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Abstract: Biological invasions are one of the most significant threats to marine biodiversity, and can be facilitated and amplified by climate change. Among all aspects of invasion biology, biotic interactions between invaders and native species are of particular importance. They strongly influence the invasion velocity as well as species responses to climate-induced stressors. Yet the effects of biotic interactions and other important demographic processes remain overlooked among most studies of climate-mediated invasions. We critically assessed current modelling techniques for forecasting marine invasions under climate change, with a particular focus on their ability to account for important biotic interactions and demographic processes. We show that coupled range dynamics models currently represent the most comprehensive and promising approach for modelling and managing marine invasions under climate change. We show, using the crown-of-thorns seastar (Acanthaster planci), why model architectures that account for biotic interactions and demographic and spatial processes (and their interaction) are required to provide ecologically realistic predictions of the distribution and abundance of invader species, both under present-day conditions and into the future. We suggest potential solutions to inform data-poor situations, such as Bayesian parameter estimation and meta-analysis, and identify strategic and targeted gaps in marine invasion research.

1 Forecasting marine invasions under climate change: biotic

2 interactions and demographic processes matter

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- 25 interactions.
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- 27

28 Abstract

29 Biological invasions are one of the most significant threats to marine biodiversity, and can be 30 facilitated and amplified by climate change. Among all aspects of invasion biology, biotic interactions 31 between invaders and native species are of particular importance. They strongly influence the 32 invasion velocity as well as species responses to climate-induced stressors. Yet the effects of biotic 33 interactions and other important demographic processes remain overlooked among most studies of 34 climate-mediated invasions. We critically assessed current modelling techniques for forecasting marine invasions under climate change, with a particular focus on their ability to account for 35 36 important biotic interactions and demographic processes. We show that coupled range dynamics 37 models currently represent the most comprehensive and promising approach for modelling and 38 managing marine invasions under climate change. We show, using the crown-of-thorns seastar 39 (Acanthaster planci), why model architectures that account for biotic interactions and demographic 40 and spatial processes (and their interaction) are required to provide ecologically realistic predictions 41 of the distribution and abundance of invader species, both under present-day conditions and into the 42 future. We suggest potential solutions to inform data-poor situations, such as Bayesian parameter 43 estimation and meta-analysis, and identify strategic and targeted gaps in marine invasion research.

44

45 **1. Introduction**

46 Marine invasive species are a major threat to biodiversity worldwide and can have profound 47 ecological and economic impacts on marine ecosystems (Bax et al., 2003). Although the criteria that 48 categorise a species as invasive remain somewhat controversial, invaders are commonly characterised as species that undergo rapid increases in abundance and/or spatial occupancy with 49 50 adverse effects on recipient ecosystems (Valery et al., 2008). This definition includes the case of 51 'native invaders' that can spread within their historical range by exploiting niche opportunities 52 resulting from human activities and/or loss of other species: by attaining extreme abundances and 53 exerting severe per-capita effects on local communities, native invaders can indeed cause ecological

54	impacts that rival those of non-native invaders (Valery et al., 2009; Carey et al., 2012). Whether
55	native or not, invaders can impact recipient communities directly through competition, predation,
56	and hybridization, and indirectly by modifying habitats and potentially disrupting their suitability.
57	Over 1500 species have invaded locations throughout the world's oceans, and more are discovered
58	every year (European Environment Agency, 2012). The potential economic costs incurred by even a
59	single marine invasive species can reach US\$250 million yr ⁻¹ (Williams & Grosholz, 2008) and
60	eradication seems possible only in highly constrained situations (Bax et al., 2002). Future climate
61	change is predicted to increase the introduction and spread of invasive species, accelerating marine
62	invasions and resulting in widespread biodiversity loss (Garcia Molinos et al., 2016).
63	The ecological traits that commonly characterize marine invasive species are
64	disproportionately favoured under climate change, potentially exacerbating future impacts of marine
65	invasions (Poloczanska et al., 2013). This is because marine invaders often tend to be generalist
66	and/or opportunists with relatively plastic life histories (Clavel et al., 2011), making them able to
67	better adapt to rapidly changing environmental conditions and fare better in warming waters than
68	native species (Sorte et al., 2013; Bates et al., 2013). By relaxing some of the physiological constraints
69	on temperature-dependent growth and survival while also altering connectivity, human-induced
70	climate change has already enabled some non-native invasive species to expand into regions where
71	they previously could not survive and reproduce, as exemplified by the green 'killer' algae Caulerpa
72	taxifolia in the Mediterranean (Walther et al., 2009). Additional climate-related factors that might
73	enhance a species' invasive ability include: extensions of spawning periods and increases in per
74	capita reproductive output (Walther et al., 2009); altered timing of recruitment and faster growth in
75	warmer years (Stachowicz et al., 2002); faster developmental rates (Walther et al., 2009); and
76	modified local dispersal patterns due to altered hydrodynamic conditions (Diez et al., 2012). In the
77	case of native invaders, climate-driven environmental changes at local scales (e.g. eutrophication,
78	altered connectivity due to changes in ocean currents) can favour the dominance of invaders in parts
79	of their historical range where they previously could not survive or reproduce (Carey et al., 2012).

80 Despite these established physiological and demographic responses to climate change, there 81 have been few attempts to forecast the potential impact of invasive species under climate change 82 and test the efficacy of alternative management actions (Sorte, 2014). Most existing knowledge is 83 based on local field observations or mesocosm experiments (e.g., Cockrell & Sorte, 2013) that are 84 often conducted at small scales and/or do not necessarily represent realistic environmental 85 conditions. More integrated approaches that combine empirical data on local and regional ecological 86 processes with simulation models are urgently needed in marine invasion biology to improve our 87 knowledge of impending invasions and to manage existing and future invasive species (Fordham, 88 2015).

89 A commonly overlooked consequence of climate change affecting marine invasions is the 90 way climate change alters ecological interactions in native communities (Sorte et al., 2010). Climate-91 driven changes in invasive ability affect the way native communities are organised, facilitating the 92 formation of novel ecological communities characterised by new arrangements and ecological 93 interactions (Lurgi et al., 2012). Such new configurations can create ecological vacuums that facilitate 94 future invasions, especially if top predators are depleted (as frequently reported in response to 95 global change; Cheung et al., 2015). Other anthropogenic stressors such as fisheries exploitation, 96 terrestrial runoff, and eutrophication can act in synergy with climate change to facilitate not only 97 invasions by alien species but also state-shifts of species dominance, as for example, in the case of 98 invasive jellyfish (gelatinous plankton; Fig. 1) (Licandro et al., 2010; Lynam et al., 2011). These 99 interactions can be complex, with climate change and other anthropogenic stressors having both 100 direct and indirect effects on the strength of biotic interactions (e.g. competition, predation). 101 Consequently, not only is the dominance of invasive species likely to change owing to synergies 102 between anthropogenic stressors, but also the number and strength of their biotic interactions 103 between invasive and other species, with potentially multiplying effects brought about by trophic 104 cascades (Lynam et al., 2011).

105 Anticipating and managing future threats from invasive species to marine biodiversity thus 106 requires accurate forecasts of marine invasions that account for biotic interactions between native 107 and invasive species, and how they are likely to change in response to multiple anthropogenic 108 stressors. Here we appraise the quantitative methods that have been applied to forecast marine 109 invasions, focusing on their strengths and shortcomings, and on whether they can explicitly account 110 for biotic interactions. We then implement a spatially explicit simulation model as a proof-of-concept 111 of how biotic interactions, demographic processes and their climate-induced variation can and 112 should be integrated into forecasts of marine invasions under climate change. Our model organism is 113 Acanthaster planci, the crown-of-thorns seastar, which is a major threat to the Great Barrier Reef, 114 and the only threatening process of contemporary global change that is amenable to direct 115 management actions (De'Ath et al., 2012). Rapid outbreaks of A. planci currently pose one of the 116 most serious management problems for the Great Barrier Reef, leading to conservation implications (e.g., extirpation of foundation species and destruction of essential fish habitats) that are similar to 117 those of any non-native invasive species. 118

119

120 2. Recent developments for forecasting marine invasions under climate change

121 2.1 Species distribution models

Correlative species distribution models (SDMs; i.e. ecological niche, bioclimatic envelope, or habitat 122 123 suitability models) describe or predict the probability of presence or spatial abundance of a species 124 across environmental gradients or in a specific geographical area based on habitat suitability 125 (Pearman et al., 2008). SDMs have very simple data requirements, needing only point location data 126 and associated environmental variables (Table 1). However, predictions are often constrained by 127 important limiting assumptions (Elith et al., 2010; Robinson et al., 2011). Indeed, SDMs typically 128 assume that species occurrences represent the range of environmental conditions in which an 129 organism can persist (Schurr et al., 2012) and rarely account for demographic processes such as 130 dispersal in an ecologically realistic way (Travis et al., 2013). These assumptions are particularly

concerning in the case of recently introduced invasive species because their ranges are by definition
expanding (e.g., Kearney *et al.*, 2008), thus representing a non-equilibrium distribution (Thuiller *et al.*, 2005). As a result, models calibrated in the native range often underperform in the exotic range
(and vice versa) (Fitzpatrick *et al.*, 2007), an issue that can be partially addressed by considering the
species' global range (Mainali *et al.*, 2015).

136 The failure of SDMs to account explicitly for biotic interactions (as well as demographic 137 processes) has been identified as a major limitation of these models, affecting predictions of 138 distributional shifts under changing climatic conditions (Araujo & Luoto, 2007). While biotic 139 interactions can keep a species in check in climatically suitable conditions, they can also fail to 140 restrict invasions in new territories where a predator or competitor is absent or in low abundance 141 (Fig. 1) (Mainali et al., 2015). In such a situation, SDMs unrealistically consider the invaded range as 142 climactically broader than the native range (e.g., Fitzpatrick et al., 2007). Recognition of these 143 limitations has prompted the development of new methods for incorporating biotic interactions into 144 SDMs (Kissling et al., 2012). These methods include: (i) adding the occurrence of an interacting species as an additional covariate in the SDMs (Araujo & Luoto, 2007); (ii) developing a separate SDM 145 146 for the interacting species and using it to constrain the distribution of the focal species, minimizing 147 the issues of false absences and collinearity where both species are related to the same 148 environmental predictors (Schweiger et al., 2008); or (iii) calibrating an interaction matrix among 149 species to define the error matrix for multivariate logistic regression models (Kissling et al., 2012). 150 Existing methods for incorporating biotic interactions into SDMs remain problematic for at 151 least two reasons: biotic interactions can change over time (even more so in the context of an 152 invasive species under climate change; Fig. 1) and it is difficult to include more than one interaction 153 at a time. Therefore, biotic interactions remain absent from most SDMs under the assumption that, 154 at least at biogeographic scales (as opposed to local; Wisz et al., 2013), biotic interactions are not a 155 determinant of invasive species distributions (Mainali et al., 2015), which seems unrealistic in most 156 situations (Araujo & Luoto, 2007). Recent studies using SDMs to forecast marine invasions have

- focused primarily on the susceptibility of environments to invasions for management purposes (de
 Rivera *et al.*, 2011; Jones *et al.*, 2013). Biotic interactions have, however, been consistently ignored in
 these marine SDMs (Robinson *et al.*, 2011).
- 160

161 2.2 Biophysical models

162 Biophysical models (i.e. process-based models) rely on species physiological tolerance limits and, in 163 doing so, enable species distributions to be modelled across environmental gradients without using 164 occurrence data (Kearney et al., 2008) (Table 1). Biophysical models should, in theory, yield more 165 robust forecasts of climate-driven distributional shifts because they explicitly account for 166 relationships between climate conditions and organismal performance. In doing so, biophysical 167 models overcome problems associated with non-equilibrium situations, since they do not rely on 168 occurrence data that could misrepresent the species' potential range due to biotic interactions (see 169 above) or human-driven impacts such as depletion from harvesting (Buckley et al., 2010). Biophysical 170 models are increasingly used to model range dynamics in response to climate change (Kearney et al., 171 2008; Cheung et al., 2011) or environmental gradients (Monahan, 2009), and can be coupled with 172 SDMs to constrain their predictions (Elith et al., 2010; Buckley et al., 2011; Fordham et al., 2013b). 173 For example, biophysical models have been used to show that invasion of the Indo Pacific lionfish 174 (Pterois volitans) into the Mediterranean is unlikely to occur due to low connectivity between 175 suitable sites (Johnston & Purkis, 2014). Biophysical models subsequently allowed to recreate the 176 success/failure of invasions of introduced fish in the Hawaiian Islands, providing insight into the demographic properties that predispose fish species to successful invasion (Johnston & Purkis, 2016). 177 178 Biotic interactions cannot currently be implemented in biophysical models in their original form but 179 would represent an important and desirable extension to this class of models (Buckley et al., 2010; 180 but see Tingley *et al.*, 2014).

181

182 2.3 Spatially explicit demographic models

183 Spatially explicit demographic models, which directly account for species vital rates in model 184 predictions, are used with increasing frequency to model the effects of climate change on the range 185 dynamics and persistence of species, including those in the marine realm (e.g., Fordham et al., 186 2013b). While incorporating important information on habitat suitability (e.g., Mellin et al., 2012), 187 such models relax some of the limiting assumptions constraining SDMs since they explicitly account 188 for dispersal and source-sink dynamics, enabling demographic rates (such as growth or fertility) to 189 vary in space and time (Dunstan & Bax, 2007). Models can be either population-based (i.e. they 190 account for population-level parameters such as survival and fertility rates, dispersal kernels) or 191 individual-based (e.g. incorporating individual heterogeneity in parameters such as body size, 192 movement and feeding behaviour, phenotype). For both population- and individual-based 193 demographic models, user-friendly and fully customisable modelling platforms are now broadly 194 available (Lurgi et al., 2015) (Table 1). Most recently, some of these frameworks have been adapted 195 to explicitly account for simple (one-way) biotic interactions in predictions of how climate change is 196 likely to affect species range dynamics (e.g., Fordham et al., 2013a). 197 In spite of readily available modelling platforms, and available demographic data for some 198 species, marine applications of spatially explicit demographic models for invasive species remain 199 scarce. Demographic (stage-structured) models have for example been used to predict the future 200 population growth of invasive species using laboratory mesocosms to estimate survival, growth, and 201 fecundity rates within epibenthic communities under present-day conditions and with ocean 202 warming (Cockrell & Sorte, 2013). This approach is informative in situations where the population 203 dynamics of local communities are explained mainly by intrinsic demographic properties of the 204 constituent species. Demographic models have also been used to understand how range dynamics 205 can be affected by environmental changes and to forecast potential effects on abundance and 206 geographic distributions. For example, commercial fisheries researchers now use hybrid 207 demographic models (named Dynamic Bioclimate Envelope Model), which explicitly account for 208 demographic and range dynamics (Cheung et al., 2009; Cheung et al., 2011), to incorporate

competition for resources into predictions of species distributional shifts (Fernandes *et al.*, 2013).
 Forecast latitudinal shifts decreased by 20% when species interactions were considered, further
 highlighting the importance of biotic interactions in forecasting distributional shifts and marine
 invasions.

213 In aggregate, if we are to better forecast marine biological invasions and understand their 214 effects on recipient communities, there needs to be a much stronger focus on developing 215 quantitative approaches that account for key ecological processes (demography and biotic 216 interactions) in simulation models of marine invasions. Coupled range dynamics models, accounting 217 for metapopulation processes and simulating the mutually reinforcing effects of climate change and 218 biotic interactions (Fig. 1), provide appropriate modelling frameworks that have not yet been used 219 to simulate marine invasions. This is despite the necessary tools being widely accessible, and similar 220 methodologies having been developed for modelling species range dynamics under climate change in 221 terrestrial ecosystems (both aspects reviewed by Lurgi et al., 2015) including invasive terrestrial 222 species (Fordham et al., 2012) and harvested marine species (Fordham et al., 2013b). The 223 demonstrated utility of this approach indicates the immediate need for an assessment of its 224 transferability to the case of marine invasions. 225 226 3. Incorporating biotic interactions into forecasts of marine invasions 227 To demonstrate the feasibility of coupling demographic models with SDMs (i.e. coupled range

dynamics models) in order to forecast spatially explicit changes in the range and abundance of marine invasive species, we developed a population-based cellular automaton (Durrett & Levin, 1994). We use this coupled range dynamics model to show (*i*) how biotic interactions can be incorporated into forecasts of invasion dynamics under climate change and (*ii*) the extent to which doing so influences model outcomes and potential management applications (Box 1; see Supplementary Material SM1 for a full description of the framework). We chose the coral-eating crown-of-thorns seastar (*A. planci*) as a model organism. Outbreaks of *A. planci* have been a major contributor to the loss of half of the coral cover on Australia's Great Barrier Reef since 1985 (De'Ath *et al.*, 2012). It was suggested that the frequency of such outbreaks has increased over the last
century, partly as a result of increasing terrestrial runoff and primary productivity that promotes
larval survival (Fabricius *et al.*, 2010). Since *A. planci* can become sporadically hyperabundant in its
native range, threatening the regional persistence of many corals and causing as much ecological
damage as any non-native invasive species, it makes an interesting 'proof-of-concept' case study for
modelling (and managing) marine invasions under climate change.

242 We considered two different model-based scenarios: a trophic interaction between A. planci 243 and its coral prey (Scenario I) vs. no biotic interactions (Scenario II). We then developed three 244 artificial seascapes reflecting increasing levels of habitat clustering (from evenly distributed to highly 245 aggregated suitable habitat) to gauge the potential effect of patch structure (and corresponding 246 connectivity) on the population dynamics and distribution of A. planci. Climate change was simulated 247 based on a latitudinal change in potential climate suitability, with the southernmost habitats 248 becoming more suitable and northernmost habitats becoming less so over the 100-year time period 249 considered (Lamare et al., 2014). Finally, we accounted for demographic traits and processes 250 including fertility, dispersal, population growth, and density-dependent survival (e.g., accounting for 251 the fact that individuals die and populations are reduced to non-outbreaking sizes once they reach a 252 critical density threshold; Pratchett, 2005) (Box 1 and Supplementary Material).

253 Ecologically realistic fluctuations in total population size mirrored the outbreaking dynamics 254 observed on the Great Barrier Reef (Fabricius et al., 2010) only when biotic interactions were 255 explicitly modelled (Scenario I; Fig. 2A). Occupancy patterns were characterised by temporal 256 fluctuations that reflected lagged changes in the spatial distribution of prey abundance (Fig. 2A 257 bottom panel). In contrast, in the scenario without biotic interactions (Scenario II), we show a steady 258 decline in the total occupied range area and total population abundance of the invasive species over 259 time (Fig. 2B). The effects of habitat clustering were more pronounced when no biotic interactions 260 were considered (differences among rows in Fig. 2B). More clustered aggregations of suitable habitat 261 generated smoother changes in population dynamics as habitat suitability shifted in response to 262 climate change. The mechanism behind this is a greater connectivity among local populations within 263 highly clustered habitats, which facilitates synchronisation among populations, homogenising the 264 response to climate change. In Scenario I, this greater level of connectivity in highly clustered 265 habitats also caused higher outbreak population sizes of A. planci. Moreover, climate change only 266 affected occupancy patterns in Scenario I, with the average spatial extent an outbreak (i.e. number of 267 occupied cells at each peak) decreasing over the 100 year period (Fig. 2A bottom panel). Conversely, 268 there was no evidence of decrease in the size of the outbreaking population over time (Fig. 2A top 269 panel).

270

271 4. Forecasting and managing marine invasions under climate change

272 Previous research has started to unravel the importance of accounting for population dynamics when 273 trying to forecast range shifts and changes in abundance (Keith et al., 2008; Fordham et al., 2013b). A 274 more recent, critical consideration is how to incorporate intra- and inter-specific biotic interactions 275 into forecasts of future trends in abundance and geographical range limits under climate change 276 (Figure 1). Such biotic interactions can strongly influence the effect of climate change on marine 277 invasions, sometimes even reversing the direction of species-specific responses to a particular 278 stressor (when a species is affected by a stressor only in the presence or absence of another species) 279 (e.g., Teng & Apperson, 2000). If we are to fully understand and better forecast marine invasions, we 280 need coupled range dynamics models that are able to incorporate the most relevant aspects of 281 species-level biology and ecology, along with their major interactions. Our coupled range dynamics 282 model for A. planci builds upon recent and flexible platforms for modelling single-species invasions 283 (e.g., Savage & Renton, 2014), providing a proof-of-concept that, for this simple system, direct biotic 284 interactions can be integrated into forecasts of marine invasions under climate change with relative 285 ease. Notably, our "proof-of-concept" modelling exercise demonstrates that accounting for simple 286 prey-predator interactions strongly influences forecasts of range movement and population

abundance; and that real-world population trends (i.e., those observed on the Great Barrier Reef)
can only be reproduced using simulations that account explicitly for biotic interactions. Our findings
highlight the importance of identifying the most important sources of environmental and biotic
interactions and then integrating them with an appropriately scaled spatially explicit demographic
model to forecast invasions under climate change.

292 Our modelling framework provides a generic tool that can readily be applied to any other 293 marine pest (see Python code in Supplementary Material) where data is available for model 294 parameterisation. Its flexibility allows to incorporate variable biotic interactions under climate 295 change, as well as the impact of thermal or other stress on demographic rates (e.g., decreased 296 fertility; Fordham et al., 2013b). Nonetheless, we suggest that only the most pertinent biotic 297 interactions should be included, based on expert knowledge, published literature, meta-analysis or 298 experimentation. This is because not all aspects of ecosystems can or should be accounted for in 299 model projections since doing so will result in over-parametrized models that are computationally 300 unwieldy and difficult to validate or duplicate (Grimm et al., 2005; Fulton et al., 2015). Finally, it is 301 worth noting that the specificities and constraints particular to the model we developed for A. planci 302 can be easily relaxed to capture different processes and mechanisms affecting corals, such as 303 bleaching and cyclones. Including recent data-driven observations of coral impact and recovery 304 following disturbance (Mellin et al., 2016) in the model is a key next step forward.

Arguably, tight integration of the ecological processes considered above into a comprehensive modelling framework for marine invasions can be dauntingly complex and prohibitively challenging, partly because of the difficulties in collecting the data needed to parameterise such models. However, there are solutions. Plausible parameter estimation can be achieved using approximate Bayesian computation (Beaumont, 2010) or the elicitation of expert knowledge (Martin *et al.*, 2005). Model parameters can then be calibrated by comparing model predictions with independent observations (Wells *et al.*, 2015). Indeed, not all model parameters will have a significant effect on

312 model outcomes, and sensitivity analysis (McCarthy *et al.*, 1995) can help determine where future

313 research efforts should be focused to improve model parameters and subsequent predictions. In the 314 case of A. planci for example, our sensitivity analysis showed that natural mortality rate was the most 315 important determinant of population size and occupancy (Suppplementary Material). Since natural 316 mortality is typically difficult to quantify (Pratchett et al., 2014), estimates are somewhat uncertain 317 and future research efforts should therefore focus on improving such estimates of mortality. Second, 318 while it is crucial to consider stressors other than temperature and the potential interactions among 319 them, there remain significant gaps in our understanding of responses to such stressors, as well as 320 how species-specific responses will propagate at the community level (Sorte, 2014). This is where 321 meta-analyses can provide invaluable sources of information on how an organism might respond to a 322 given stressor based on the taxon, life stage, habitat, and potential interactions with other stressors 323 (e.g., Przeslawski et al., 2015). Meta-analyses can also help define the strength and direction of 324 interactions among stressors in an integrative model, irrespective of divergences in defining the type 325 of interactions considered (i.e. synergistic, antagonistic, and additive effects) (Piggott et al., 2015). 326 Two critical post-hoc steps will determine the successful uptake of model outcomes by 327 stakeholders, namely (i) model validation and (ii) quantification of uncertainty through each step of 328 the model. Demographic models are typically validated by hindcasting abundance over the period for 329 which independent observations are available, and comparing model predictions with observations 330 (Wells et al., 2015). Ideally, in the most data-rich situations, validation can also be done using genetic 331 estimates of population relatedness and source-sink dynamics (Fordham et al., 2014). Uncertainty on 332 the other hand, is a neglected issue that can be complex to address. Attempts have been made to 333 quantify data-related (observational or aleatory) vs. model-based (epistemic) uncertainty (Fordham 334 et al., 2013c), and software developed to allow uncertainty in model parameters (and their 335 interactions) to propagate through to model outputs and influence decision-making (Fordham et al., 336 2016).

The framework described here can and should be used to examine and rank the efficacy of
alternative control strategies (in space and time) including: actively removing the invader; altering

339 habitat suitability (e.g., through predator protection in no-take areas); and managing key dispersal 340 corridors for the invasive species or its predators. The approach can also be used address whether 341 management effort should focus on controlling the centre (source) of a population or the spreading 342 periphery (Williams & Grosholz, 2008) under climate change. Due to epistemic uncertainty, forecasts 343 of any invasion should be considered with caution, and it will often be more desirable to focus on 344 differences among scenarios rather than on specific forecasts per se. In this way, the benefit of a 345 particular management action should be measured against its counterfactual, i.e. what would 346 happen if resources were spent on an alternative control option (Wilson et al., 2006), to provide a 347 more sound basis for decision making than individual forecasting.

348

349 5. Conclusion

350 During recent decades, invaluable knowledge has been gained about the mechanisms and 351 consequences of biological invasions in warming oceans, and there is now a need to shift attention 352 from the properties of invading organisms to forecasting invasions in a changing world. Our 353 methodology begins this task by building on previous modelling efforts to incorporate range dynamics, demography, and biotic interactions. Importantly, methodologies exist to tackle data 354 355 limitation issues (e.g. Bayesian parameter estimation, meta-analysis, expert elicitation), making 356 demographic model development tractable as part of an adaptive learning process. We suggest that 357 strategic pathways should be developed to inform model inputs, interactions among stressors and 358 their inherent uncertainty- the successful integration of which will determine model uptake and benefits in terms of conservation. Finally we emphasize the importance of validating model 359 360 predictions and interpreting model results in a way that reduces the effects of epistemic uncertainty. 361

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- 567 Table 1: Modelling techniques currently available for forecasting marine invasions under climate
- 568 change: data requirements, ecological processes captured, and examples of previous applications.

			D	ata re	equire	ement	ts				
Model designation	Occurrence	Abundance/density	Environmental data	Physiological data	Demographic data	Dispersal	Individual behaviour	Predator Prey	Larval Connectivity	Processes accounted for	Marine examples
SDM	0	٥	0							Species- environment relationships	(de Rivera <i>et al.,</i> 2011) (Tyberghein <i>et al.,</i> 2012) (Jones <i>et al.,</i> 2013)
Biophysical models			٥	٥						Physiological tolerance	(Fordham <i>et al.,</i> 2013b) (Cheung <i>et al.,</i> 2015)
Population-based demographic models		D	D		D	D				Growth, survival, dispersal	(Dunstan & Bax, 2007) (Cheung <i>et al.</i> , 2011) (Cockrell & Sorte, 2013) (Fordham <i>et al.</i> , 2013b)
Individually-based demographic models			0		٥	0		٥		Reproduction, aggregation, Behaviour	(Rijnsdorp <i>et al.</i> , 2009) (Anderson <i>et al.</i> , 2013)

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581 growth (*Scenario II*). Essential aspects of the model can be summarised as follows (see Supplementary Material
582 for full model description and implementation details):

- 583 Habitat suitability: defined based on 2D simulated seascapes characterized by variable levels of clustering 584 (i.e. aggregation) from numerous small patches (cluster 1) to a few large patches (cluster 3). The 585 distribution of habitat suitability values across grid cells was kept constant among clustering levels. The 586 resulting maps carry information on habitat suitability, which in turn determines the carrying capacity. 587 Simulating the effects of climate change: This was achieved by altering dynamically the potential climate 588 suitability of each local unit of the meta-population (grid cell) at each iteration of the model, and combining 589 it with the original habitat suitability layer. The temporal change in habitat suitability across the seascape 590 reflected a southerly range shift commonly observed in conjunction with latitudinal range dynamics 591 (Parmesan, 2006), with northernmost habitats becoming progressively unsuitable and southernmost 592 habitats becoming more so. 593 Demographic traits: We modelled fertility, survival, dispersal and population growth. Survival and fecundity ٠ 594 varied spatiotemporally in response to environmental variability (see below). 595 Local populations connectivity via dispersal processes: We allowed propagules (i.e. pelagic larvae) of the 596 invasive species and its interacting prey species (Scenario I only) to disperse across the seascape. We 597 defined dispersal from local populations based on a dispersal kernel and individual-level probabilities of 598 dispersal. Adults were considered sessile. 599 Environmental stochasticity accounted for stochastic variation in population growth rates. ٠ 600 Biotic interactions: Predator-prey interactions between A. plancii and a generic coral prey species were 601 simulated using Lotka-Volterra (predator-prey) equations (Scenario I only). 602 Density dependent processes were modelled by allowing population density to increase up to the carrying 603 capacity, after which individuals die and density returns to non-outbreaking levels. 604 We ran 100 simulations of 120 time steps each, discarding the first 20, which were used as the burn-in period. 605 We summarised the outputs across simulations in terms of abundance and occupancy of the invasive species 606 and its coral prey (Scenario I only). We ran a sensitivity analysis with the main model parameters varying
- between ± 20 % over a total of 200 models as determined by Latin hypercube sampling, and then used boosted
 regression trees to determine the most important parameters (Supplementary Material).

609



613 Figure 1. One conceptual model of mutually reinforcing effects of climate change and other 614 anthropogenic stressors on native invasive jellyfish (gelatinous plankton), with biotic interactions 615 (i.e., predator-prey relationships) represented by the arrows. (A) Increasing terrestrial runoff and 616 nutrients loads contribute to eutrophication, leading to unusually high phytoplankton (plankton) 617 concentrations associated with low oxygen concentrations (Miller & Graham, 2012). These 618 conditions promote the growth of jellyfish populations, sustained by plankton resources usually 619 consumed by fish stocks and fish larvae (nekton). Fish stocks are subsequently impacted by this 620 reduced availability of plankton resources, as well as by continuously increasing fishing effort (e.g. 621 Pauly et al., 2002). The reduced size of fish stocks results in a reduced uptake of planktonic 622 resources, thus made available to sustain further jellyfish blooms (Licandro et al., 2010; Lynam et al., 623 2011). (B) Climate change favours gelatinous plankton species that are able to adapt to new 624 environmental conditions and increase in abundance rapidly (Lynam et al., 2011). The composition 625 of nekton communities and fish stocks is altered not only as increasing fishing efforts remove fish predators (Pauly et al., 2002) but also as surface temperature increases leading to the dominance of 626 627 (sub)tropical species (Cheung et al., 2013). Because these subtropical species are unlikely to prey on 628 the same plankton species as their temperate peers, planktonic resources not consumed by fish are 629 more readily available to sustain increasingly frequent and extensive jellyfish blooms.



Figure 2. Forecasts of a marine invasion process under climate change using a spatially explicit 633 634 demographic modelling framework. Model parametrisation is based on a synthetic example for the coral-eating crown-of-thorns seastar (Acanthaster planci) and its coral prey (see text). (A) Scenario I 635 636 includes a trophic interaction between the marine invasive species and its coral prey, while (B) 637 Scenario II considers only dispersal and population growth. In both panels (A, B), top and bottom 638 rows show population size and spatial occupancy over time, respectively; columns represent levels 639 of clustering (i.e. aggregation) in suitable habitat from cluster 1 (numerous small patches) to cluster 640 3 (few large patches). Climate change was modelled using variable habitat suitability layer from time 641 step 1 to 100 (the length of simulations). See Supplementary Material for a detailed description of 642 the model implementation.