of citizen science initiatives for quantifying the distribution of species at their range edges and predicting changes in habitat suitability under climate change at their distributional limits. We found that strategic citizen science initiatives operating at species range edges can improve the representation of species occurrence records in publicly available datasets considerably, especially near species' distribution limits. These data are of considerable value, given they increased extent of available occurrence data by 278 and 438 km poleward for snapper and King George whiting, respectively, than was previously documented in online databases (i.e. ALA) where species occurrence records were focused on regions of species' core distributions. Further, while data from these initiatives accounted for a relatively small proportion of the entire data set across the Australian domain (i.e. 2.3% and 52.7% for snapper and King George whiting respectively), the majority of the data within Tasmania alone came from the Tassie Fish Frame Collection Program and Redmap (i.e. 81% and 85.7% for snapper and King George whiting respectively). Redmap acted as a 'canary in the coalmine' to document extralimital species arrivals and raise awareness of range-extending species (Nursey-Bray et al. 2018). This was then complimented by the Tassie Fish Frame Collection Program, which used consistent communication amongst a smaller targeted group of fishers to sustain ongoing data collection. Therefore, cross-pollination between initiatives increased data collection potential and increased the potential scope to a broader citizen science audience (Bonney et al. 2014). Lastly, fishery independent sampling at the range edge was conducted to account for any biases associated with fishery-dependant sampling (i.e. size limits, seasonal closures, bag limits etc), and accounted for a relatively small proportion of the range edge data (14% and 18% of occurrences for snapper and King George whiting respectively in Tasmania). Therefore, citizen science programs can be effective in gathering the bulk of the data, allowing for more targeted research sampling trips to compliment the citizen science datasets.

Quantifying the contribution of citizen science initiatives

Our analyses demonstrate how a combination of citizen science datasets can be integrated for the development of marine SDMs by following a series of strategic data thinning and assessment steps (Table 1). Combining data from different initiatives, which use different data collection methods (i.e. opportunistic vs. structured sampling), is well known to increase the data available for questions in regards to biodiversity, conservation and ecology (Peterson et al. 2020, Callaghan et al. 2021). The integration of species occurrence data was important for capturing the environmental variation experienced by these species throughout their distributions and highlighted that data from species range edges are required to parameterise models that effectively predict habitat suitability for species at their distributional limits. When comparing historical spatial predictions of models which included data collected by the Tassie Fish Frame Collection Program and Redmap, we found models which included these targeted citizen science programs predicted higher mean suitability across all seasons around Tasmania by 9–31% and 31–41% for snapper and King George whiting respectively. For snapper, whose distribution extends further north to tropical waters, the difference in spatial projections within Tasmania between the models which included and excluded occurrence records at the range edge was more pronounced (i.e. accounting for a greater area where spatial predictions of suitable habitat were higher when including data at the range edge to train the model). This is likely due to the broad thermal habitat range of snapper, and therefore by including occurrence records at the range edge increases the probability of occurrence in colder waters. For King George whiting, whose mainland distribution is restricted to the southern waters of Victoria, South Australia, and Western Australia (and therefore having a narrower thermal range), differences in model projections were more pronounced in the east and south-east coasts, likely caused by the relatively similar thermal habitat in the north of Tasmania compared to the mainland.

Comparing spatial predictions of habitat suitability

While the total area where differences between the models may be relatively small for King George whiting, including data from targeted citizen science at the range edge still improves model prediction accuracy at the range edge. For example, in Georges Bay, on the east coast—an emerging nursery area for King George whiting (Graba-Landry et al. 2022), mean historical habitat suitability projections from the model which included data from the TTFC Program and Redmap were 22–26% higher than the model which excluded these data (Fig. S5, Table S7). Further, differences in model projections between the two species may also be caused by potential progression in their range shift. For example, it is still unclear whether snapper persist as a self-sustaining population in Tasmania (Graba-Landry et al. 2022), whereas King George whiting in Tasmania are likely self-sustaining and genetically distinct from their mainland counterparts (Jenkins et al. 2016). Therefore, snapper may have a greater area of higher projected suitability when the model is trained on TFFC and Redmap data rich in range edge occurrences, as the expanding portion of the range of snapper may encompass more of the Tasmanian region than that of King George whiting. Nevertheless, whether differences are due to differences in the suitable thermal habitat ranges of each species or differences in their progression in the range extension pathway (Bates et al. 2014), data collected from citizen science initiatives at the range edge improved model projections for future habitat suitability.

Using SDMs to project future shifts

Implications for warmer winters for snapper and King George whiting

Under future predictions, for both species, habitat suitability is predicted to increase more so in the winter season (snapper: 126.33–249.31%, King George whiting: 51–132%) which has implications for the successful overwintering of new recruits, and therefore establishment into Tasmania. As the SDM provided evidence of suitable habitat across the entire Tasmanian domain (at least for the later juvenile and adults life stages typical of the datasets used for model training) conditions allowing for successful recruitment and overwinter survival of recruits may be limiting the persistence of snapper in the south and south-west of Tasmania. This may also be the case on the east coast of Tasmania for King George whiting, where reported catch is considerably less than in the north (although this may result in part from less fishing effort and reporting). For snapper, who typically spawn in the spring and summer at higher latitudes (Wakefield et al. 2015, Graba-Landry et al. 2022), sufficient spawning temperatures are necessary for a successful spawning event, and should temperatures be below the threshold, spawning will not occur (Wakefield et al. 2015). Studies across Australia suggest a period of consistent temperatures exceeding 17–18 °C are necessary for spawning for snapper (Saunders et al. 2012, Wakefield et al. 2015). Therefore, while new recruits may survive at 15 °C, their fitness may be compromised. Current mean summer SSTs in Tasmania range between 16.62 °C (W)–19.12 °C (NEN) and suggest potential for spawning in the north. However, under future predictions SSTs in all regions (except the west coast) exceed 17.33 °C followed by autumns which exceed 15 °C in all regions, which may be sufficient to enable adequate spawning, settlement and therefore recruitment of snapper in most regions of Tasmania under future warming.

For King George whiting, as spawning generally occurs in the autumn, when temperatures and day length decrease (Ham and Hutchinson 2003), warmer winters will therefore be beneficial particularly for larval and juvenile stages, thereby enabling successful recruitment and overwintering of these critical life-history stages in Tasmania. Current (i.e. 2018) average winter temperatures in the north and east coast of Tasmania (as far south as Bicheno; 41° 52′ 58″ S, 148°, 19′ 51.6″ E) range from 13.3–13.7 °C (Copernicus Marine Monitoring Service 2018). However, under future warming (RCP8.5 scenario), winter temperatures are predicted to increase by as much as 3 °C in the north-east regions of Tasmania, with predicted winter temperatures ranging from 16.8–17.7 °C. Given that current emissions scenarios are headed towards RCP6.0 and RCP8.5 (IPCC 2019), successful spawning and recruitment of King George whiting in the east and southeast of Tasmania is likely.

Adding local habitat predictors to improve SDMs

Adding local environmental habitat predictors in SDMs has been suggested to improve the model's predictive accuracy but these improvements are often difficult to quantify (Hazen et al. 2021). By calculating the distance to a key habitat for King George whiting—seagrass, from open access mapped data, we were able to include proximity to seagrass as a predictor in the King George whiting SDM. Furthermore, by rasterizing these distances by grid cell we were able to stack this variable with the oceanographic variables to make spatial predictions in habitat suitability. Through model selection and validation we have demonstrated that using a local environmental predictor is not only possible but improves predictive accuracy and skill. Seagrass habitat provides protection from both physical disturbance (Bostrom and Mattila 1999) and predation (Flynn and Ritz 1999, Hindell et al. 2000, 2002), and increases food availability (Connolly 1994, Edgar 1999, Jenkins et al. 2002), therefore creating important nursery areas for many juvenile fishes (Jackson et al. 2001), including King George whiting (Jenkins et al. 1995).

Caveats / areas for consideration

In our current SDM we assumed the presence of seagrass to be static under future change, and we acknowledge that is a limitation of our current model given that vegetated marine habitat are themselves likely to undergo future climate-driven range shifts (Babcock et al. 2019). However, using regional habitat predictors such as proximity to seagrass is encouraged, as this increases the predictive capacity of SDMs (Kaplan et al. 2016). Some seagrass populations have already undergone a redistribution, specifically, contracting at the warm-edge of their range, or extending at the cold-edge of their range (Duarte et al. 2018). Given the temperate locality of Tasmania, future warming may lead to range extensions of temperate seagrasses which are currently limited to the North, and North-East coasts *(i.e., Posidonia australis* and *Amphibolis antarctica*, Rees 1993), or increase performance for seagrass communities at the centre or cold-edge of their distribution *(e.g. Zostera mulleri, Heterozostera tasmanica*, *Halophila australis*, Rees 1993), which may be beneficial for future recruitment of King George whiting. Therefore, the next logical step in building a more comprehensive SDM is to include projected spatial change in habitat types, in addition to projected climate change. In addition to this step, accounting for potential biases in sampling data, such as accounting for recreational fishing effort, in the generation of pseudo-absence points for the SDM would further increase the confidence in the model results. Lastly, while the SDMs of our two species predict an increase in habitat suitability within the Tasmanian domain under future climate change, our models only account for predicted changes to sea surface temperature and as such they do not account for other environmental changes associated with climate change, which may dampen predicted increases to habitat suitability. More complex models which include predicted changes to ocean biogeochemistry, which affect an organism's performance (i.e. $p\mathrm{CO_2}$, salinity, and oxygen) may provide more comprehensive predictions of habitat suitability. Furthermore, as SST data and predictions are temporally aggregated (i.e. by season), our estimates do not account for the potential maximum and minimums which may occur during the spawning season, which may further enable successful spawning and recruitment. Lastly, successful settlement and juvenile growth is also largely influenced by food and resource availability (Murphy et al. 2013), which was not accounted for in our SDMs.

Future directions for citizen science at the range edge

We have demonstrated that a fundamental component in collecting data on range-extending species is collaboration across many sectors both within and outside of the citizen science space. For example, collaboration between Redmap and the Tassie Fish Frame Collection Program was fundamental in enhancing the success of both initiatives. Collaboration bolstered data collection (fish frame donations, photos, geographic information), helped both programs reach a broader audience and extended science communication about range-extending species in Tasmania to a broader audience. Furthermore, citizen science observation at the species' range edges facilitated the development for the SDMs that produced improved predictions of habitat suitability at these distributional limits. Due to the very nature of being at the range edge, understanding the potential establishment or future shifts of these range-extending species will require ongoing monitoring (Graba-Landry et al. 2022), and would therefore require continued engagement with the citizen science community (Pecl et al. 2019b). Further scope to engage across a suite of citizen science programs would be beneficial for collecting data for range extending species beyond the recreational fishing community (though we acknowledge Redmap observers are approximately 50% divers and 50% fishers). Rapid advances in technology allows for anyone with an interest to be able to sensor their environment and collect data (Bonney et al. 2014). Although there is an Australian-wide citizen science project register, an online hub specific to marine citizen science programs would be useful for the general public to engage and provide information irrespective of their interests or abilities (i.e. photography, diving, fishing, education, clean-ups). Such a central hub would not only reach a wider audience but allow for different institutions and initiatives to collaborate and identify gaps within their own program which could be supplemented within programs elsewhere (Bonney et al. 2014). We advocate for cross-pollination across different citizen science initiatives to limit redundancy between similar initiatives, provide the opportunity to share resources, and ultimately maximize community outreach and data collection efforts (Bonney et al. 2014) for quantifying and predicting the distributions of species at their range edges.

Acknowledgements

We thank the Tasmanian fishing community for their efforts in donating fish frames, and the fishing and diving community for contributing photographic observations to Redmap since 2009, both of which were essential for the success of this project. We also thank the following businesses and organisations for operating as drop-off points for frames donated by the public and for promoting the program: Anaconda Cambridge, Anaconda Launceston, BCF Devonport, BCF Launceston, C.H. Smith, Coastal Marine, Deegan Marine, East Coast Tackle, Fisherman's Shed, Franklin Marine, Franklin Marine, Freycinet National Park Visitor Centre, Morris' Store, Seamaster Devonport, Spot On Hobart - The Fishing Connection, St Helens Slipway & Marine Shop, Tackleworld Burnie, Tamar Marine. Thank you also to IMAS technical, support staff and students involved, including Andrew Nicholls, Elijah Atherton, Ruari Colquhoun, and Mike Williams. This study was conducted under the University of Tasmania Animal Ethics Approval Number A0018088, and scientific research permit provided by the Department of Primary Industries, Water and Environment Number 21080. Funding was provided by the Australian Government via the Fisheries Research and Development Corporation (2018-070).

Author Contributions

This manuscript was from a larger project supported by the Fisheries Research and Development Council, describing the biology, ecology, and impact of three range-extending fish species in Tasmania: yellowtail kingfish, snapper and King George whiting. This team is a multidisciplinary group ranging from fisheries biologists, statistical modellers, traditional ecologists, and outreach officers. SRT, CC, AGL conceived the idea, SRT, BW, JH, DM, AGL, GP collected the data, AGL, CC, and BW analysed the data, ST produced the figures, AGL led the writing, and all authors contributed to editing and reviewing the manuscript.

Data Accessibility

Data used and/or analysed during the current study are available from the corresponding author on reasonable request, and are available from the IMAS repository in the IMAS Data Portal: https://data.imas.utas.edu.au/static/landing.html

Supplemental Material

The following materials are available as part of the online article at https://escholarship.org/uc/fb

Table S1. Sources and number of fish frames used for sampling for each study species in Tasmania between 2019-2021.

Table S2. Variance inflation factors for predictors of best ocean suitability model for snapper (Chrysophrys auratus) and King George whiting (Sillaginodes punctatus).

Table S3. Akaike Information Criterion and degrees of freedom used for model selection for the best generalised additive mixed model for to predict the preferred habitat for a) snapper (Chrysophrys auratus) and b) King George whiting (Sillaginodes punctatus).

Table S4. Details of CMIP5 models downscaled to support projections of suitable habitat for snapper (Chrysophrys auratus) and King George whiting (Sillaginodes punctatus).

Table S5. Results of pairwise contrasts of linear model assessing the difference in proportional change of habitat suitability of snapper (Chrysophrys auratus) at a resolution of 0.004° between hindcasted predictions (1998–2018) and forecasted predictions (2036–2065) across six regions of Tasmania and four seasons.

Table S6. Results of pairwise contrasts of linear model assessing the difference in proportional change of habitat suitability for King George whiting (Sillaginodes punctatus) at a resolution of 416 m between hindcasted predictions (1998 – 2018) and forecasted predictions (2036–2065) across six regions of Tasmania and four seasons.

Table S7. Mean, standard deviation (SD), minimum and maximum predicted habitat suitability values of models which included (i.e. all data) and excluded data from the Tassie Fish Frame Collection Program and Redmap for King George whiting in George's Bay, Tasmania.

Figure S1. Evidence of model overfitting in GAMM with and without knots applied to the SST smoothing term for the snapper SDM: pa ~ s(SST) + s(depth) + (1|year).

Figure S2. Spatial and temporal semi-variograms to assess a) spatial and b) temporal autocorrelation for the data used for the optimal habitat suitability model

for snapper (Chrysophrys auratus) (i.e. applying spatial thinning of 20 km per day).
Figure S3. Spatial and temporal semi-variograms to assess a) spatial and b) temporal autocorrelation for the data used for the optimal habitat suitability model for King George whiting (Sillaginodes punctatus) (i.e. applying spatial thinning of 10 km per day).
Figure S4. Differences (absolute change) in spatial projections of historical habitat suitability (1998–2018) across four seasons for snapper (a, c, d, g) and King George whiting (Sillaginodes punctatus) between models using the entire data set, and models which excluded data from the TFFC Program and Redmap).
Figure S5. Differences in spatial projections of historical habitat suitability (1998–2018) during the winter season for King George whiting (Sillaginodes punctatus) between models using the entire data set, and models which excluded data from the TFFC Program and Redmap) in George's Bay, on the east coast of Tasmania.

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