

## TITLE PAGE

# **Powerful yet challenging: Mechanistic Niche Models for predicting invasive species potential distribution under climate change**

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# 1 **Powerful yet challenging: Mechanistic Niche Models for predicting invasive** 2 **species potential distribution under climate change**

## 3 4 **Abstract**

5 Risk assessments of invasive species are among the most challenging applications of species  
6 distribution models (SDMs). This challenge arises from the disequilibrium in invasive distributions,  
7 where recorded occurrences do not fully represent the species' potential range. The spatiotemporal  
8 dynamics of invasive populations are shaped by intraspecific variability, human-mediated  
9 introductions, novel biotic interactions, climate change, and ecological niche shifts, which are only  
10 indirectly incorporated into correlative SDMs. Predicting future potential distributions under these  
11 conditions requires moving beyond traditional frameworks reliant on historical climatic data to models  
12 that explicitly capture the mechanisms underlying species potential. Mechanistic niche models (MNM)  
13 address these limitations as process-explicit models that integrate species' physiological performance  
14 across environmental gradients. By incorporating physiological constraints and vital rates, MNMs  
15 define species distribution limits, offering a mechanistic understanding of species-environment  
16 relationships and enabling more robust predictions under changing conditions. However, a unified  
17 MNM framework remains elusive. In this review we delve into the theoretical foundations of MNMs,  
18 emphasizing their advantages over correlative approaches, especially for invasive species. We provide  
19 insights into diverse modelling techniques across taxa and examine the benefits and limitations of  
20 MNMs for predicting species distributions under novel conditions. Our systematic review revealed that  
21 MNMs have been applied sparingly to invasive species, focusing primarily on insects and plants, likely  
22 due to high data requirements. While MNMs do not explicitly capture spatial processes, they remain  
23 the most suitable approach for defining species distribution limits under novel conditions, but their  
24 success depends on the relevance of input data and effective parameterization, including genotype  
25 selection, model type, experimental conditions, and physiological curve-fitting techniques. MNMs offer  
26 significant potential for advancing ecological research and providing robust tools for evidence-based  
27 management decisions. By addressing key challenges, they can enhance our understanding of invasive  
28 species and other populations in disequilibrium under changing environmental conditions.

29  
30 **Keywords:** Alien species, Biophysical, Ecophysiological niche models, Distribution forecast, Invaded  
31 range, Metabolic rates, Systematic review, Vital rates.

## 32 **Challenges for modelling invasive species using species occurrence data**

33 Understanding the constraints of species distribution and abundance has been a central goal in ecology  
34 for decades (Andrewartha and Birch, 1954). This topic remains highly relevant as climate change  
35 reshapes species distributions (Sutherland et al. 2013; Pecl et al. 2017; Lenoir et al. 2020). Invasive  
36 species provide unique insights into how organisms expand their ranges and respond to novel  
37 conditions, offering a basis to understand and predict the impacts of climate change on native species  
38 distributions (Cadotte et al. 2021).

39 Species Distribution Models (SDMs) are the most widely used tools for spatially explicit predictions of  
40 species' environmental suitability (Guisan et al. 2017) and have been extensively applied to explore  
41 invasive species' potential (Guisan et al. 2014). SDMs use statistical models to describe relationships  
42 between species occurrence or abundance records and spatial predictors (e.g. temperature,  
43 precipitation). These relationships are then used to map occurrence probabilities and make forecasts  
44 across time and space (Elith and Leathwick 2009; Elith 2017).

45 However, correlative SDMs face critical limitations, including observation bias, the inability to capture  
46 non-equilibrium or source-sink dynamics, statistical extrapolation fallacies, and the lack of integration  
47 of species dispersal or biotic interactions (Lee-Yaw et al. 2022). Some of those limitations might be  
48 particularly relevant for invasive species, since they show non-equilibrium distributions because of  
49 incomplete range expansion, transient dynamics, or niche shifts from native and invaded ranges (Gallien  
50 et al. 2012; Elith et al. 2017). Biased observed occurrences challenge SDMs for all organisms (Dubos  
51 et al. 2022) but might be even more complex for species with rapid colonization speed like invasives  
52 (Gallien et al. 2012; Moudrý et al. 2024). Approaches such as pooling species, accounting for imperfect  
53 detection, and implementing autoregressive structures can help address spatial and sampling biases in  
54 species' native range (Dorazio 2014; Fithian et al. 2015; Pacifici et al. 2017; Hui 2023; Soley-Guardia  
55 et al. 2024). However, mitigating bias for alien species in their invaded ranges is more complex, as  
56 additional mechanisms beyond heterogeneous sampling effort or imperfect detection are involved (as  
57 depicted in **Figure 1**, and exemplified in a specific case in **Box 1**). As a result, invasive species  
58 distributions are frequently under- or over-predicted, as current records fail to reflect their potential  
59 ranges (Hui 2023).

60 Given the need to understand invasive species potential distributions for global biodiversity  
61 conservation, and the limitations of correlative approaches, alternative methods have been proposed. In  
62 this review we aim to (i) decompose the mechanisms behind biases or limitations that cause correlative  
63 SDM failure in invasive species, (ii) justify and define the foundations of mechanistic niche models  
64 (MNMs) and their potential for invasive species to solve correlative limitations. Specifically, MNMs  
65 (or ecophysiological models) aggregate process-explicit distribution models that explicitly test  
66 responses to specific environmental factors, approaching the species fundamental niche. Other process-

67 explicit models such as demographic models, or abundance dynamics will not be considered in this  
68 review, since they approach the realized niche, and thus they might fail to predict invasive species  
69 dynamics under changing conditions. While discussing these different mechanistic models, we will also  
70 (iii) explore how MNMs have been applied to project invasive species potential distributions and (iv)  
71 assess whether MNMs truly address the limitations of correlative SDMs for invasive species.

72

### 73 **Complex source-sink dynamics: Global trade and disturbance might drive invasive** 74 **species presence**

75 The presence of species outside their native ranges is primarily a consequence of human movement  
76 across the globe (Turbelin et al. 2017). Globalisation has facilitated the crossing of previously  
77 impenetrable geographic barriers, sometimes even transporting species in regions (i.e. geographic  
78 space) which climatic conditions are outside the species' native niche (i.e. environmental space).  
79 Transportation networks, trade, and international travel now serve as effective vectors for introducing  
80 non-native species (Westphal et al. 2008; Hulme et al. 2021; Gippet and Bertelsmeier 2021).

81 Historical empires have also left a legacy on global biodiversity. For instance, Lenzner et al. (2022)  
82 demonstrated how the colonial activities of four European empires—British, Spanish, Portuguese, and  
83 Dutch—structured current alien floras worldwide. Their study revealed that flora compositional  
84 similarity is higher than expected among regions previously under the same empire's influence. In one  
85 example, South African Aizoaceae plants, long cultivated in British gardens, likely facilitated the  
86 invasion of species such as hottentot-fig (*Carpobrotus edulis*), baby sun rose (*Aptenia cordifolia*), and  
87 pink ice plant (*Drosanthemum floribundum*) in Europe (Preston 1988; Campoy et al. 2018).

88 In addition to global trade, increased propagule pressure might allow urbanised areas to temporally  
89 sustain invaders. Urbanisation is a major driver of exotic species richness (Heringer et al. 2022).  
90 Disturbed communities often host lower biodiversity and have been described as less resistant to  
91 invasions, although this relationship may vary with the invasion stage (Stachowicz and Tilman 2005;  
92 Guo et al. 2024). Lower biotic resistance and increased resource availability in disturbed environments  
93 explain the presence of the bermuda buttercup (*Oxalis pes-caprae*) in its invaded range (González-  
94 Moreno et al. 2015).

95 Highly populated areas are subject to higher invasive propagule pressure due to global trade, which  
96 increases the likelihood of successful establishment (Borden and Flory 2021). For example, the  
97 pinewood nematode (*Bursaphelenchus xylophilus*) in China is more likely to occur in areas with high  
98 human population density (Robinet et al. 2009). Connectivity, such as road networks, further facilitates  
99 human-mediated species distribution by amplifying plant invasions and enabling dispersion in disturbed  
100 habitats (Son et al. 2024). Connectivity not only enhances range expansion but also the likelihood of

101 species detection. Spatial autocorrelation in species records (not only at the invaded range) often reflects  
102 uneven sampling efforts and site accessibility (e.g. roads, urban areas; Dormann et al. 2007; Botella et  
103 al. 2020). An interesting case involves the invasive bluegill (*Lepomis macrochirus*), where the fish's  
104 presence in ponds correlates with the visibility of those ponds from nearby roads. Increased visibility  
105 attracts fishing activities, a key introduction pathway for this species (Kizuka et al. 2014).

106 Even though connectivity might explain the arrival of a species in a specific location, it does not  
107 guarantee species success. Approximately 40% of global invasive species were intentionally introduced  
108 for their charismatic appeal or specific functional uses, such as terrain stabilisation, fishery support, or  
109 culinary purposes (Turbelin et al. 2017). These intentional introductions often occurred outside the  
110 species' native climatic niches. Human activity has been found to drive the establishment of non-native  
111 plants on islands, but not their subsequent invasion (Pfadenhauer et al. 2024). Records in citizen science  
112 platforms such as iNaturalist may fail to indicate whether observations represent casual or wild  
113 populations (López-Guillén et al. 2024), impacting correlative SDM predictions. Similarly, Hui (2023)  
114 highlights that occurrence records often lack details on whether they represent established or sink  
115 populations, which would pose distinctive expansion risk. Consequently, invasive occurrences are  
116 strongly influenced by the impact of human activities and movement.

117 Overall, urban and disturbed areas exhibit increased alien species richness due to heightened propagule  
118 pressure, reduced biotic resistance, and increased resource availability. Whereas using the native range  
119 occurrences to capture species presence in the invaded range might fail due to underestimation around  
120 urbanized areas, using the invaded range occurrences to predict future distribution might fail as well  
121 since occurrences do not constitute established populations. The usage of both native and invaded  
122 ranges registers has been proposed (Broennimann and Guisan 2008) but this approach might require  
123 niche conservatism, which will be discussed in the next section.

124

### 125 **Niche shifts: Invasive species might grow in conditions outside their native niche**

126 After arriving in a novel environment, one of the primary factors determining a species' establishment  
127 is habitat suitability (Weiher and Keddy 1995). Habitat suitability depends on the climate, resource  
128 availability, and the presence of native competitors or predators (Hirzel and Le Lay 2008). Invasive  
129 species often thrive in environments resembling their native habitats but with fewer natural enemies,  
130 allowing rapid spread—a concept known as the Enemy Release Hypothesis (Keane and Crawley 2002).  
131 For example, invasive mammals are more likely to establish when introduction sites fall within their  
132 native climatic niche (Broennimann et al. 2021). However, invasive species can also experience shifts  
133 of their niche during invasion (Guisan et al. 2014), in which case fitting the SDMs with data from both  
134 the native and invaded ranges could capture better the current species distribution (Broennimann and  
135 Guisan 2008; Kearney et al. 2010).

136 When contrasting realised niches from invaded and native ranges, studies with plants generally support  
137 niche conservatism (Petitpierre et al. 2012; Liu et al. 2020a). However, while arriving in conditions  
138 belonging to the realized native niche may facilitate initial establishment, it does not guarantee invasive  
139 success (Broennimann et al. 2007; Divíšek et al. 2018). This discrepancy might be due to (i)  
140 evolutionary processes that lead to a differentiation of the fundamental niche during the invasion  
141 process and/or (ii) even though the fundamental niche is conserved, only a subset of it was occupied in  
142 the native range (due to habitat availability or biotic interactions) (Broennimann et al. 2007; Qiao et al.  
143 2017). This second case falls within the niche variation hypothesis, that suggests that populations  
144 released from competition (i.e. natural enemies for invaders), are able to expand their realised niche  
145 (Van valen 1965, Bolnick et al. 2007) For example, island endemics such as amphibians and reptiles  
146 demonstrate high potential to expand their realised niches, illustrating how environmental matching  
147 (i.e. matching conditions from occurrences between native and invaded range) is not always required  
148 for invasion (Liu et al. 2020b; Stroud 2020). Diverging metrics for niche contrasts accounting for habitat  
149 availability have hindered conclusive evidence regarding niche conservatism in invasive species (Bates  
150 and Bertelsmeier 2021).

151 Beyond habitat availability, evolutionary processes can explain invasive species success outside the  
152 abiotic conditions observed in the native range (Broennimann et al. 2007; Pearman et al. 2008). Rapid  
153 adaptation associated with the lack of natural enemies, founder effect and/or genetic drifts (Eckert et al.  
154 1996), plays a critical role in invasive success, potentially leading to niche evolution (Pearman et al.  
155 2008; Colautti and Barrett 2013; Fenollosa and Munné-Bosch 2019a; Campoy et al. 2021). For  
156 example, differential thermal sensitivity (i.e. fundamental niche shift) was reported between individuals  
157 from the native and invaded ranges in the hottentot-fig under controlled conditions (*Carpobrotus edulis*,  
158 **Box 1**). In such cases, using occurrences from the native range to fit SDMs is discouraged. For example,  
159 for the Asian yellow-legged hornet (*Vespa velutina nigrithorax*), correlative SDMs performed better  
160 when native distribution data were excluded (Barbet-Massin et al. 2018). Mixed results were observed  
161 for invasive beetles, with two of five species showing niche conservatism (Duncan et al. 2009), while  
162 cane toads (*Rhinella marina*) demonstrated a realised niche shift (Tingley et al. 2014).

163 Overall, whereas environmental matching might contribute to species establishment into novel regions,  
164 native occurrences do not always explain species potential growth on the invaded range. Native realised  
165 niche unfilling due to habitat or dispersal limitation and biotic interactions, as well as fundamental niche  
166 shifts due to genetic bottlenecks and/or rapid adaptative processes in response to enemy release and/or  
167 founder effects, explain this climatic mismatch. Selecting the proper data for fitting SDMs (only native,  
168 only invaded, both or specific subsets of occurrences) would require a full characterization of those  
169 processes, which is not usually available.

170

## 171           **Non-equilibrium distribution: lag-phase, range expansion and management**

172   Time plays a complex and non-linear role in defining the distribution of invasive species (Broennimann  
173   et al. 2014; Theoharides and Dukes 2007; Robeck et al. 2024). After a species arrives in a novel  
174   environment, the lag period before noticeable population growth varies significantly, creating an  
175   "invasion debt" (González-Moreno et al. 2017; Evers et al. 2021; Duncan 2021). This establishment lag  
176   phase is influenced by certain functional traits, with annual self-fertilising or non-sexual reproduction  
177   species being less likely to experience prolonged lags (Robeck et al. 2024). Once established, the spatial  
178   spread of an invasive species is often determined by local environmental conditions and reproductive  
179   strategies. Species with high fecundity and adaptability tend to colonise new areas more rapidly  
180   (Capellini et al. 2015; Allen et al. 2017). A recent meta-analysis found that invasive plants' population  
181   growth rates increase with residence time, highlighting how these vital rate changes can complicate  
182   predictions of species potential (Suárez-Seoane et al. 2017; Gruntman and Segev 2024).

183   Climate shifts, land-use changes, management actions or resource availability can trigger sudden  
184   outbreaks, accelerating the spatial and temporal spread of invasive species. These shifts can lead to  
185   rapid, unpredictable changes in distribution patterns. In the case of the spotted knapweed (*Centaurea*  
186   *stoebe*), its invasion followed an initial spread phase in ruderal habitats, and a niche expansion into  
187   climates not occupied in the native range was observed after an extended lag phase (Broennimann et al.  
188   2014). Additionally, conservation actions—such as mitigation efforts or habitat restoration—can  
189   further influence invasion dynamics, although these are often underrepresented in distribution models  
190   (Pyšek and Richardson 2010). SDMs fitted at different scales can be strongly informative to design  
191   management actions and monitor invasion potential, as done with the giant hogweed (*Heracleum*  
192   *mantegazzianum*) in Switzerland (Shackleton et al. 2020). Overall, registered occurrences at a given  
193   time often fail to capture the full potential of invasive species, as they are shaped by establishment lags,  
194   adaptive processes, and management interventions as well as by the complex source-sink dynamics  
195   discussed previously.

196   Populations within the invaded range may have different potential distributions. High intraspecific  
197   variability within invaded ranges due to multiple introductions, along with hybridisation and rapid  
198   adaptation, can result in population differentiation within a single species' invaded range, potentially  
199   leading to niche differentiation (Pearman et al. 2008; Pearman et al. 2010; Colautti and Barrett 2013).  
200   For example, local adaptation in purple loosestrife (*Lythrum salicaria*) was observed along a 1000-  
201   kilometer climatic gradient in the invaded range (Colautti and Barrett 2013). Rapid adaptation during  
202   range expansion may lead to genetically distinct populations, as demonstrated by wolves (*Canis lupus*)  
203   in Central Europe (Szewczyk et al. 2019). SDMs calibrated with occurrences from both confirmed and  
204   unconfirmed populations of the invasive turtle pond slider (*Trachemys scripta*) revealed contrasting  
205   projections, emphasising its strong expansion potential (Cordier et al. 2020). SDM calibration with

206 naturalised populations outperformed SDMs calibrated using combined native and invasive records of  
207 common ragweed (*Ambrosia artemisiifolia*) (Dullinger et al. 2009). Similarly, models calibrated with  
208 early invasion data may underperform compared to those using established populations (Václavík and  
209 Meentemeyer 2009).

210 Human assistance to exotic species outside their climatic niche can also promote invasive populations  
211 differentiation and fundamental niche shifts within the invaded range. We propose coining this  
212 phenomenon as “invasive nurturing” (i.e. assisting organisms outside their climatic niche opening the  
213 possibility for adaptation). Botanical gardens exemplify this phenomenon, assisting species to survive  
214 outside the environmental conditions of the native range, with extensive documentation in China (Ni  
215 and Hulme 2021), Indonesia (Junaedi et al. 2021), and Europe (Klonner et al. 2019). Urban trees planted  
216 outside their native niches also exhibit wider realised niches than native species (Kendal et al. 2018).  
217 Economic interests, such as the ornamental trade, contribute to this process, as seen with sacred bamboo  
218 (*Nandina domestica*) in the USA (Beaury et al. 2021; Bradley et al. 2022).

219 Populations at the edges of a species’ range—where physiological stress, drift, expansion load, and  
220 swamping gene flow from range interiors are more pronounced—add further uncertainty to distribution  
221 models (Gaston 2009; Sexton et al. 2009). The centre-periphery hypothesis posits that demographic  
222 performance declines from the centre of a species' range towards its edges, potentially overestimating  
223 distribution when edge populations are treated as established ones. While this hypothesis has been  
224 supported in marginal climates (Bontrager et al. 2021; Perez-Navarro et al. 2022), calls for its re-  
225 evaluation highlight the need for empirical studies, particularly for invasive species (Purves 2009;  
226 Csergő et al. 2017; Pironon et al. 2017; Angert et al. 2020; Chevalier et al. 2021; Kunstler et al. 2021).  
227 Interestingly, probably due to the expansion dynamics, invasive plants often exhibit higher growth rates  
228 in edge populations compared to central populations (Gruntman and Segev 2024).

229 Despite its critical importance, intraspecific variability (including population’s variability within  
230 species range) remains underrepresented in distribution models (Pearman et al. 2010; Collart et al.  
231 2021). The high sampling effort required to capture this variability and the absence of established  
232 frameworks to integrate it pose significant barriers (Collart et al. 2021; Song and Li 2023). This gap in  
233 modelling limits the ability to accurately predict distributions for species with variable populations,  
234 particularly those undergoing rapid expansion or adaptation in their invaded ranges.

235

### 236 **Hybridization, genetic admixture and genetic drift might hinder invasive species** 237 **identification**

238 Identification challenges are a general limitation of correlative SDMs as they depend on occurrence  
239 data. Small, camouflaged, elusive, or subterranean species pose additional barriers to accurate  
240 monitoring (Jarić et al. 2019; Richter et al. 2021). However, these challenges are exacerbated in invasive

241 species. Hybridisation, strong genetic admixture, or genetic bottlenecks because of the fast adaptation  
242 processes at novel environmental conditions might hinder a clear identification, leading to incomplete  
243 or inaccurate occurrence records.

244 Crypticity in species identity in its invaded range (Jarić et al. 2019) or during range expansion (Rosche  
245 et al. 2024) represent a significant source of observational bias, deeply affecting the outputs of  
246 correlative SDMs. While citizen science platforms such as iNaturalist provide valuable insights into  
247 invasive species distribution, the quality of data—particularly proper species identification—requires  
248 careful consideration (López-Guillen et al. 2024).

249 Fast adaptations, genetic admixture, and hybridisation during invasive expansion can lead to significant  
250 genetic and morphological complexities, making species identification challenging, particularly in  
251 plants. Examples include the native-invasive admixture of common reed (*Phragmites australis*) (Pyšek  
252 et al. 2018), genetic clusters of hottentot-fig (*Carpobrotus edulis*) (Campoy et al. 2018; Novoa et al.  
253 2023), shifts in cytotype frequency in the spotted knapweed (*Centaurea stoebe*) (Treier et al. 2009;  
254 Rosche et al. 2024), the enigmatic complex of lantana (*Lantana camara*) (Goyal et al. 2015), and  
255 confusion between devil's backbone (*Kalanchoe daigremontiana*) and its invasive hybrid *K. ×*  
256 *houghtonii* (Herrando-Moraira et al. 2020). Taxonomic uncertainty can also hinder invasive species  
257 monitoring, as seen with peppermint shrimp (*Lysmata vittata*), where conflicting morphological  
258 descriptions, inconsistent terminology, and limited molecular data complicate identification (Aguilar et  
259 al. 2022).

260

### 261 **Predicting to novel conditions requires a full understanding of species' physiological** 262 **limitations**

263 Different climatic scenarios can significantly alter species' potential for persistence and colonisation  
264 (Pironon et al. 2017). This necessitates training models not only with past and current environmental  
265 conditions but also with information on species' ability to face novel conditions (Kearney and Porter  
266 2009) including extreme climatic events (Perez-Navarro et al. 2022). Incorporating such data is critical  
267 for predicting species distributions under climate change scenarios.

268 Novel environmental conditions can result from environmental drivers falling out of the explored  
269 ranges, or because novel combinations arise (Elith 2017). Climatic or bioclimatic variables of known  
270 species locations are the predominant predictors used in invasive SDMs, often supplemented with  
271 topographic, pedological, and anthropogenic variables (López-Tirado and Gonzalez-Andújar 2023).  
272 However, novel climatic conditions, which by definition have not been observed, require the  
273 understanding of the species' fundamental niche to make accurate predictions (Kearney et al. 2009;  
274 Elith 2017; Briscoe et al. 2023).

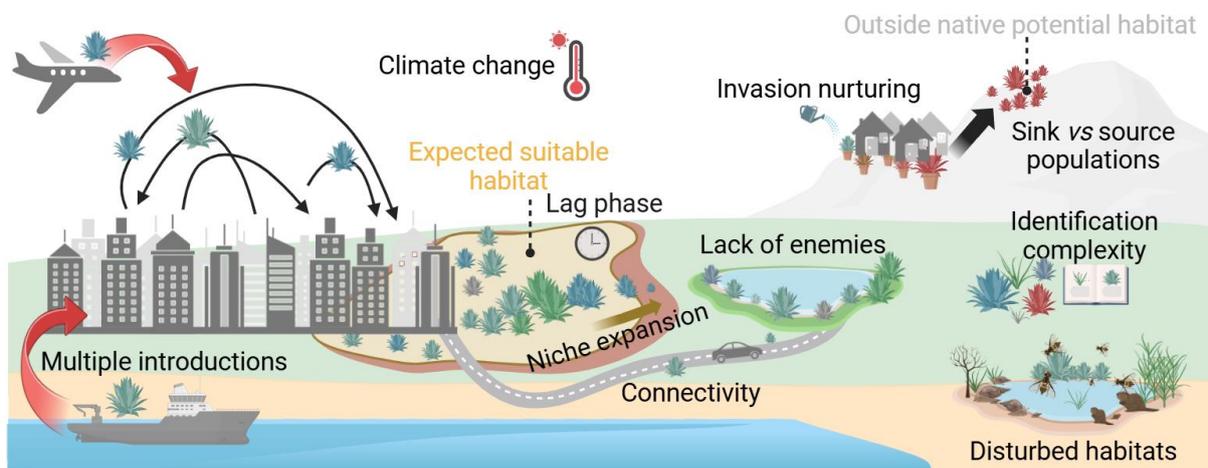
275 Correlative SDMs assume that abundance reflect species physiological limitations, which are  
276 homogeneous within the species range. However, physiological plasticity is a complex trait susceptible  
277 to local adaptation (Fenollosa and Munné-Bosch 2019b). Lower temperature physiological limits are  
278 not constant across the invaded range of the cane toad (Kolbe et al. 2010), as it isn't some woody species  
279 drought tolerance to extreme events (Perez-Navarro et al. 2022). Such dynamics remain unaddressed in  
280 correlative SDMs that rely on past and present conditions on registered presences to define species  
281 physiological limits, which limits their predictive accuracy to under changing climates.

282

### 283 **Invasive species spatio-temporal complexities as an adaptation laboratory**

284 The distribution of invasive species is uniquely shaped across space and time (Laxton et al. 2022,  
285 **Figure 1, Box 1**). Since the species distribution on the invaded range is in equilibrium with their  
286 environment, their distributions and impacts are affected by factors beyond abiotic conditions and are  
287 changing at relatively fast rates (Werner et al. 2024). Alternatives to correlative SDMs offer promising  
288 approaches to capturing these complexities, especially under climate change scenarios. This is crucial  
289 not only for addressing the biodiversity threats posed by invasive species but also for advancing our  
290 understanding of ecological adaptation over relatively short time-periods.

291



292

293 **Figure 1. Schematic representation of spatio-temporal complexities of invasive species**  
294 **distributions, from their arrival to their expansion.** Multiple introductions increase propagule  
295 pressure and facilitates invasions. Some species might not occupy all potential climatic niche due to lag  
296 phase and might shift with climate change. Connectivity to disturbed habitats and without natural  
297 enemies of the introduced species might facilitate and accelerate invasive spread. Invasion nurturing  
298 facilitates climate discovery to novel areas. Not all occurrences might constitute established or source  
299 populations. Identification complexities might hinder invasive species registrations. For further details,  
300 refer to the text. Created with BioRender.

301

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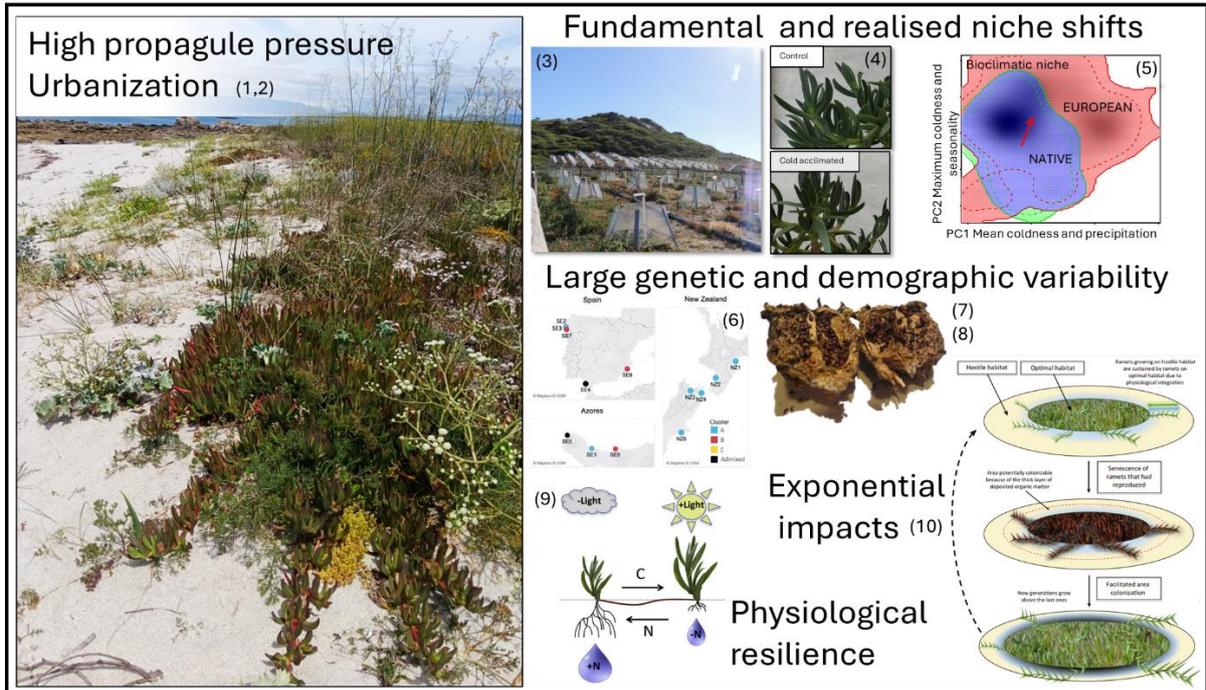
302 **BOX 1. Spatio-temporal complexities of an invaders case study, the hottentot-fig invasion.**

303 The invasive hottentot-fig (*Carpobrotus edulis*) is a succulent clonal plant native to the Cape region of  
304 South Africa. Its reptant stems form dense mats, enabling it to thrive in diverse environments (Wisura  
305 and Glen 1993). The species has successfully invaded Mediterranean climate regions, spreading  
306 extensively across coastal sand dunes, rocky coasts, and sea cliffs in Europe (Campoy et al. 2018). This  
307 invasion negatively impacts native communities, reducing local richness and diversity (Vilà et al. 2006;  
308 Santoro et al. 2012; Sarmati et al. 2019). Additionally, *C. edulis* modifies soil conditions through  
309 necromass production, altering pH, moisture, nutrient content, and microbial activity (Santoro et al.  
310 2011; Novoa et al. 2013; Vieites-Blanco and González-Prieto 2018).

311 Here, we selected ten examples that exposed mechanistic determinants behind *C. edulis* success that  
312 limit the predictive capacity of correlative SDM as a case example (**Numbered in Figure 2**). **(1)**  
313 Ornamental interest increases propagule pressure both within and outside its suitable range. For  
314 instance, in its native range, the species experiences annual rainfall of 464 mm but invades areas like  
315 Galicia (NW Spain), which receive 1228 mm (Picture: E. Fenollosa). **(2)** The species presence is  
316 associated with habitat disturbance (Lechuga-Lago et al. 2017). **(3,4)** Differential stress responses have  
317 been observed between native and invasive populations under varying water and temperature conditions  
318 (Pictures from Campoy et al. 2021 and Fenollosa and Munné-Bosch 2019a). **(5)** Realised niche shift  
319 towards colder regions was found between European (invasive) and the native ranges (Fenollosa and  
320 Munné-Bosch 2019a). **(6)** Multiple genetic clusters have been identified within invaded ranges (Novoa  
321 et al. 2023). **(7)** Large intraspecific variability in seed production has been observed over short distances  
322 (Fenollosa et al. 2021). **(8)** Populations form persistent soil seed banks with different longevities  
323 (Fenollosa et al. 2020). **(9)** CAM shift and physiological integration enable resilience to resource  
324 heterogeneity (Roiloa 2019). **(10)** Growth and death cycles regulate the exponential impacts of the  
325 invasion (Fenollosa et al. 2016). This case study illustrates the spatio-temporal complexities of invasion,  
326 demonstrating the limitations of correlative SDMs and emphasising the importance of mechanistic  
327 approaches.

328

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329

330 **Figure 2.** Ten studies compendia with the invasive hottentot-fig (*Carpobrotus edulis*) via mechanistic  
 331 lens, highlighting the elements that shape its distribution, hindering accurate forecasts using correlative  
 332 SDMs. Pictures credit is acknowledged in Box 1.

333 **Mechanistic Niche Models: forecasting species potential from physiological limitations**

334 Given that correlative SDMs may be unreliable for species with non-equilibrium distributions (Briscoe  
 335 et al. 2019; Lee-Yaw et al. 2022), alternative or complementary approaches are needed to predict  
 336 invasive species distributions, determine potential habitats, and understand eco-evolutionary processes  
 337 under climate uncertainty. In response, ecologists are increasingly incorporating biological processes  
 338 into distribution predictions.

339 There are a range of process-explicit models that explicitly account for processes such as physiology,  
 340 dispersal, demography evolution and biotic interactions (Briscoe et al. 2019; Urban et al. 2022). Here  
 341 we focus on models that capture physiological constraints by explicitly incorporating the mechanistic  
 342 links between the functional traits of an organism and its environment (Kearney and Porter 2009). These  
 343 models are variously referred to as eco-physiological models, biophysical models, mechanistic SDMs  
 344 or mechanistic niche models, with terminology depending partially on the extent to which mechanistic  
 345 links are identified via experimental data (e.g. on physiological tolerances, thermal performance) or  
 346 calculated using first principles (Gates 1980). For simplicity, we refer to these collectively as  
 347 mechanistic niche models (MNMs) hereafter but highlight the implications and potential challenges of  
 348 differences in parameterisation.

349 We focus on MNMs because they are grounded in the species' fundamental niche, making them  
350 particularly suited for predicting the potential distribution of invasive species, including under climate  
351 change. MNMs use experimental data or calculated physiological limitations—such as thermal limits  
352 and water requirements—to define species' range limits and project distributions (Kearney and Porter  
353 2009; Evans et al. 2015). By incorporating biological mechanisms from experimental data including  
354 physiological tolerances (e.g. thermal limits, growth rates) and demographic traits (e.g. survival and  
355 fecundity), MNMs provide a nuanced understanding of species distributions independent of recorded  
356 occurrences. In principle, this would allow predictions under novel environmental conditions, and could  
357 aid conservation and management efforts, such as identifying critical thermal thresholds or optimising  
358 invasive species management.

359 While MNMs share some similarities with process-explicit models that also aim to capture demographic  
360 responses to environments (i.e. demographic distribution models; Merow et al. 2017), we differentiate  
361 them here by emphasizing their mechanistic basis in physiological processes and constrains as a  
362 function of environmental variables, as opposed to relying primarily on demographic patterns from field  
363 data or modelling individual's physiological processes without considering environmental influence.

364 Building MNMs demands a substantial amount of detailed, species-specific empirical data linked to  
365 relevant environmental variables. Physiology has been proposed as a key component of species  
366 distribution models (SDMs) (e.g. Schwinning and Parsons 1996; Kearney and Porter 2009), and the  
367 need for combined expertise in modelling, demography, and environmental physiology has hindered  
368 the widespread adoption of MNMs (e.g. Buckley et al. 2010; Kearney et al. 2012; Woodin et al. 2013).  
369 Kearney and Porter (2009) identified a major barrier in linking behavioural, morphological, and  
370 physiological traits with GIS datasets on climate and terrain. To address this challenge, they proposed  
371 using biophysical ecology, a field rooted in ectotherm studies (Tracy 1982) that applies thermodynamic  
372 principles to organisms to derive mechanistic models of their physiological processes and responses  
373 (Gates 1980). Biophysical models require data on species' morphological, physiological and  
374 behavioural traits, and can be parameterised using data from a range of sources including museum  
375 specimens, behavioural observations, physiological experiments and allometry (recently reviewed by  
376 Ridell et al. 2023). Biophysical models have mainly been used in ectotherms, though their use in  
377 endotherms is growing (Angilletta 2009; Briscoe et al. 2023; Ridell et al. 2023). Similarly, dynamic  
378 energy budget (DEB) models, which can be integrated within biophysical ecology (Kearney et al. 2010),  
379 have been also proposed for modelling resource allocation and species distribution in plants (Schouten  
380 et al. 2020; Russo et al. 2022).

381 Key data inputs of MNMs include physiological parameters, such as metabolic rates, thermal tolerances  
382 (upper thermal limit, lower thermal limit, activity window), developmental rate, hypoxia tolerance, and  
383 growth rates under environmental gradients (Evans et al. 2015). However, physiological constraints

384 may occur in a hierarchical manner, with some processes (or during certain developmental stages) being  
385 more sensitive to environmental change. For example, species survival is often possible over a wider  
386 range of temperatures than locomotion or reproduction (Buckley and Kingsolver 2012). Overall, data  
387 requirements for MNMs vary significantly depending on the organism type, as different species demand  
388 unique physiological, demographic, or environmental datasets to accurately represent their responses  
389 to ecological conditions.

390 While MNMs have primarily focused on environmental variables such as temperature, other key  
391 mechanistic elements that shape species distributions could also be incorporated. Although temperature  
392 significantly influences species performance, species-specific critical temperatures often fail to fully  
393 explain biogeographical patterns (Sunday et al. 2012), mainly because they are often not solely or  
394 directly related to range limits and need to be integrated with other parameters in biophysical models  
395 (Chevalier et al. 2024). Other global gradients—such as oxygen levels, light availability, pressure, pH,  
396 and water balance—play vital roles in shaping species distributions. These factors covary with latitude,  
397 elevation, and ocean depth, and species exhibit strong physiological and behavioural adaptations to  
398 these abiotic variables within their historic ranges (Spence and Tingley 2020). A greater focus on these  
399 underexplored variables into MNMs could enhance the models' ability to predict distributions across  
400 diverse environments and under changing climate conditions (Kearney et al. 2018; Telemeco et al.  
401 2022).

402 Mechanistic niche models mark a significant advancement in ecological modelling by linking  
403 physiological processes with species distributions to deliver biologically grounded predictions. Unlike  
404 correlative SDMs, MNMs explicitly incorporate physiological and demographic data, allowing in  
405 principle for more robust projections under novel environmental conditions, such as those induced by  
406 climate change or species invasions. By simulating species interactions with key environmental  
407 factors—such as temperature, water availability, and other gradients—MNMs enhance our  
408 understanding of the fundamental niche. Despite their substantial data and parameterisation  
409 requirements, making them currently difficult to apply to large numbers of species (as SDMs can do,  
410 e.g. Adde et al. 2024), these models provide unparalleled insights into ecological dynamics.  
411 Consequently, MNMs are essential for advancing ecological research and optimising conservation and  
412 management strategies in a rapidly changing world (Kearney and Porter 2009; Elith et al. 2010; Higgins  
413 et al. 2020).

414

## 415 **MNMs on invasive species**

416 Mechanistic niche models have emerged as a powerful tool for understanding the environmental and  
417 biological constraints shaping the distribution of species (Kearney and Porter 2009; Evans et al. 2015;  
418 Briscoe et al. 2019). Relative to SDMs, MNMs are still not widely used, but modelling invasive species  
419 distributions has been one of their main applications (Briscoe et al. 2019). To explore the number of  
420 studies that have attempted to predict invasive species distributions from physiological limitations,  
421 understand the diversity of nomenclature and model types, as well as types of empirical data used to  
422 parametrize the model, we performed a systematic review of published studies using MNMs in invasive  
423 species worldwide (**Supplementary material 1**). Briefly, we based our search on Briscoe et al. 2019  
424 search terms to obtain three types of models: MNMs, demographic distribution models (DDMs) and  
425 individual-based models (IBMs), combined with filters to detect studies with invasive species. Although  
426 demographic distribution and individual-based models were out of the scope, we included them in the  
427 search terms to check if some of them could be also categorized as MNMs. This was common for IBMs,  
428 which simulate populations considering discrete individuals each with a set of attributes. We included  
429 IBMs that accounted for individual's performance in response to environmental constraints from  
430 experimental data, as well as DDMs that were fitted using experimental data (and not field data, as  
431 discussed in the previous section).

432 Mechanistic niche models have been used to a very limited extent. Our systematic review resulted in  
433 53 articles including MNMs for invasive species from 2007 to 2024 (**Figure 3**). This relatively low  
434 number highlights the challenges of gathering the complex data required to construct MNMs and apply  
435 them effectively in the field. Additionally, the lack of unified nomenclature to name these models across  
436 studies further complicates their application. In this regard, our systematic review revealed diverse  
437 model nomenclature usages when building MNMs with invasive species. Across the 53 articles authors  
438 named MNMs as: physiologically based (Higgins et al. 2012), biologically informed (Lozier and Mills  
439 2011), biophysical (Tingley et al. 2014), temperature-driven (Logan et al. 2007), ecophysiological  
440 (Ginal et al. 2021), process-based (Gutierrez et al. 2007), mechanistic phenology (Iwamura et al. 2020)  
441 and phenotypically explicit model (Brass et al. 2024). Surprisingly, we found that a full description of  
442 physiological processes that constrain species performance under different environmental conditions  
443 was rather rare. Instead, researchers have been attempting to include some key processes or  
444 physiological constraints, and in some cases use pre-built frameworks or transferring physiological data  
445 from other species. Since some of those pre-built frameworks can include some data from species  
446 occurrences, when they do, they do not constitute mechanistic but hybrid approaches. Some examples  
447 of these pre-built frameworks (some of them could be mechanistic, or hybrid depending on the data use  
448 to parametrize it) are the CLIMEX model mainly used for insects (e.g. Ponti and Gutierrez 2023), the  
449 TTR (Thornley transport resistance) (Higgins and Richardson 2014; Higgins et al. 2020) or dynamic  
450 vegetation models such as LPJ-GUESS for plants (Leiblein et al. 2016), DBEM (dynamic bioclimate

451 envelop models) for fishes (Zhu et al. 2020), and NicheMapper for ectotherms and endotherms  
452 (Kearney et al. 2008; Kolbe et al. 2010; López-Collado et al. 2013; Tingley et al. 2014; Strubbe et al.  
453 2023). Considering the strong data requirements for a fully mechanistic approach, we decided to include  
454 and discuss benefits and limitations of all those approaches, which in some cases will not be suited to  
455 understand invasive species potential distribution under novel environmental conditions. When  
456 classifying the studies in our review by MNM modelled taxonomic groups, over 50% focused on insects  
457 while nearly 20% addressed plants (**Figure 3**). Invasive insects such as the tomato pinworm (*Tuta*  
458 *absoluta*; Ponti et al. 2021; Early et al. 2022; Ponti and Gutiérrez 2023), mosquitos (*Aedes sp.*; Iwamura  
459 et al. 2020; Pasquali et al. 2020; Brass et al. 2024) and plants, such ambrosia (*Ambrosia artemisiifolia*;  
460 Chapman et al. 2014; 2017; Leiblein-Wild et al. 2016) have been frequent subjects of these models due  
461 to their ecological impact and ability to rapidly colonise new environments. The extensive usage of  
462 MNMs in insects responds mainly to these species' strong dependence on temperature as well as their  
463 potential to act as vectors for disease (Rebaudo and Rabhi 2018). Besides insects and plants, four articles  
464 reported MNMs with amphibians, microorganisms (virus, Taylor et al. 2019), three with other  
465 vertebrates (a mammal, (Tablado and Revilla 2012), a reptile (Lin et al. 2019) and a fish (Zhu et al.  
466 2020)), and one study with a mollusc (Feng et al. 2020) (**Figure 3, Supplementary Material 2**).

467 Of the 53 articles found, 25 (47.2%) included projections of invasive species distribution under climate  
468 change scenarios, while the remainder focused on present environmental conditions. However, some of  
469 these studies aim was not solely to project species distribution under climate change conditions, but  
470 other applications. The second most common application of MNMs was to explore the contributions of  
471 environmental versus non-environmental drivers in shaping invasive species distributions (**Figure 3**).  
472 To do so, authors built both correlative models and MNMs and contrasted the resultant projections  
473 sometimes considering variables of interest. One of the examples of this application is the study of the  
474 sub-Antarctic insect by Pertierra et al. (2020). In this work, a MNM was parametrized from vital rates  
475 as function of temperature obtained after laboratory experiments where survival, growth and fecundity  
476 were monitored in larvae exposed to 0, 2, 4, 6 and 8°C for 30 days simulating the austral summer. The  
477 contrast of this MNM to a correlative SDM revealed high potential for the species to expand their  
478 invaded range and exposed how its current distribution is shaped by human presence.

479 Other applications of MNM in invasive species included: comparing multiple invaders' potential  
480 distribution to assist management actions decision-making (Gutierrez and Ponti 2013), test niche  
481 conservatism or niche shifts between invaded and native ranges (Tingley et al. 2014) and understand  
482 the role of intraspecific variability in species distributions (Kolbe et al. 2010). In some cases, both native  
483 and invasive species distributions were parameterized, such as the pathogen Bsal (*Batrachochytrium*  
484 *salamandrivorans*) with the threatened native fire Salamandra (*Salamandra salamandra*) to determine  
485 extinction risk (Deiß et al. 2024). In addition, some articles also used MNMs to predict invasion  
486 dynamics, but to do so, mechanistic models were coupled with occupancy data to predict spread. This

487 is the case of the study by Walter et al. (2023), where the temperature-dependent developmental  
488 performance of the spongy moth (*Lymantria dispar dispar*) was used as a covariate within a Bayesian  
489 occupancy model that considered tree canopy cover, local diffusive spread, habitat connectivity and  
490 population density from pheromone-baited traps. Other studies predicted invasion spread from  
491 physiological data by parametrizing the model with time-dependant rates (Hartley et al. 2010). In this  
492 study by Hartley et al. (2010) a degree-day model of development was used to model growth and  
493 distribution of the Argentine ant (*Linepithema humile*) in Hawaii, resulting into a rate-of-spread, and  
494 predicting future range expansion.

495 Our review identified several approaches used to meet data requirements for constructing MNMs.  
496 Thermal tolerance was the most frequently used variable to build response curves for invasive MNMs  
497 (e.g. Ginal et al. 2021 in an invasive frog, Brass et al. 2024 for an invasive mosquito). Following  
498 temperature, the relationship of temperature with species phenology or developmental rates was the  
499 second most common studied process to parametrize MNMs. Some examples include modelling the  
500 timing of the breeding season with invasive rabbits (Tablado and Revilla 2012), or Ambrosia's cold  
501 limitation by phenology (Chapman et al. 2014). Contrastingly, Zhang et al. (2021) built an MNM with  
502 soil water and nutrient requirements data from a microcosm experiment with cogongrass (*Imperata  
503 cylindrica*). Beyond environmental variables, other mechanisms that have been included when building  
504 MNMs in invasive species are multiple trophic systems (e.g. with the invasive yellow star-thistle in  
505 Gutierrez et al. 2008), demographic stochasticity (e.g. with the invasive European rabbit in Tablado and  
506 Revilla 2012) or evolutionary dynamics (e.g. with the dengue mosquito *Aedes aegypti* in Kearney et al.  
507 2009). Whilst survival has been the most selected trait in the reviewed studies, other traits, such as  
508 reproductive components or specific metabolites levels have also been incorporated to reflect species  
509 performance. For example, corticosterone levels influence avian range limits (Treen et al. 2015) or  
510 glycogen stores reflect the optimal status for aquatic ectotherms (Maazouzi et al. 2011).

511 Whereas some studies based the MNM on energy budget models (or more generally, resource allocation  
512 models), others were built from laboratory tests conducted under a limited number of experimental  
513 conditions (e.g. five different temperatures) or combined both via energy-mass balance equations. All  
514 modelling approaches result in a model where a performance variable is a function of the environmental  
515 conditions. Whereas laboratory-based models are constrained by the data used for parameterisation (e.g.  
516 specific laboratory-tested temperatures, life stage selected), resource allocation models are limited by  
517 the equations used, which are based on prior knowledge of the species. Regarding laboratory-based  
518 models, Fadda et al. (2024) modelled the ambrosia beetle (*Xyleborus bispinatus*) performance by fitting  
519 a convex function to growth rate data obtained from individuals exposed to a temperature gradient (17,  
520 20, 26, 29, 35 °C) over 36 days. Similarly, Pertierra et al. (2020) exposed midge larvae to 0, 2, 4, 6, and  
521 8 °C for 30 days, while Lin et al. (2019) subjected invasive lizard adults to four temperature groups: 10,  
522 12, 14, and 16 °C for 28 days. In contrast, Feng et al. (2020) used a plateau model, representing the

523 abiotic niche with three connected segments of differing slopes. This model was fitted with data from  
524 various experiments conducted at different temperature intervals.

525 On another hand, MNMs that use energy-mass balance equations can take multiple complexity levels  
526 (Briscoe et al. 2023). An example of an energy budget model is the MNM of the cane toad (*Rhinella*  
527 *marina*) in Australia. For this species, core body temperature was modelled by solving a steady-state  
528 energy balance equation (Kearney et al. 2008). While such approaches produce a continuous thermal  
529 curve, they require extensive species-specific knowledge. For instance, Kearney et al. (2008)  
530 incorporated numerous parameters for amphibians, including equations for heat exchange via cutaneous  
531 evaporation, surface-body mass functions, the distance of an average adult from the ground, active  
532 posture surface fraction, postural change effects, nocturnal activity regimes, relationships between body  
533 temperature and water loss, movement capacity and frequency at different temperatures, feeding rates,  
534 annual water balance, metabolic rate and body temperature relationships, cutaneous and respiratory  
535 water loss rates, water excretion, lethal temperatures for eggs and larvae, egg development rates at  
536 different temperatures, and sensitivity to pond configurations.

537 Individual's representativity must be considered when building MNMs, since it might limit our ability  
538 to capture invasive species' non-equilibrium dynamics. Kolbe et al. (2010) showed that low temperature  
539 tolerance is not a constant trait across the invaded range of the cane toad, and therefore, just a sampling  
540 site to collect individuals would not represent the potential expansion of the species. For this reason,  
541 some works considered using multiple genotypes (Chapman et al. 2017), selected a source population  
542 likely to be the introduction point (Coulin et al. 2019) or using at least a second generation to avoid  
543 maternal effects (Pertierra et al. 2020).

544 Factors limiting species distributions are not always replicable under controlled conditions,  
545 necessitating alternative approaches. This challenge is particularly relevant for species with low growth  
546 rates (e.g. trees) or those whose distributions are shaped by the interaction of multiple factors. For  
547 example, there has been recent criticism on the use of physiological thermal limits obtained from  
548 physiological experiments to capture the species distribution limits, particularly at lower temperatures,  
549 since adaptive and/or facilitative mechanisms could allow species to survive in temperatures below  
550 physiological limits (Chevalier et al. 2024). Unlike direct methods, inverse data collection (from  
551 individuals occurring in areas with differentiated environmental conditions) can capture environmental  
552 complexity beyond fixed temperature regimes (Evans et al. 2016). Latitudinal, altitudinal, or moisture  
553 gradients have been employed to parameterise some parts of MNMs for invasive species (Augustinus  
554 et al. 2020; Pasquali et al. 2020). However, it is crucial to note that inverse methods model the realised  
555 niche rather than the fundamental niche. Given that the realised niche of invasive species may not fully  
556 represent their potential range, projections based on such models may be biased, limiting their reliability  
557 for predicting future distributions.

558 Another used method to integrate more environmental conditions rather than a single environmental  
559 variable is the one taken by Merow et al. (2017), who modelled the invasive garlic mustard (*Alliaria*  
560 *petiolata*) and Japanese barberry (*Berberis thunbergii*) by collecting demographic data from an  
561 experimental setup including a series of transplant plots across diverse environments within the invaded  
562 range. However, categorising this approach as a MNM is delicate, as the model was defined as a  
563 demographic distribution model, but data from experimentation (not under fully natural conditions) was  
564 used to explore physiological responses to the environment. More importantly, the capacity of these  
565 type of models to capture invasive species fundamental niche to project their potential to novel  
566 conditions is strongly limited by the fact that non-novel conditions are explored. Experimental design  
567 and data parametrization must be wisely designed according to the study aim and species status.

568 During the filtering phase of our systematic review, we identified several articles that integrate both  
569 physiological limit data and species occurrence records (hybrid models), sometimes based on pre-built  
570 frameworks. Depending on how these models are parameterised, they may either inherit the limitations  
571 of correlative SDMs or align more closely with MNMs by incorporating non-environmental drivers,  
572 but the limit will be difficult to assess in most cases (Chevalier et al. 2024). CLIMEX was the most  
573 frequently used pre-built framework in the reviewed studies, appearing in 13 of the 53 articles, mainly  
574 with insects (but see Webber et al. (2011) and Shabani and Kumar (2015) for plants). CLIMEX is a  
575 commercially available software (Sutherst and Maywald 1985), specifically developed for modelling  
576 invasive species, which assumes a normalised concave growth response of species to various factors,  
577 with minimum, maximum and optimum values. In CLIMEX and other pre-build mechanistic  
578 frameworks, reaction norms in response to environmental factors can be fitted with experimental data  
579 but also with species occurrences, and only the first case will be a mechanistic approach (Ponti and  
580 Gutierrez 2023).

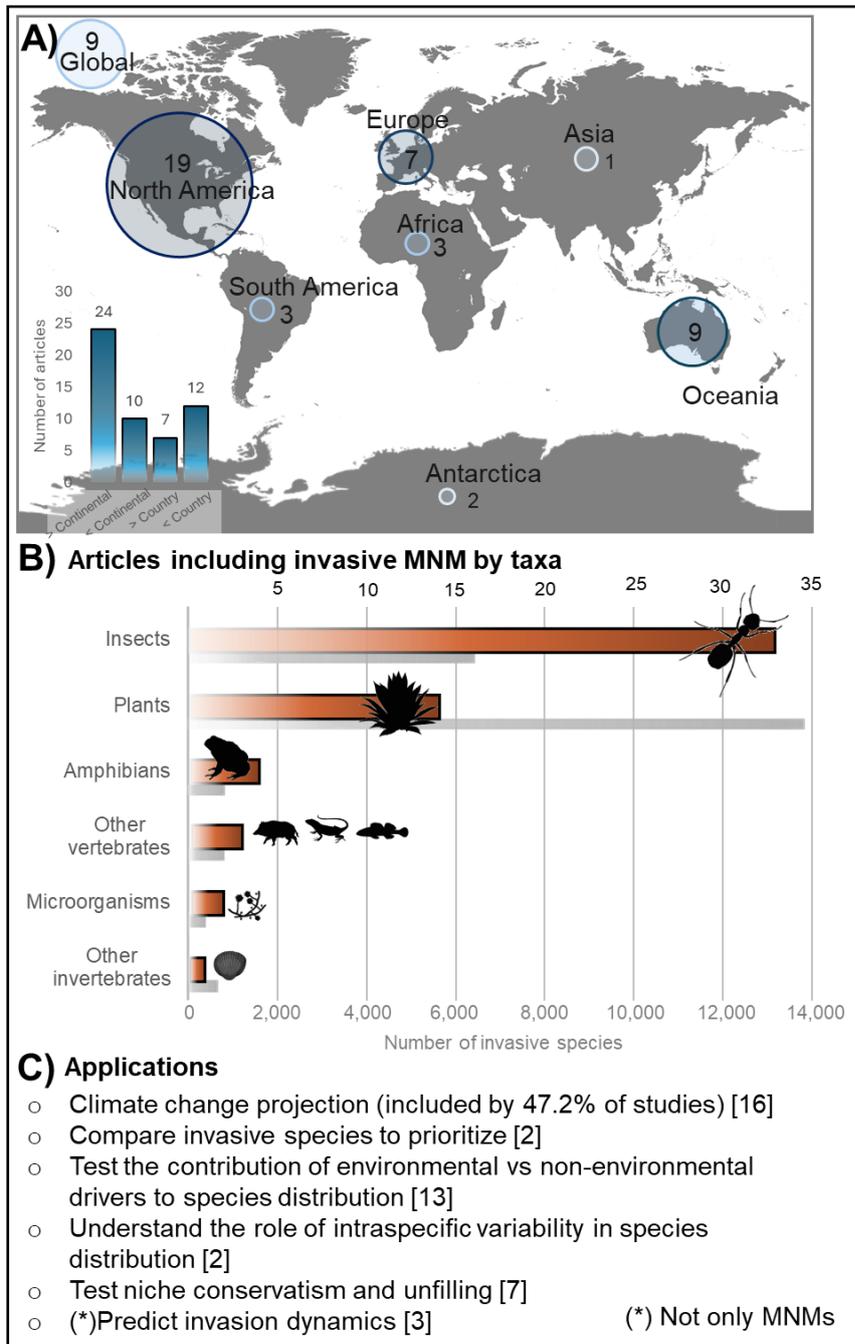
581 Some studies using the CLIMEX framework derived species physiological limits from native versus  
582 invasive occurrence data (Shabani and Kumar 2015). While this approach accounts for realised niche  
583 shifts between native and invaded ranges, it remains constrained by reliance on registered occurrences,  
584 which may not fully capture the species' potential range. For example, the usage of previously described  
585 thermal curves (e.g. Walter et al. 2023) from populations from the native range might not represent the  
586 invasive individuals. Recently, Formoso-Freire et al. (2023) demonstrated how a hybrid model  
587 combining an MNM with a correlative SDM for the invasive Asian hornet (*Vespa velutina*) provided  
588 insights into both the temporal dynamics of range expansion and long-term potential distributions. Since  
589 hybrid models also allow the inclusion of dispersal aspects in invasive species (Robinet et al. 2009;  
590 Klonner et al. 2019) the authors suggest are appropriated when aiming to model invasion rates under  
591 global change, particularly in data-limited contexts (Rodríguez et al. 2019; Bosch-Belmar et al. 2021;  
592 Guillaumot et al. 2022; Tourinho et al. 2023). However, considering the recent work by Chevalier et al.  
593 (2024) we are critical with combining physiological thermal limits with species presence, especially for

594 invasive species with non-equilibrium distributions and complex spatio-temporal dynamics. These  
595 critical physiological measures need to be instead integrated, together with other parameters, in a  
596 mechanistic model.

597 Beyond CLIMEX, other pre-built frameworks being used for invasive species fall within a subset of  
598 MNMs that integrates species' thermodynamical relationships with their environment and includes):  
599 TTR (Higgins et al. 2020), or LPJ-GUESS (Leiblein-Wild et al. 2016). These models focus on  
600 simulating energy, resource transport, and physiological processes to estimate species performance and  
601 potential growth. TTR models simulate the transport of nutrients, water, and other resources and tend  
602 to focus on quantifying the resistance to transport between tissues and ultimately estimate individual's  
603 potential growth (Higgins and Richardson 2014; Higgins et al. 2020). Similarly, NicheMapper is based  
604 on energy balance equations and are mainly applied to endotherms and ectotherms (Kearney and Porter  
605 2019; Briscoe et al. 2023). These biophysical models have been used mainly on invasive amphibians,  
606 and they use detailed physiological parameters such as metabolic rates and survival, development or  
607 growth in response to temperature, given these taxa strong dependence on temperature. Other models  
608 not yet used in invasion research include: Phenofit (Chuine and Beaubien 2001), Sortie-ND (Canham  
609 and Murphy 2016), 3-PG model (Gupta and Sharma 2019) and AquaMaps (Kaschner et al. 2006).

610 Despite the high variation in model types and integrated processes identified in our review, the  
611 geographical distribution of studies was relatively limited. Consistent with findings from other  
612 systematic reviews on correlative SDMs (Lantscher et al. 2018; López-Tirado and Gonzalez-Andújar  
613 2023), North America accounted for the highest number of invasive species MNM studies (**Figure 3**).  
614 However, most MNMs were developed at global scales, spanning more than one continent. The strong  
615 data requirements for MNMs likely contribute to this inequality. Access to well-equipped laboratory  
616 facilities or experimental installations, combined with large budget grants available in more privileged  
617 regions, disproportionately supports the development of MNMs in wealthier areas. Addressing this  
618 imbalance may require increased international collaboration and capacity-building efforts to ensure  
619 broader representation in MNM research.

620



621

622 **Figure 3.** Summary of the systematic review performed to evaluate the usage of Mechanistic Niche  
 623 Models with invasive species. **A)** Continental distribution of MNMs with invasive species. Bubble size  
 624 and colour intensity reflect the number of articles in each continent. On the left bottom, scale of the  
 625 articles. **B)** Taxonomic group used for the examination of invasions using MNMs (brown), and global  
 626 number of invasive species according to IPBES 2023 (Roy et al. 2024) (grey). Note that each series has  
 627 its own axis, reflecting no-proportionality between variables. Even though insects are predominant  
 628 protagonists in invasive MNMs, the number of invasive plants is much higher than the number of insect  
 629 invasive species. Species icons obtained from BioRender. **C)** Applications of MNMs for invasive  
 630 species. Under brackets, the number of articles.

## 631 **A unified framework for invasive mechanistic niche modelling**

632 Despite several articles covering the do's and don'ts, key aspects to consider, top hazards, and step-by-  
633 step guides for correlative SDMs (for recent articles see e.g. Araújo et al. 2019; Zurell et al. 2020;  
634 Sillero et al. 2021; Hui 2023; Soley-Guardia et al. 2024; Davis et al. 2024), a framework for designing,  
635 building, and reporting MNMs in invasive species is still missing (but see Kearney and Enriquez-  
636 Urzelai (2023) framework for developing eggs mechanistic modelling, Ridell et al. (2023) review on  
637 biophysical models, Da Re et al. (2022) unified modelling framework for invasive *Aedes* mosquitos and  
638 Buchadas et al. (2017) review on dynamic models for invasive species management). We propose here  
639 the following steps when building an MNM for determining the potential distribution of invasive  
640 species, schematized in **Figure 4**.

641 **1) Research aim.** Given the importance of the research aims on the parameterization of the MNM, the  
642 first step when building an invasive MNM is to delimit the ecological question, management goal, or  
643 knowledge gap that we intend to address. As discussed in the previous section, MNMs are adequate for  
644 determining the potential for expansion of an invasive species toward higher latitudes, estimating  
645 distribution shifts with climate change, quantifying the niche overlap with threatened species, or  
646 potential biocontrol agents, test the contribution of environmental versus non-environmental  
647 distribution drivers or detect niche unfilling (**Figure 3**). The research aim will allow us to distinguish if  
648 we should look for upper thermal limits (in case we want to assess niche shifts towards warmer climates;  
649 but see Chevalier et al. 2024), quantify vital rates (if we aim to find species reproductive limits) or to  
650 prepare an experimental design with competition and density-dependence (in case we want to model  
651 species competition with climate change). In biophysical models, multiple complexity levels can be  
652 included. For example, we can aim to model the heat budget of a single life stage, multiple life stages,  
653 include activity or not only include temperature balances but also water and food for instance (Briscoe  
654 et al. 2023). Finally, the spatio-temporal complexity associated with the invasion process must be  
655 gathered (**Figure 1**). These key aspects include the overlap between niches obtained from native and  
656 invaded occurrences, if the species has ornamental interest that could led to invasion nurturing, if it has  
657 commercial interest that could lead to increased propagule pressure in highly connected areas, if there  
658 are any identification complexities, and the time since introduction. The choices made at this stage will  
659 shape the outcomes of the MNM, making it essential to align model complexity and data requirements  
660 with the research aim.

661 **2) Genetic integrity.** Prior to building a physiological model the species material must be selected  
662 according to the research aims, the degree and importance of the described genetic variability and  
663 considering the invasion dynamics literature. In **Figure 4** we depicted four species material selection  
664 strategies for MNMs used in the reviewed literature. However, some of them might limit our capacity  
665 to overcome correlative SDMs limitations for invasive species, and thus, must be carefully selected.  
666 For example, Kolbe et al. (2010) showed that individuals from different populations of the cane toad

667 within the invaded range had differential low-temperature tolerances. To capture such intraspecific  
668 variability, it is required to sample multiple populations from the invaded range representing the  
669 climatic and geographic niches (Gallien et al. 2012). Other alternatives, such as using a single  
670 population, can be considered in case low variability across populations has been described for this  
671 species for the selected trait, or to use data from the native range only if we know the trait is maintained  
672 between native and invaded ranges. Sensitivity analysis can assist delimiting the importance of intra or  
673 inter-population variability over certain traits. One approach to include trait variation is the one taken  
674 by Strubbe et al. (2023), who first built species-level model for several bird species. The species-level  
675 model was subjected to a sensitivity analysis uncovering the most influential variables, which were used  
676 to build a and an intraspecific-level model accounting for trait variation. However, it must be noted that  
677 fitting a physiological model from a single population will not allow capturing range-edge processes.  
678 In all cases we encourage reporting the niche margin index (NMI) described by Broennimann et al.  
679 (2021), which reflects the relative distance of a population inside or outside the niche after estimating  
680 it and can also be used in a climate change context (Pearman et al. 2024). Since closely related species  
681 are likely to possess similar niche requirements (Wiens et al. 2009; Crisp and Cook 2012) a final  
682 alternative would be to use data from similar species could be a way to address data scarcity (James et  
683 al. 2021). In addition to species origin, we must consider life stage that we will be considering for our  
684 physiological model. Larvae are commonly used in insects' models given their sensitivity to climate  
685 change (Kingsolver and Buckley 2020).

686 **3) Environmental drivers and response variables.** MNM building requires the selection of  
687 environmental driver(s) and response variables as well as the delimitation of the relevant interval (e.g.  
688 temperature from 0 to 10°C) including the forecasted increase or decrease under climate change  
689 scenarios (e.g. +2°C in mean temperature). Environmental drivers can include abiotic factors  
690 (Temperature, humidity, soil moisture, and atmospheric CO<sub>2</sub>) and biotic factors (predators, competitors,  
691 host species, and symbionts). Environmental drivers' selection must follow an understanding of the  
692 abiotic and biotic factors that limit species survival, growth, and reproduction, and the spatial resolution  
693 at which they should be used (Spence and Tingley 2020), but these may strongly differ depending on  
694 the organism type. In case a biophysical model is used, which is often a preferred choice for endotherms,  
695 ectotherms and plants, a first step will be to design and decompose the model. Recent reviews by Riddell  
696 et al. (2023) and Briscoe et al. (2023) present multiple approaches taken for this crucial step. Interactions  
697 between environmental variables (e.g. moisture and temperature) frequently occur and should be  
698 considered when designing experiments to measure physiological responses. In addition to  
699 environmental variables, response or performance variables must be carefully selected. Performance  
700 measurements can include vital rates, metabolic rates, or specific metabolite accumulation, and its  
701 selection will depend on our research question, scale of the study, and type of organism. Multivariate

702 approaches can be also considered to integrate trade-offs in response curves (Evans et al. 2015,  
703 Fefferman and Romero 2013).

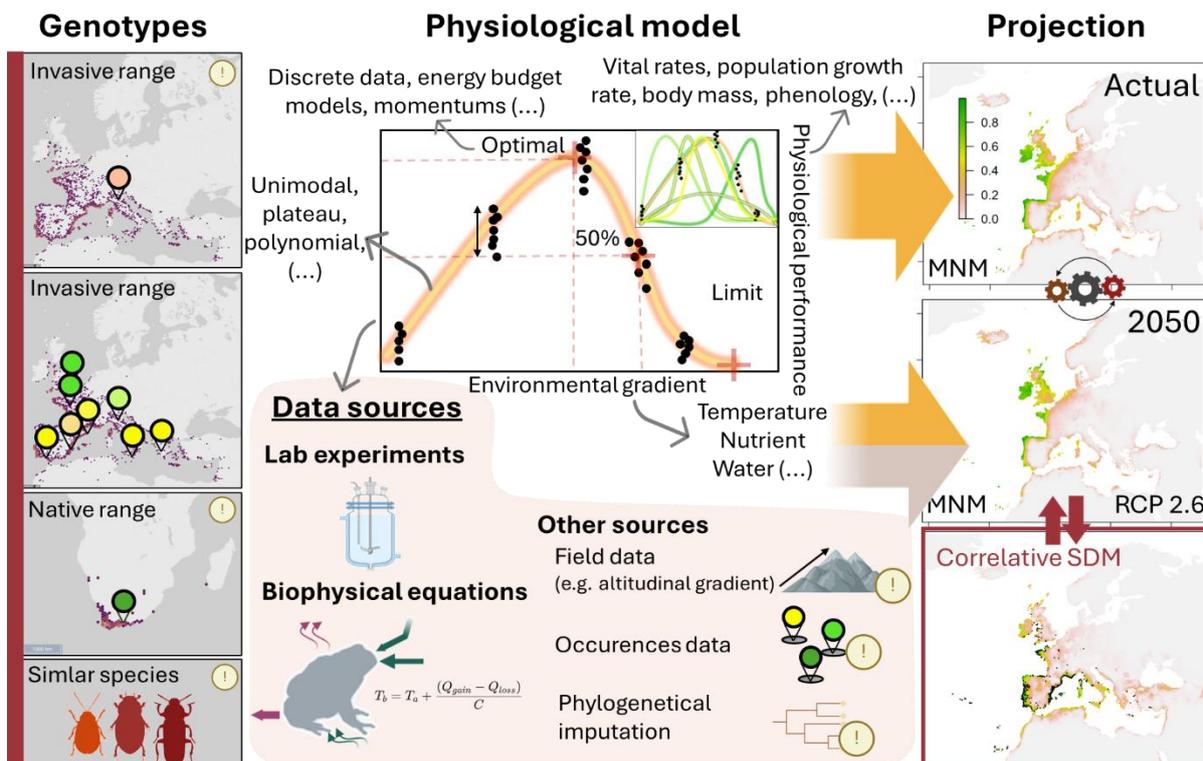
704 **4) Physiological model: parameter estimation and model fitting.** If the MNM is fitted using  
705 biophysical ecology, parameter estimation is required depending on our model complexity level (life-  
706 stages, energy and water balance, locomotion, etc. See point 3). For species response curves, both linear  
707 and non-linear or asymmetric physiological responses should be considered to properly capture the  
708 trade-offs organisms face under changing climates (Fenollosa and Munne-Bosch 2019b; Buckley et al.  
709 2022). Selecting the appropriate equations for baseline models depends on the species' physiology and  
710 can range from simple linear models to more complex non-linear equations that account for thresholds  
711 and tipping points in species' responses to environmental variables. Some of the observed studies used  
712 convex functions (Fadda et al. 2024), a plateau model (Feng et al. 2020). In insects, the theoretical  
713 temperature-dependent developmental rate curve is generally assumed to follow a unimodal shape, with  
714 a linearity zone before the optimal temperature (Rebaudo and Rabhi 2018). However, multiple models  
715 have been used to fit those curves, such as Logan-10, Lactin-2, Briere-2, Taylor, Beta models (Rebaudo  
716 and Rabhi 2018) showing slightly different projections at extreme temperatures. We must consider as  
717 well if we are interested in understanding species response to a wide environmental range, discrete  
718 conditions or if the physiological model will be used to extract only optimal, mean or limit points. Using  
719 at least five experimental conditions is common to fit a thermal curve (e.g. Lin et al. 2019; Pertierra et  
720 al. 2020; Fadda et al. 2024), but the experimental design will depend on the modelling aim. Temporal  
721 regimes must be considered, for example deciding if the physiological model is fitted with constant or  
722 cycling temperatures. Beyond laboratory experimentation, some alternative data sources include  
723 phylogenetic imputation (James et al. 2021; Fadda et al. 2024) or the integration of expert knowledge  
724 (Murray et al. 2012).

725 **5) Physiological model projection.** Once response curves are fitted, the next step is translating the  
726 physiological model into geographic space. This usually requires estimating environmental conditions  
727 experienced by the organism at relevant temporal and spatial scales (see point 3 above). This may  
728 involve using microclimate models to translate gridded climate data into predictions of historic, current  
729 or future microclimates, ideally considering behaviour and habitat use of the target organism (Kearney  
730 et al. 2020; MacLean et al. 2021). Our review revealed substantial diversity in the temporal and spatial  
731 resolution of environmental drivers, ranging from monthly air temperatures (e.g. Tablado and Revilla  
732 2012) to hourly soil or air temperatures (e.g. Hartley et al. 2010; Chapman et al. 2014). The usage of  
733 ERA5 climatic data is recommended to build microclimatic models (Klinges et al. 2022). To evaluate  
734 climate change impact on invasive species distribution, a forecast of the chosen variable under different  
735 climate change scenarios must be acquired. The temporal resolution of environmental data is as  
736 important as its spatial resolution (Guisan et al. 2019). An MNM based on energy budget might still  
737 work at global scale, but an MNM based on physiology and fine-scale processes might not make much

738 sense if applied to large scale based on very coarse environmental maps. We recommend reporting the  
 739 variable used for the geographic projection as well as the rationale of the chosen temporal and spatial  
 740 resolution when building MNMs. Once the potential distribution is obtained, we might be interested  
 741 into comparing projected distribution areas (Vaughan and Ormerod 2005; Levine et al. 2009; Wilson  
 742 2011; Huang et al. 2018) and use it for a closer examination of specific regions, such as invasion  
 743 hotspots, protected areas or range edges, can yield critical information on species spread, habitat  
 744 suitability, and the effectiveness of management interventions. Finally, contrasting MNM with  
 745 correlative SDM following standard procedures might be strongly informative to detect non-  
 746 environmentally driven occurrences and further understand the invasion process (e.g. Higgins et al.  
 747 2020; Dormann et al. 2012).

748 **6) Limitations acknowledgement.** A final recommended step is to revise the whole modelling process  
 749 and acknowledge potential limitations of the mechanistic model. A few examples that we might miss  
 750 out when building MNMs (depending on how they are built) are dispersion, habitat availability, other  
 751 species relevant interactions, further intraspecific variability, hysteresis responses, interaction between  
 752 multiple environmental variables, impact of spatial and temporal resolution of the environmental  
 753 variables and modelled processes, life stages considered, extreme events and memory or priming  
 754 responses (See full description in Suárez-Seoane et al. 2017; Briscoe et al. 2019; Briscoe et al. 2023;  
 755 Riddell et al. 2023). Sensitivity analysis can be used for unknown parameters and/or include trait  
 756 variability into the model (Mitchell et al. 2016; Strubbe et al. 2023).

757



758

759 **Figure 4.** Elements to consider when building Mechanistic Niche models for invasive species, from  
760 genotype selection, the construction of the physiological model and geographic projection. Exclamation  
761 signs symbolise that by taking those approaches the model might not be suited for invasive species  
762 projections.

763

#### 764 **Revisiting correlative SDMs limitations: when and how is an MNM appropriate?**

765 Beyond being limited to selected environmental drivers and available data, the limitation of MNMs is  
766 that, while they offer detailed, process-driven insights into species' physiological responses to  
767 environmental conditions, they may miss important fine-scale temporal and spatial information. This  
768 can include factors like microhabitat features, local competition, and biotic interactions that are often  
769 implicitly captured by correlative SDMs (Davis et al. 2024). MNMs excel at providing broad-scale  
770 predictions by linking species distributions to underlying mechanisms such as thermal tolerance,  
771 metabolic rates, or water balance (Kearney and Porter 2009). At the same time, if parametrized with  
772 fine-scale variables, MNMs are very useful at the range edge, where climate is limiting (Briscoe et al.  
773 2016). However, it must be noted that sometimes species might occur beyond their physiological limits  
774 thanks to adaptative or facilitative mechanisms (Chevalier et al. 2024). Essential spatio-temporal  
775 invasion complexities such as human activity influences, like trade, transportation, urbanisation, and  
776 land-use changes, introduce additional layers of complexity that are not easily modelled through  
777 physiological limitations frameworks. In this section we will revisit whether MNM can overcome all  
778 the limitations of correlative SDMs for invasive species.

779 Overcoming correlative SDM limitations by MNMs is not an easy endeavour, especially for modelling  
780 large number of species (which SDMs can do, e.g. Adde et al. 2024, but see the mechanistic model built  
781 for 20 birds in Europe: Strubbe et al. 2023), an effort that will largely depend on how our MNM is  
782 constructed (**Figure 4**). Careful parameterisation is essential to ensure that MNMs address specific  
783 challenges associated with correlative SDMs in invasive species modelling. MNMs can overcome  
784 almost all correlative SDM limitations when our aim is to understand its potential distribution under  
785 novel climates (as well as the derived applications described in **Figure 3**). For applications such as  
786 estimating invasion speed or reconstructing the history of an invasion, MNMs alone are not the most  
787 suitable approach (Wilson et al. 2007), although estimated dispersal capacity from an MNM (e.g.  
788 Kearney et al. 2008) could be incorporated into spatially explicit models such as IBMs.

789 MNMs might fail when (1) predicting species distribution limits where species is not being limited by  
790 the environment, (2) a single environmental factor is used, and the species response strongly depends  
791 on the interaction with another (e.g. temperature and moisture), (3) model is not complex enough to  
792 capture real conditions the species is submitted to. This last point includes not selecting the proper

793 temporal and spatial resolution and range of the modelled processes and environmental matching data,  
794 but also not capturing intraspecific or interpopulation variability.

795 Conversely, MNM will be better than correlative SDMs to predict future distribution when: (1) the  
796 species is on early stages of invasion and invasive region has a lot of novel environments not captured  
797 in native range, (2) it is known that biotic interactions are likely to be very different at the invaded  
798 range, (3) the species shows strong genetic diversity on the invaded range leading to identification  
799 complexities, (4) the species is used for commercial interests (i.e. planted trees) and are naturalized and  
800 not invasive in certain areas outside the native range, (5) time-lags are driving the invader expansion at  
801 the invaded range, (6) there are strong range-edge processes taking place. In case 3 and 6, the MNM  
802 must be fitted with representative genotypes across the invaded range and/or at range-edge.

803 Although the usage of hybrid models such as CLIMEX fitted using occurrence data might bypass data  
804 needs, the capacity of those models to respond certain research questions will be strongly limited  
805 depending on specifically how this model is populated. Models including data from invasive species  
806 occurrences, will not allow us to build predictions under novel conditions, especially on early invasion  
807 stages.

808 Other mechanistic approaches such as demographic distribution models, individual-based models or  
809 dynamic models are better fitted to simulate population responses after a specific perturbation, a  
810 management action or calculate invasion expansion rate (Briscoe et al. 2019). Domisch et al. (2018)  
811 further argue that spatially explicit modelling (i.e. considering spatially-explicit processes, such as in  
812 DDMs or occupancy dynamics models) is an underused tool in conservation planning, offering the  
813 potential to integrate species' distributions with habitat connectivity and management strategies Further  
814 steps would be the inclusion of genetic dynamics or evolutionary processes within SDMs and MNMs  
815 to capture species' adaptive potential, further improving the model's predictive power (García-Ramos  
816 and Rodríguez 2002; Kearney et al. 2009; Beninde et al. 2016; Bush et al. 2016).

817

## 818 **Conclusions**

819 Meaningful management decisions from SDMs require understanding the modelling decision process  
820 (Guisan et al. 2013; Schuwirth et al. 2019). Mechanistic niche models constitute an essential tool to link  
821 physiology with management decisions by explicitly considering the drivers of species distribution  
822 (Evans et al. 2015). MNMs are particularly suited for predicting potential distribution of invasive  
823 species as these organisms are often distributed across the landscape under non-equilibrium conditions  
824 that are difficult to simulate with correlative approaches.

825 Despite their potential, the application of MNMs to not only invasive but also other species remains  
826 limited due to substantial data requirements. Hybrid approaches, particularly those focused on invasive  
827 insects, dominate the field. The decisions made during MNM parameterisation—from genotype  
828 selection and fitting techniques for physiological models to projecting potential distributions—critically  
829 affect their accuracy and appropriateness for specific applications.

830 The ideal MNM design would incorporate biophysical models parameterised with laboratory  
831 experimental data obtained by submitting considering trait multiple representative genotypes across the  
832 invaded range to a wide range of environmental predictors. However, such designs demand expensive  
833 and time-consuming experimental efforts, limiting their feasibility. While building fully mechanistic  
834 models may be impossible—given that the necessary experimental data will probably never be  
835 available, but also particularly given the context-dependent and spatio-temporal complexities of  
836 biological invasions (Laxton et al. 2022)—aim-oriented MNM for invasive species will definitely  
837 constitute better management tools than correlative SDMs to predict invasive species potential under  
838 climate change conditions at early invasion stages. Beyond the revised applications when MNMs would  
839 be a good choice, we also encourage the usage of MNMs to assess potentially invasive species risk  
840 under climate change.

841 Integrating phylogenetic signals can reveal evolutionary constraints on species' responses to novel  
842 environments (Wiens et al. 2009), while trait-based approaches highlight the potential of functional  
843 traits to inform climatic niches (Medeiros et al. 2023). Cross-disciplinary collaboration—bridging  
844 physiology, physics, genetics, and ecology—can enhance the development of robust MNMs and  
845 standardise reporting practices, ultimately improving their reproducibility and broader applicability.

846 Finally, the insights gained from MNMs extend beyond invasive species modelling, offering valuable  
847 contributions to understanding climate-driven range shifts and guiding management actions for broader  
848 biodiversity conservation (Caplat et al. 2013; Wallingford et al. 2020).

849 **SUPPLEMENTARY MATERIAL**

850 **Supplementary Material 1.** Detailed procedure followed to conduct the systematic review.

851 **Supplementary Material 2.** Complete list of articles included in the systematic review, including all  
852 published articles using mechanistic niche models for invasive species up to the present date.

853

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1 **Supplementary Material 1.** Detailed procedure followed to conduct the systematic review.

2 To evaluate the existence of literature using mechanistic niche models to forecast invasive species distribution, we  
 3 performed a systematic review. Due to the multiple terminology related to mechanistic niche models we compiled  
 4 and deleted duplicates from multiple SCOPUS searches.

5 In 2019, Briscoe et al compiled all literature using process-explicit models until that date used for multiple purposes.  
 6 Since here we focus exclusively on the potential of mechanistic niche models for invasive species, we used the  
 7 literature list compiled by Briscoe et al. (2019) and filtered the studies evaluating invasive potential. Moreover, we  
 8 used the search terms used to re-do the search and include the work published in the last 5 years. As Briscoe et al.  
 9 did, we limit our search to studies that project the distribution of the species, with filtering studies that included in  
 10 their title, keywords or abstract “species distribution model” or “occupancy dynamics” or the terms “geographic  
 11 distribution”, “species distribution” or “species range”. We included only research articles within the subject fields  
 12 “Environmental science” and “Agricultural or biological science” or “Multiple” (We included ‘Multiple’ to capture  
 13 articles in journals such as PLoS One, PNAS that publish research on a range of topics). The search was conducted  
 14 on the 15<sup>th</sup> of September 2024. Despite the aim of the systematic review is to find all articles performing mechanistic  
 15 niche models, we used the search terms from Briscoe et al. 2019 to acquire also demographic distribution models  
 16 and individual-base models since as discussed in the review the limit might be a bit diffuse and we preferred to revise  
 17 all articles in case a few might include estimates of the fundamental niche, which might categorize them as MNMs.

Type of process-explicit model	Scopus search terms	Number of items
Mechanistic niche models (or Ecophysiological models)	( TITLE-ABS-KEY ( ( "species distribution model" OR "range dynamics" OR "occupancy dynamics" OR ( "species distribution" AND predic* ) OR ( "species range" AND predic* ) OR ( "geographic distribution" AND predic* ) ) AND ( ecophysiol* OR eco-physiol* OR mechanistic OR biophysical OR "physiol* based" OR "physiol* driven" ) AND ( invasive* OR invader* OR *alien* OR non-native* OR neophy* OR neobiot* OR ias OR exotic* OR invasion OR pest* ) ) AND NOT SRCTITLE ( human OR medic* ) ) AND ( LIMIT-TO ( SUBJAREA , "AGRI" ) OR LIMIT-TO ( SUBJAREA , "ENVI" ) OR LIMIT-TO ( SUBJAREA , "MULT" ) OR LIMIT-TO ( SUBJAREA , "BIOC" ) OR LIMIT-TO ( SUBJAREA , "EART" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) )	107
Demographic distribution models	( TITLE-ABS-KEY ( ( "species distribution model" OR "range dynamics" OR "occupancy dynamics" OR ( "species distribution" AND predic* ) OR ( "species range" AND predic* ) OR ( "geographic distribution" AND predic* ) ) AND ( demograph* OR "integral projection model" OR "matrix population model" OR "transition matrix" OR "population model" OR "population growth rate*" OR "vital rate*" ) AND ( invasive* OR invader* OR *alien* OR non-native* OR neophy* OR neobiot* OR ias OR exotic* OR invasion OR pest* ) ) AND NOT SRCTITLE ( human OR medic* ) ) AND ( LIMIT-TO ( SUBJAREA , "AGRI" ) OR LIMIT-TO ( SUBJAREA , "ENVI" ) OR LIMIT-TO ( SUBJAREA , "MULT" ) OR LIMIT-TO ( SUBJAREA , "BIOC" ) OR LIMIT-TO ( SUBJAREA , "EART" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) )	139

Individual based models	( TITLE-ABS-KEY ( ( "species distribution model" OR "range dynamics" OR "occupancy dynamics" OR ( "species distribution" AND predic* ) OR ( "species range" AND predic* ) OR ( "geographic distribution" AND predic* ) ) AND ( "individual based model*" OR "agent based model" OR individual-based OR agent-based OR ibm ) AND ( invasive* OR invader* OR *alien* OR non-native* OR neophy* OR neobiot* OR ias OR exotic* OR invasion OR pest* ) ) AND NOT SRCTITLE ( human OR medic* ) ) AND ( LIMIT-TO ( SUBJAREA , "AGRI" ) OR LIMIT-TO ( SUBJAREA , "ENVI" ) OR LIMIT-TO ( SUBJAREA , "MULT" ) OR LIMIT-TO ( SUBJAREA , "BIOC" ) OR LIMIT-TO ( SUBJAREA , "EART" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) )	25
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19 Duplicated articles were identified and removed by DOI. Still 4 articles about medical treatments from the journals  
20 “Breast Cancer Research and Treatment” and “Cancer” were found and discarded. After removing duplicates and  
21 medical research articles, the total number of articles was: 235, from 1996 to 2024. However, about 50% of the  
22 articles did not actually include a mechanistic niche model in invasive species and contain only mechanistic diffusion  
23 for example or evaluated the correlation of invasive species abundance with a non-invasive target species when  
24 performing a correlative SDM. After individually checking all articles, only 97 were found to perform a MNM,  
25 demographic distribution, or individual-based model with one or more invasive species.

26 From those articles, we selected the ones that fit into the definition of MNMs: process-explicit models where  
27 measurements or calculations of physiological limitations of the environment on vital rates are used to define species’  
28 range limits and used to project species potential distribution (Kearney and Porter, 2009; Evans et al. 2015).  
29 Demographic distribution models that were built solely from field data, and individual-based models that did not  
30 include environmentally explicit performance were discarded.

31 From those articles we recorded the following information: Species studied and their taxonomic group, whether the  
32 study was based on one or more species, aim of the study, name of the model used, type of the model, if climate  
33 change projections were included, which type of empirical data was used to parametrize the model, scale of the  
34 projection, captured processes and insights to advance in biological invasions forecasting.

35 The obtained list of articles can be found in **Supplementary Material 2**.