



**Predicting the future of our oceans – evaluating genomic forecasting approaches in marine species**

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Abstract:	Climate change is restructuring biodiversity on multiple scales and there is a pressing need to understand the downstream ecological and genomic consequences of this change. Recent advancements in the field of eco-evolutionary genomics have sought to include evolutionary processes in

	<p>forecasting species' responses to climate change (e.g. genomic offset), but to date, much of this work has focused on terrestrial species. Coastal and offshore species, and the fisheries they support, may be even more vulnerable to climate change than their terrestrial counterparts, warranting a critical appraisal of these approaches in marine systems. First, we synthesize knowledge about the genomic basis of adaptation in marine species, and then we discuss the few examples where genomic forecasting has been applied in marine systems. Next, we identify the key challenges in validating genomic offset estimates in marine species, and we advocate for the inclusion of historical sampling data and hindcasting in the validation phase. Lastly, we describe a workflow to guide marine managers in incorporating these predictions into the decision-making process.</p>

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## Response to Reviewers

We thank both reviewers and the Subject Editor for their helpful comments and revisionary suggestions that have significantly improved this manuscript. We provide a response to each of the reviewer's comments below, but briefly, we have strengthened our arguments and opinion throughout the text, clarified some key processes and methodologies and expanded our discussion of how best to implement these approaches in a marine management setting. New text has been detailed below in bold italicized font.

### Reviewer One:

**C1\_1:** The manuscript succinctly evaluates genomic forecasting approaches in marine species, acknowledging the pressing need to comprehend the downstream ecological and genomic consequences of climate change. However, given that the manuscript is submitted as an Opinion piece, it would benefit from a clearer statement of the specific Opinion and objective to guide readers more effectively. In the following, I provide some feedback and suggestions to the different sections. The introduction adeptly establishes the context of climate change impacts on marine ecosystems. However, as mentioned above, it could be enhanced by explicitly stating what should be done in the authors opinion and maybe provide a more detailed roadmap of the manuscript's sections to reinforce the importance of evaluating genomic forecasting in the marine context.

**R1\_1:** We agree with the reviewer that a clear statement of our central opinion was lacking here and we have since explicitly stated our main arguments and provided a roadmap on lines 119-127 (see below).

“In this opinion piece, we review the literature on the genomic basis of climate adaptation in marine species (section 3), evaluate current examples of genomic offset estimates in marine systems (section 4), assess the potential for validation of these estimates (section 5), and finally we discuss the utility of these estimates in informing fisheries policy (section 6). ***Here, we argue that the wealth of data available from long-term monitoring programs in exploited marine species provides an unprecedented opportunity for validating offset estimates in an otherwise logistically challenging environment. We also argue that implementing offset estimates in marine management will enable a more comprehensive assessment of the impacts of climate change on exploitation.***”

**C1\_2:** In the following section the authors provide a comprehensive overview of potential drivers of adaptation in marine species, including temperature, salinity, and other environmental factors. The authors effectively integrate recent studies to support their arguments. However, consider providing more context or examples for certain terms, e.g., "large effect" and "small effect" chromosomal rearrangements to aid readers less familiar with these concepts. Similarly, Table 1 is quite helpful in summarizing current publications. But the clarity could be enhanced by ensuring that the terminology used in the table aligns precisely with that in the main text. Also, a brief explanation of the methodologies used (e.g., redundancy analysis, generalised dissimilarity modelling) could be included for readers unfamiliar with these techniques.

**R1\_2:** We agree with the reviewer that some concrete examples and more detailed explanation of methodologies is necessary here to improve readability- thank you for this suggestion. To address this, we have added text to lines 136-149 that reads:

“For some species with high connectivity and gene flow, like Atlantic cod (*Gadus morhua*), herring (*Clupea harengus*), horse mackerel (*Trachurus trachurus*), and northern sand lance (*Ammodytes dubius*), a few “large effect” chromosomal rearrangements seem to explain most of the climate-associated genomic variation (e.g., Barth et al. 2017; Kess et al. 2020; Fuentes-Pardo et al. 2023a). **For example, a large 10Mb inversion on chromosome 21 discriminates northern and southern populations of horse mackerel in Europe (Fuentes-Pardo et al. 2023a).** In other cases, a signature of local adaptation is restricted to many regions of “small effect” in the genome, requiring dense genomic data for detection, as seen in Arctic charr (*S. alpinus*), Atlantic silversides (*Menidia menidia*) and the Baltic copepod (*Eurytemora affinis*) (Wilder et al. 2020; Kess et al. 2021; Stern et al. 2022). **Here, adaptive SNPs are dispersed across most of the genome, rather than being concentrated in one particular region, constituting a signature of polygenic adaptation.**”

We have also added text to lines 221-231 that reads:

To derive the offset estimate, allele frequencies of putatively adaptive, climate-associated loci are the response variables to environmental predictor data to model climate-associated genomic variation using any number of modelling approaches. **The most common modelling approaches include generalized dissimilarity modelling (GDM) and gradient forest (GF)—both of which accommodate for nonlinear associations of genomic and environmental data. The former uses distance matrices to model climate-associated genomic variation while the latter employs a regression-tree approach that is especially suitable in the context of steep environmental gradients (Fitzpatrick & Keller 2015).** The model is then used alongside environmental data from both current and future time periods and across the species’ range to predict current and future adaptive indices, respectively.

We also wanted to point out that we now define common garden experiments on lines 302-304 in response to a comment from reviewer two. “The only examples of experimental validation to date are from terrestrial species, where genomic offset estimates were compared to population performance measured in common garden settings—**where distinct populations are grown under the same environmental conditions to identify differences in fitness** (e.g. Fitzpatrick et al. 2021; Gain et al. 2023).”

**C1\_3:** The authors further highlight the importance of validating genomic offset estimates, which is highly important, but often neglected. To strengthen this section, consider providing more details on the potential biases or limitations associated with validation methods. Additionally, discussing the implications of such biases on the reliability of genomic offset estimates would add depth to the analysis.

**R1\_3:** We agree that while we’ve highlighted the unique opportunity for validation in marine systems, we haven’t fully addressed the shortcomings of these possible validation methods. For instance, one of the biggest challenges to common garden-based validation in marine systems is the long generation times of many exploited species (and species of conservation concern). To address this concern, we’ve added the following text in section 5:

Lines 315-324: “Although very informative and likely the gold standard, the potential for experimental validation of offset estimates through either reciprocal transplant or common garden experiments in marine species are limited by comparison with terrestrial plants or animals. This is largely due to the added complexity of these experiments in the marine environment, but some exceptions exist. For instance, Jacobs et al. (2022) reared fertilized eggs of Atlantic silversides (*Menidia menidia*) in temperature-controlled water baths and

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compared growth rates amongst treatments. ***However, long generation times in many exploited marine species (e.g. 20 years in deepwater redfish, *Sebastes mentella*, COSEWIC 2010) means that the short timescales with which common garden experiments are typically performed will provide only a snapshot of response.***

Lines 336-339: ***“These approaches to validation, although powerful, are biased toward exploited species whose stocks are already depleted from fishing and thereby teasing apart the relative impacts of climate change and exploitation will be critical in these cases.”***

**C1\_4:** The last section effectively outlines the steps required to integrate genomic offset estimates into marine management. Maybe a more explicit discussion of potential challenges or limitations that marine managers may encounter in implementing these predictions would enhance the practicality of the proposed workflow? Finally, the conclusion summarizes the main findings and emphasizes the potential of genomic offset in marine species. To enhance this section, consider reiterating the identified gaps or uncertainties in the field and suggesting potential directions for future research.

**R1\_4:** We agree with the reviewer that a more detailed discussion of challenges and limitations is needed here in order for these methods to be implemented in a management setting. To address this, we have added the following text to section 6:

Lines 344-348: ***“Validating offset estimates in the marine environment will continue to be an important avenue for future work, but the integration of these estimates in marine management is even more vital. This is because existing management approaches typically rely on SDMs, which although informative, are best used to compliment methods that explicitly consider adaptation.”***

Lines 366-373: ***“Although straightforward in theory, this proposed workflow can be challenging to implement in practice given constraints on budget and time. For instance, generating dense genomic datasets for many individuals and populations can be expensive and thus targeting a smaller subset of climate-associated loci might be a feasible alternative. Additionally, sampling from all known populations across a species range can be logistically challenging and thus selecting a subset of populations that best represent variation (both genomic and environmental) in the system could be an alternative approach.”***

We have also significantly revised the second paragraph of the Conclusions section to emphasize directions for future work, and we conclude with a much stronger statement. Lines 399-409 now read:

***“Here, we argue that future work should focus on leveraging the wealth of long-term population data available for many economically and ecologically vital marine species to validate offset estimates when more traditional approaches are logistically challenging. A particularly exciting avenue for future work is the potential for generating models of past climate-associated variation with historical samples. Beyond validation, there is even greater uncertainty on how to apply offset estimates in real-world fisheries management and marine conservation scenarios. To this end, we provide a ‘standard operating procedure’ for marine managers, outlining how to generate offset estimates and modify workflows in the face of budgetary and time constraints. Genomic offset has the potential to transform***

***marine management and is highly complementary to other genetic and non-genetic approaches to conserving vital marine resources.”***

**C1\_5:** As a general comment, I suggest being a bit more consistent in terminology throughout the manuscript, particularly regarding the use of terms such as "genomic offset" and "genomic vulnerability." Also, it would be helpful for the reader to incorporate more explicit connections between sections to improve the overall flow and coherence of the manuscript. In summary, the manuscript provides a valuable exploration of genomic forecasting in marine species. Addressing the suggested refinements will contribute to the clarity and impact of the manuscript, making it a more accessible and influential contribution to the field.

**R1\_5:** We agree with the reviewer that consistency in terminology is key to readability here. The term 'genomic vulnerability' now only appears once in section 2 where we mention that Bay et al. (2018) used this term before 'genomic offset' became ubiquitous. Throughout the rest of the manuscript, we use 'genomic offset' to avoid confusion. We still use the term 'vulnerability' at points in the manuscript, but this does not refer to the genomic offset approach but rather species' response or vulnerability to climate change more generally.

**Reviewer Two:**

In the manuscript 'Predicting the future of our oceans – evaluating genomic forecasting approaches in marine species' Layton et al. present an overview of the emerging field of genomic forecasting and highlight several studies from marine systems that have employed genomic forecasting approaches such as the calculation of genomic offset. They then discuss several challenges pertaining to the validation of such approaches and present a clear and feasible roadmap for researchers to validate such approaches going forward, particularly utilising experimental evidence and linking to historical population or distribution data and hindcasting models. This is a very timely paper and was clear and easy to read. I thoroughly enjoyed it. Many of the points that the authors make are not well known amongst the marine science community and I believe it will be particularly useful in this context.

I have only a few minor comments:

**C2\_1:** L127: Vranken et al only show genomic evidence for putative adaptation (which is later acknowledged in Table 1). I suggest the authors re-word the section that says this is 'clear evidence for adaptation' - this also goes against their main point that GEA analyses are correlative only and require validation.

**R2\_1:** We agree with the reviewer that 'clear evidence' should be revised. The text on 134-135 now reads:

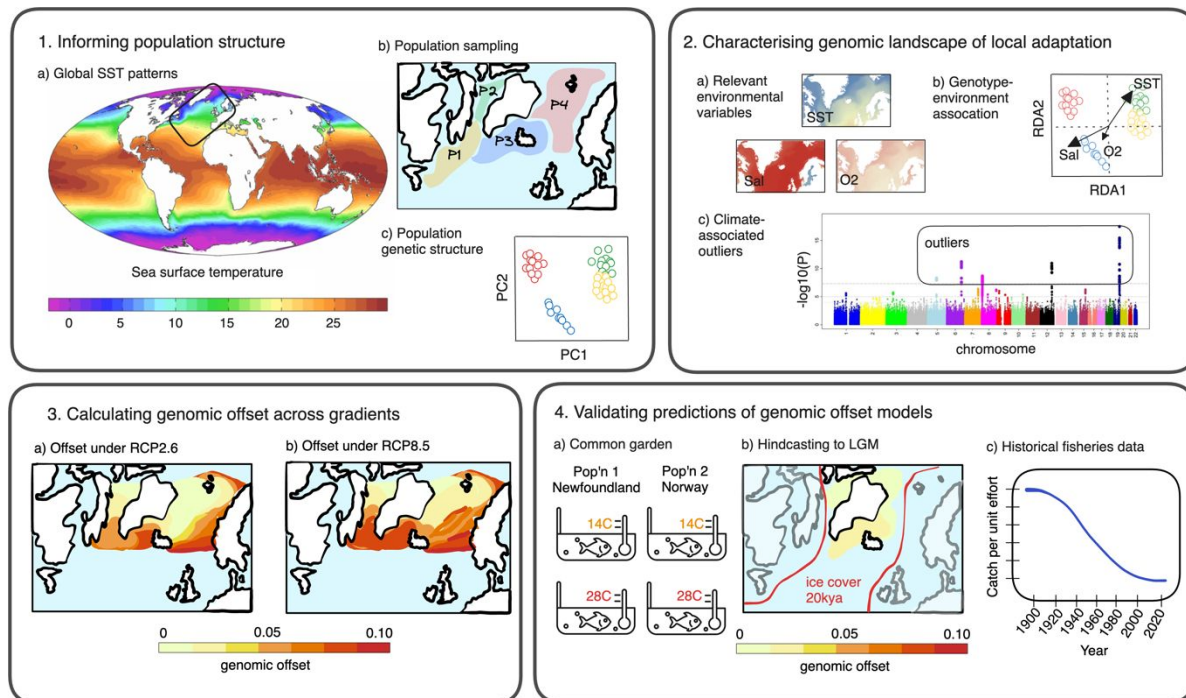
“...recent studies employing genome-wide data have **provided strong evidence** for climate-associated adaptation in several marine taxa (e.g. Drinan et al. 2018; Vranken et al. 2021).”

**C2\_2:** Figure 1. The font is slightly hard to read and seems quite informal here. I like the infographic style but suggest changing to a more standard font style. I also suggest changing the location 'Labrador' to somewhere recognisable globally for readers not familiar with the location. I also suggest the authors either define what a common garden experiment is for readers, as it seems as though the target audience are not necessarily going to be familiar with these and insert relevant examples or references either in the Figure legend or main text.



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**R2\_2:** We thank the reviewer for these helpful revisionary suggestions. We have since changed the font to improve readability and we have changed the location to Newfoundland, which we believe is a more globally recognizable location. See revised figure here:



We have also addressed the comment about common garden experiments and have added new text to lines 300-307 that reads:

“The only examples of experimental validation to date are from terrestrial species, where genomic offset estimates were compared to population performance measured in common garden settings—*where distinct populations are grown under the same environmental conditions to identify differences in fitness (e.g. Fitzpatrick et al. 2021; Gain et al. 2023)*. For instance, Fitzpatrick et al. (2021) reported a negative relationship between genomic offset and common garden performance consistent with significant power of offset estimates to predict population response to climate change, exceeding that of climate differences alone.”

1 **Predicting the future of our oceans – evaluating genomic forecasting approaches in**  
2 **marine species**

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7 **Running head:** Genomic forecasting in marine species

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## 38 1. Abstract

39 Climate change is restructuring biodiversity on multiple scales and there is a pressing need  
40 to understand the downstream ecological and genomic consequences of this change.  
41 Recent advancements in the field of eco-evolutionary genomics have sought to include  
42 evolutionary processes in forecasting species' responses to climate change (e.g. genomic  
43 offset), but to date, much of this work has focused on terrestrial species. Coastal and  
44 offshore species, and the fisheries they support, may be even more vulnerable to climate  
45 change than their terrestrial counterparts, warranting a critical appraisal of these approaches  
46 in marine systems. First, we synthesize knowledge about the genomic basis of adaptation in  
47 marine species, and then we discuss the few examples where genomic forecasting has been  
48 applied in marine systems. Next, we identify the key challenges in validating genomic offset  
49 estimates in marine species, and we advocate for the inclusion of historical sampling data  
50 and hindcasting in the validation phase. Lastly, we describe a workflow to guide marine  
51 managers in incorporating these predictions into the decision-making process.

## 52 2. Introduction

53 Climate change results in severe environmental change, with recent years being the  
54 warmest on record throughout the industrial period (Cheng et al. 2023). The global increase  
55 in average temperature is accompanied by a suite of environmental changes including  
56 increases in the frequency and intensity of extreme weather events, regional temperatures,  
57 atmospheric water vapour, and ocean heat, as well as decreases in pH, dissolved oxygen,  
58 and land and sea ice cover. For marine ecosystems, increased glacial runoff and rising sea  
59 temperatures pose significant challenges (He & Sillman 2019). The consequences of these  
60 impacts are evidenced by distributional shifts in many taxa (e.g., Poloczanska et al. 2013),  
61 with populations at the trailing edge declining and populations at the leading edge shifting  
62 poleward or into deeper waters (Polyakov et al. 2020; Pinsky et al. 2020). In fact, marine  
63 species and the fisheries they sustain appear to be more vulnerable to climate change than  
64 their terrestrial counterparts (Pinsky 2021). Given the global reliance on marine resources,  
65 these changes will undoubtedly impact food security and economic stability (Payne et al.  
66 2021). Consequently, there is a need to 'future-proof' marine ecosystems and conservation  
67 areas through proactive management based on a sound understanding of the ecological and  
68 genetic impacts of climate change (Tittensor et al. 2019).

69 There is a pressing necessity to predict climate change impacts in marine species  
70 and ecosystems to inform conservation planning and strategies. These predictions are  
71 particularly relevant to global fisheries and aquaculture, which provide a major source of  
72 nutrition to developed and developing countries (Bene et al. 2016). For instance, ocean  
73 warming has been linked to significant decreases in production capacity and shifts in the  
74 distribution of fisheries-targeted species (e.g., tuna, Monllor-Hurtado et al. 2017). Predicting  
75 range shifts in marine taxa remains a significant challenge and ultimately requires  
76 information on existing ranges, predictions of future environments, capacity for adaptive and  
77 plastic responses to environmental change, dispersal potential, and ecosystem structure and  
78 function. Marine species' ranges largely conform to their thermal limits (Sunday et al. 2012)  
79 and therefore even small changes in the thermal profile of a given marine region can have  
80 measurable consequences on population survival and subsequent extirpation.

81 A growing body of research has focused on developing tools to predict the impacts of  
82 climate change on wild populations. Ecological niche modelling - akin to species distribution  
83 modelling (SDM) - has been used in the last 20 years to map the probability of occurrence of  
84 a species across a landscape (Kearney & Porter 2009). However, traditional SDMs do not  
85 consider adaptive responses of populations to environmental change, for instance through  
86 multigenerational selection of advantageous genomic variants (e.g., standing genetic  
87 variation), or through the expression of epigenetic variants leading to acclimation via  
88 phenotypic plasticity. More recently, genomic offset - also termed genomic vulnerability (Bay

89 et al. 2018) - has been applied to both terrestrial and marine taxa to predict potential future  
90 maladaptation driven by climate change (e.g., Fitzpatrick & Keller 2015; Laruson et al. 2022;  
91 Layton and Bradbury 2021). This approach maps the contemporary spatial turnover of  
92 adaptive alleles onto current environmental conditions and then calculates the offset  
93 between present and future climate-associated genomic composition as a measure of  
94 maladaptation to climate change. In other words, genomic offset is an estimate of the  
95 change in genomic composition that would be required to track predicted climate change.  
96 Despite some limitations and challenges, including validation and management buy-in  
97 (Rellstab et al. 2021), the approach seems to accurately estimate climate change  
98 vulnerability when compared to experimental predictions (e.g., Fitzpatrick et al. 2021).  
99 Bernatchez et al. (2023) provide a comprehensive overview of this method, among others, in  
100 their recent review of genomics-based monitoring approaches, but to date, no study has  
101 assessed these methods in specific ecological contexts. Given the potential of genomic  
102 offset estimates to inform climate change predictions, and the observation that marine  
103 species are already being impacted by climate change, an evaluation of the method's  
104 applicability to marine species is warranted.

105 There are several reasons why estimating genomic offset can be useful for managing  
106 and conserving marine ecosystems and species. The poikilothermic nature of most marine  
107 fish, invertebrates, and macrophytes means that temperature is often a dominant selective  
108 pressure driving adaptive genetic diversity across populations. The low genetic structure and  
109 generally large effective population sizes ( $N_e$ ) often observed within marine species  
110 (Bradbury et al. 2008) means that the influence of genetic drift is typically minimal compared  
111 with that of natural selection. Moreover, many marine species occupy large latitudinal ranges  
112 and genomic approaches have repeatedly demonstrated putative adaptation across these  
113 variable environments. Taken together, our ability to resolve the genomic basis of climate-  
114 associated adaptation may be elevated in the marine environment compared with terrestrial,  
115 which can translate into improved power to predict population-level responses or  
116 vulnerability in these systems.

117 In this opinion piece, we review the literature on the genomic basis of climate  
118 adaptation in marine species (section 3), evaluate current examples of genomic offset  
119 estimates in marine systems (section 4), assess the potential for validation of these  
120 estimates (section 5), and finally we discuss the utility of these estimates in informing  
121 fisheries policy (section 6). Here, we argue that the wealth of data available from long-term  
122 monitoring programs in exploited marine species provides an unprecedented opportunity for  
123 validating offset estimates in an otherwise logistically challenging environment. We also  
124 argue that implementing offset estimates in marine management will enable a more  
125 comprehensive assessment of the impacts of climate change on exploitation.

### 126 **3. Genomic basis of adaptation in marine species**

127 Accurate prediction of potential maladaptation requires an understanding of how  
128 species are adapted to their environments. The number of potential drivers of adaptation in  
129 the marine environment is broad and includes numerous environmental variables such as  
130 temperature, salinity, dissolved oxygen, pH, and depth. Although theory would predict that  
131 extensive gene flow facilitated by long pelagic larval durations in marine species would  
132 erode and prevent local adaptation, recent studies employing genome-wide data have  
133 provided strong evidence for climate-associated adaptation in several marine taxa (e.g.  
134 Drinan et al. 2018; Vranken et al. 2021). For some species with high connectivity and gene  
135 flow, like Atlantic cod (*Gadus morhua*), herring (*Clupea harengus*), horse mackerel  
136 (*Trachurus trachurus*), and northern sand lance (*Ammodytes dubius*), a few "large effect"  
137 chromosomal rearrangements seem to explain most of the climate-associated genomic  
138 variation (e.g., Barth et al. 2017; Kess et al. 2020; Fuentes-Pardo et al. 2023a). For  
139 example, a large 10Mb inversion on chromosome 21 discriminates northern and southern  
140 populations of horse mackerel in Europe (Fuentes-Pardo et al. 2023a). In other cases, a

141 signature of local adaptation is restricted to many regions of “small effect” in the genome,  
142 requiring dense genomic data for detection, as seen in Arctic charr (*S. alpinus*), Atlantic  
143 silversides (*Menidia menidia*) and the Baltic copepod (*Eurytemora affinis*) (Wilder et al. 2020;  
144 Kess et al. 2021; Stern et al. 2022). Here, adaptive SNPs are dispersed across most of the  
145 genome, rather than being concentrated in one particular region, constituting a signature of  
146 polygenic adaptation. The genomic underpinnings of local adaptation can vary not only  
147 across species but also across environmental gradients, and this is especially complex in  
148 marine systems where species are distributed across both geographic and bathymetric  
149 clines.

150 Genomic signatures of thermal adaptation have repeatedly been reported and  
151 appear to be more prevalent in marine systems than in terrestrial or freshwater systems  
152 (Sasaki et al. 2022). For example, temperature-driven structure has been observed in sea  
153 scallop (*Placopecten magellanicus*) (Van Wyngaarden et al. 2017), northern shrimp  
154 (*Pandalus borealis*) (Stanley et al. 2018), capelin (*Mallotus villosus*) (Cayuela et al 2021),  
155 and Atlantic herring (*Clupea harengus*) (Fuentes-Pardo et al 2023b). Extreme thermal  
156 events can also result in a reshuffling of genetic clusters leading to local adaptation. For  
157 example, Coleman et al. (2020) demonstrated that an extreme marine heatwave caused a  
158 significant poleward shift in populations of kelp forests along the coast of western Australia,  
159 whereby ‘cool water’ alleles were replaced by ‘warm water’ alleles, resulting in a genetic  
160 tropicalisation of the populations. While within a species the same adaptive alleles can be  
161 selected multiple times in distinct geographic areas, resulting in parallel evolution of thermal  
162 adaptation (Bradbury et al. 2010), the universality of the molecular processes involved in  
163 thermal adaptation is largely unknown in marine systems, partly due to the lack of genomic  
164 resources and functional validation of the markers under selection in published studies.

165 Climate change projections not only indicate a rapid increase in ocean temperature in  
166 the next century but also lower salinity in relation to glacier melting and higher precipitation  
167 in some regions, like the northern hemisphere (Luo et al. 2016). Additionally, many marine  
168 species use a variety of habitats throughout their life cycle, some spanning freshwater and  
169 estuarine environments and thereby experiencing steep salinity clines. A significant body of  
170 work supports salinity adaptation in marine organisms (Johannesson et al. 2020), particularly  
171 in the Baltic Sea. For instance, whole genome sequencing revealed hundreds of regions  
172 across the genome of Atlantic herring (*C. harengus*) that showed significant differentiation  
173 between Baltic and Atlantic populations (Han et al. 2020). Equivalent comparisons of Baltic  
174 and Atlantic populations have yielded similar results in other species such as Atlantic cod (*G.*  
175 *morhua*) (Berg et al. 2015), sand goby (*Pomatoschistus minutus*) (Leder et al. 2021), and  
176 European plaice (*Pleuronectes platessa*) (Le Moan et al. 2021), indicating adaptation to low  
177 salinity levels. Within the Baltic, different species of mussels have also shown salinity-related  
178 adaptation between western and eastern regions (Knöbel et al. 2021). Recently, Stern et al.  
179 (2022) showed experimental and genomic evidence of Baltic copepod (*E. affinis*) rapidly  
180 adapting to decreasing salinity. Similar to thermal adaptation, species can adapt to salinity  
181 changes through either parallel or convergent evolution (Le Moan et al. 2021), involving  
182 either few genetic variants of large effect or many loci of small effect (e.g., Berg et al. 2015;  
183 Le Moan, et al. 2021).

184  
185 Additionally, it is increasingly clear that the basis of local adaptation in marine taxa  
186 extends beyond SNPs to large-scale chromosomal rearrangements, copy number variants  
187 (CNVs), and epigenetic variation. For instance, environmental adaptation in American  
188 lobster (*Homarus americanus*) was driven almost entirely by CNVs with little to no signal in  
189 SNP data (Dorant et al. 2020). In contrast, Layton et al. (2021) reported similar spatial trends  
190 in genomic offset calculated from CNV and SNP datasets in Arctic Charr populations from  
191 eastern Canada. In three-spined stickleback, differentially methylated regions (DMRs) were  
192 more significantly associated with environmental variation (salinity) than outlier SNPs (Ruiz-  
193 Arenas et al. 2017). Given these findings, Layton and Bradbury (2022) suggest a revised

194 offset approach incorporating normalized read counts and methylation scores alongside  
 195 allele frequencies which might better reflect overall (genetic + epigenetic) adaptive  
 196 processes, thereby improving prediction accuracy. Despite a complex landscape of adaptive  
 197 genomic variation in marine species, only a few studies have leveraged this information for  
 198 estimating genomic offset in the marine environment.

199

#### 200 **4. Prediction of climate change impacts using genomic tools in marine** 201 **taxa**

202 As discussed above, local adaptation to ocean climate is widespread (at least at  
 203 regional scales) across marine species in various taxonomic groups and ecological contexts.  
 204 However, climate change is expected to disrupt local adaptation in the coming years,  
 205 resulting in potential maladaptation as the speed of change outpaces natural selection in  
 206 many species and populations (Razgour et al. 2019). The ability to resolve the genomic  
 207 basis of adaptation, in conjunction with fine-scale climate projections, presents an  
 208 opportunity to leverage these datasets to forecast future climate-associated genomic  
 209 composition and maladaptation. Genomic offset, defined as the difference between current  
 210 genomic composition and the predicted future composition required to maintain adaptation,  
 211 was first introduced by Fitzpatrick and Keller (2015) and later by Bay et al. (2018) and has  
 212 been used to identify populations most vulnerable to future climate change. Additionally, the  
 213 genomic offset approach can be employed across historical timescales, for instance by  
 214 calculating the difference between current genomic composition and past genomic  
 215 composition hindcasted at the last glacial maximum.

216

217 In the past few years, this method has been increasingly employed across various  
 218 terrestrial systems (e.g., Capblancq et al. 2020), with more recent work focussing on *in situ*  
 219 validation of these offset estimates (Fitzpatrick et al. 2021). To derive the offset estimate,  
 220 allele frequencies of putatively adaptive, climate-associated loci are the response variables  
 221 to environmental predictor data to model climate-associated genomic variation using any  
 222 number of modelling approaches. The most common modelling approaches include  
 223 generalized dissimilarity modelling (GDM) and gradient forest (GF)—both of which  
 224 accommodate for nonlinear associations of genomic and environmental data. The former  
 225 uses distance matrices to model climate-associated genomic variation while the latter  
 226 employs a regression-tree approach that is especially suitable in the context of steep  
 227 environmental gradients (Fitzpatrick & Keller 2015). The model is then used alongside  
 228 environmental data from both current and future time periods and across the species' range  
 229 to predict current and future adaptive indices, respectively. The difference between these  
 230 values represents offset, with larger values indicating that a population is more likely to be  
 231 maladapted to future climate. This method has typically been used in species with strong  
 232 population structure distributed across well-defined environmental gradients, but its utility  
 233 and downstream interpretation in marine species has been understudied. However, recent  
 234 work has begun to address this gap, demonstrating its potential utility in eleven species of  
 235 fish, invertebrates and marine plants (Table 1).

236 **Table 1:** List of current publications employing genomic offset estimates in marine species.  
 237 The statistical method used to generate offset estimates, and the environmental predictors  
 238 used, is also listed (RDA=redundancy analysis; GDM= generalised dissimilarity modelling;  
 239 GF=gradient forest).

Organism	Region	Method	Included Climate Variables	Validated	Reference
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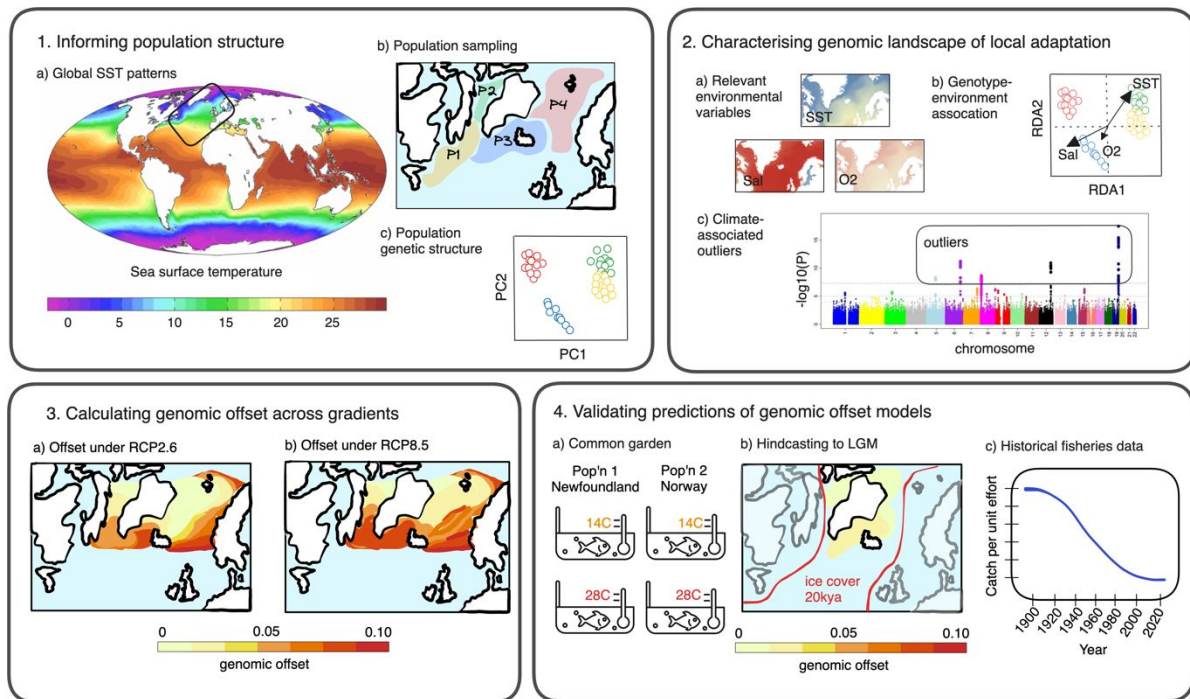
<b>Macrophytes</b>					
Eelgrass ( <i>Zostera marina</i> )	Coastal North America	RDA	Seasonal, annual bottom & surface temperature, salinity	No	Jeffery et al. (2024)
Seaweed ( <i>Phyllospora comosa</i> )	Southeastern Australia	GDM	Sea surface temperature	No	Wood et al. (2021)
Kelp ( <i>Ecklonia radiata</i> )	Western Australia	GF	Dissolved oxygen, sea surface salinity, sea surface nitrate, seawater velocity, attenuation	No	Vranken et al. (2021)
<b>Vertebrates</b>					
Arctic Charr ( <i>Salvelinus alpinus</i> )	Newfoundland/Labrador	GF	Precipitation, air temperature	No	Layton et al. (2021)
Sockeye salmon ( <i>Oncorhynchus nerka</i> )	British Columbia & Yukon	GF	Precipitation, air temperature	No	Tigano et al. (2024)
<b>Invertebrates</b>					
Multi-species: Urchin ( <i>Parechinus angulosus</i> ), crab ( <i>Cyclograpsus punctatus</i> ) & limpet ( <i>Scutellastra granularis</i> )	South Africa	GF	Sea surface temperature, sea surface salinity & air temperature	No	Nielsen et al. (2021)
Coral ( <i>Acropora digitifera</i> )	Western Australia	GF & GDM	Sea surface temperature	No	Adam et al. (2022)
Tubeworms ( <i>Galeolaria caespitosa</i> & <i>G. gemineoa</i> )	Southeast Australia	GF	Sea surface temperature	No	Gallegos et al. (2023)

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Most of these studies have focused on generating offset estimates in single species across a variety of spatial scales, with variable patterns across taxonomic groups and geographic areas. For instance, in eastern Canada, offset estimates were highest in southern populations of Arctic charr (*S. alpinus*) (Layton et al. 2021), indicative of a scenario of contraction of the southern range limit of this Arctic species. Alternatively, genomic offset

246 values were higher in northern (subarctic) populations of a widely distributed seagrass  
 247 species (*Z. marina*) across a similar area (Jeffery et al. 2024). Estimates of future offset in  
 248 *Acropora digitifera* in western Australia are more spatially complex, but populations living at  
 249 the upper thermal limits (i.e. at lower latitudes) were predicted to require less of an adaptive  
 250 shift than mid-latitude reefs (Adam et al. 2022). Similarly, Wood et al. (2021) shows a  
 251 spatially complex pattern of future offsets in a forest-forming seaweed (*P. comosa*) in  
 252 Australia, demonstrating that offset estimates do not follow a simple latitudinal cline and  
 253 rather vary with standing genetic diversity and predicted rates of climate change. Finally,  
 254 Nielsen et al. (2021) in a comparative study of three marine invertebrates, explore genomic  
 255 offset values and reveal a strong correlation among temperature and genomic variation in  
 256 some species but not others and that species-specific patterns were better predictors of  
 257 required adaptive shifts than environmental data alone. These findings suggest that broad  
 258 generalizations of climate change vulnerability in marine species, even among closely  
 259 related taxa or within similar geographic regions, might be challenging. However, they clearly  
 260 indicate that additional investigations of genomic offset in marine organisms are  
 261 necessary. This is especially true when considering validation, as no studies to date have  
 262 attempted to validate genomic offset estimates in marine species.

## 263 Generating and validating genomic offset estimates in marine environments



264

265 **Figure 1:** The first step in calculating genomic offset estimates in the marine environment is  
 266 to sample populations from across the range, ideally from steep environmental gradients, to  
 267 inform population structure in the species of interest (1a,b,c). Next, allele frequencies/read  
 268 counts/methylation scores (response) and environmental (predictor) data are used for  
 269 genotype-environment association (GEA) analyses to identify climate-associated outlier  
 270 variants (see Bernatchez et al. (2023) for a detailed overview of GEA approaches) (2a,b,c).  
 271 Allele frequencies/read counts/methylation scores from outlier variants are used alongside  
 272 current and projected future environmental data in a modelling framework to generate  
 273 genomic offset estimates (3a,b). Lastly, multiple methods can be employed to validate these  
 274 model-based offset estimates, including assessing the fitness of constituent populations in  
 275 common garden experiments (4a), generating historical offset estimates using publicly  
 276 available climate data (e.g. BioOracle) (4b), and comparing historical offset estimates with  
 277 recent/historical demographic patterns uncovered through long-term fisheries data (4c).  
 278 Abbreviations: SST, sea surface temperature; Sal, salinity; O<sub>2</sub>, dissolved oxygen.



## 279 5. Validating genomic offset in marine systems

280 Predictions of climate change vulnerability via genomic offset are correlative in nature  
281 and as such, these models can be prone to misinterpretation or errors when the underlying  
282 genomic data, climate projections, or their associations are of low resolution or inaccurate.  
283 Moreover, these models largely ignore much of the underlying complexity of real-world  
284 evolutionary scenarios including effective population size, rates of mutation and  
285 recombination (Rellstab et al. 2021). The approach assumes that there will be a non-  
286 negligible mismatch between current and future optima and that the current genotype-  
287 environment association accurately reflects spatial patterns in local adaptation, assumptions  
288 that can be impacted by demographic patterns and genetic drift (Rellstab et al. 2021;  
289 Laruson et al. 2022). For instance, spatial changes in allele frequencies may reflect neutral  
290 drift rather than selection, and this is especially likely when population size varies along  
291 environmental gradients. Laruson et al. (2022) employ simulations to demonstrate that  
292 although genomic offset is broadly correlated with population mean fitness, it could be  
293 confounded by demography, drift, genomic architecture, and the nature of the offset-fitness  
294 relationship.

295 Beyond the recent simulation study, few studies to date have attempted to validate  
296 the assumptions inherent to, or the projected vulnerabilities associated with, genomic offset  
297 calculations. In theory, validation may come from experimental studies, or comparison of  
298 predictions with existing demographic or ecological data. The only examples of experimental  
299 validation to date are from terrestrial species, where genomic offset estimates were  
300 compared to population performance measured in common garden settings—where distinct  
301 populations are grown under the same environmental conditions to identify differences in  
302 fitness (e.g. Fitzpatrick et al. 2021; Gain et al. 2023). For instance, Fitzpatrick et al. (2021)  
303 reported a negative relationship between genomic offset and common garden performance  
304 consistent with significant power of offset estimates to predict population response to climate  
305 change, exceeding that of climate differences alone. In contrast, Bay et al. (2018) used  
306 genomic offset to identify vulnerable populations of the yellow warbler (*Setophaga petechia*)  
307 and compared offset estimates to historical trends in abundance. Although they report a  
308 correlation between offset projections and demographic decline, this approach assumes that  
309 historical population trends are indicative of future trends, and it can be biased by non-  
310 selective / demographic influences on the offset prediction (Laruson et al. 2022).  
311 Interestingly, no direct attempts to validate genomic offset predictions in marine species  
312 have been published to date.

313 Although very informative and likely the gold standard, the potential for experimental  
314 validation of offset estimates through either reciprocal transplant or common garden  
315 experiments in marine species are limited by comparison with terrestrial plants or animals.  
316 This is largely due to the added complexity of these experiments in the marine environment,  
317 but some exceptions exist. For instance, Jacobs et al. (2022) reared fertilized eggs of  
318 Atlantic silversides (*Menidia menidia*) in temperature-controlled water baths and compared  
319 growth rates amongst treatments. However, long generation times in many exploited marine  
320 species (e.g. 20 years in deepwater redfish, *Sebastes mentella*, COSEWIC 2010) means  
321 that the short timescales with which common garden experiments are typically performed will  
322 provide only a snapshot of response. Alternatively, marine species, particularly exploited  
323 ones, often have extensive stock assessment and long-term monitoring programs with  
324 decades of time series data that can be used for validation in the absence of common  
325 garden experiments. Rather than comparing future estimates of climate change impact with  
326 past demographic data, time series data allows direct comparison of past demographic  
327 trends with predictions of past climate-induced maladaptation (i.e. offset). This approach,  
328 although not perfect, offers a means for validation when offset calculations are hindcast to  
329 the period over which population monitoring has occurred. Furthermore, sampling programs  
330 spanning decades present the opportunity to retrospectively test for temporal changes in

331 allele frequencies in response to climate change. Here, we can pair historical DNA (e.g. from  
332 scales or otoliths) with environmental data from the same time to estimate past climate-  
333 associated variation (e.g. [Atmore et al. 2022](#)). This dataset can then serve as the base  
334 model for computing genomic offset, both for contemporary and future scenarios. [These](#)  
335 [approaches to validation, although powerful, are biased toward exploited species whose](#)  
336 [stocks are already depleted from fishing and thereby teasing apart the relative impacts of](#)  
337 [climate change and exploitation will be critical in these cases. Nonetheless, we argue that](#)  
338 the availability of extensive population data [and historical samples](#) for many economically  
339 and ecologically relevant marine species creates an unprecedented opportunity for  
340 retrospective indirect validation in marine systems.

## 341 **6. Implementing genomic offset in marine management**

342 [Validating offset estimates in the marine environment will continue to be an important](#)  
343 [avenue for future work, but the integration of these estimates in marine management is even](#)  
344 [more vital. This is because existing management approaches typically rely on SDMs, which](#)  
345 [although informative, are best used to compliment methods that explicitly consider](#)  
346 [adaptation.](#) To first generate and integrate genomic offset estimates into marine  
347 management decisions, the following steps should be taken. First, comprehensive sampling  
348 across the range of the species of interest is needed (i.e. covering all known populations,  
349 latitudes, conservation areas, spawning areas, temperature regimes, etc.). Next, suitable  
350 genomic sampling is required to inform population structure and to produce accurate and  
351 robust allele frequencies (i.e. minimum 30 individuals per sampling location, and genomic  
352 variants through high resolution whole genome [sequencing, including pool-seq](#), or  
353 methylation sequencing at depths >2-10X). Then, high resolution long-term climate data is  
354 needed for the study region, covering biologically relevant environmental variables and  
355 preferably validated with *in situ* measurements accounting for depth and seasonal variation.  
356 To complement this, future climate change scenario models of the same resolution as  
357 contemporary climate data are required, which often show a trade-off of model resolution  
358 and geographic scale. Selection of future emissions scenarios should be justified, aligning  
359 with relevant management priorities in a region (e.g., RCP 4.5 versus 8.5). The resulting  
360 offset estimates offer valuable insights, particularly for identifying populations or areas  
361 expected to be hotspots of future maladaptation, thereby serving as focal points for proactive  
362 management. In such cases, we recommend applying genomic offset estimates in the real-  
363 world through 'assisted evolution' or restoration through transplantation, enhancing resilience  
364 to a changing climate (e.g., Wood et al. 2021). [Although straightforward in theory, this](#)  
365 [proposed workflow can be challenging to implement in practice given constraints on budget](#)  
366 [and time. For instance, generating dense genomic datasets for many individuals and](#)  
367 [populations can be expensive and thus targeting a smaller subset of climate-associated loci](#)  
368 [might be a feasible alternative. Additionally, sampling from all known populations across a](#)  
369 [species range can be logistically challenging and thus selecting a subset of populations that](#)  
370 [best represent variation \(both genomic and environmental\) in the system could be an](#)  
371 [alternative approach.](#)

372 As genomic offset models are refined and applied to other taxa of conservation  
373 interest, there will be a need to integrate predictions into management and decision making.  
374 While validating genomic offset models, through experiments or observations over time,  
375 should foster trust in the method, there are consequences to inaction as well (Salafsky and  
376 Redford 2013). The standards of proof for a model or prediction can vary depending on the  
377 potential consequences of action versus inaction, and whether management or mitigation  
378 strategies are reversible. When inaction might result in long-term ecological consequences  
379 and when there is some certainty regarding a positive outcome for a population or species, a  
380 relatively low standard of proof may suffice (Salafsky and Redford 2013). In a management  
381 context, a plain-language report that states the results of the study, the caveats of the

382 genomic offset estimates, and potential consequences of action versus inaction is vital for  
383 informing decision-making processes.

## 384 7. Conclusions

385 Climate change is restructuring marine ecosystems, diminishing biodiversity and  
386 compromising ecosystem function. The global reliance on marine resources means that  
387 these changes will undoubtedly have clear repercussions on food security, economic  
388 stability, and human health (Payne et al. 2021). Our ability to mitigate these changes and  
389 “future-proof” management decisions and conservation actions through placing them in the  
390 larger context of climate change impacts could be a powerful tool. However, achieving this  
391 will depend on a thorough understanding of the basis of biological adaptation to climate and  
392 accurate predictions of the impacts of climate change on marine species.

393 Here, we reveal a growing wealth of examples of climate-associated adaptation in  
394 marine taxa, whose demonstration is only now possible with high-depth genomic sequencing  
395 and high-resolution marine climate data. Yet, there remains a general lack of [application and](#)  
396 [validation of genomic offset estimates, heightening the uncertainty of these predictions.](#)  
397 [Here, we argue that future work should focus on leveraging the wealth of long-term](#)  
398 [population data available for many economically and ecologically vital marine species to](#)  
399 [validate offset estimates when more traditional approaches are logistically challenging. A](#)  
400 [particularly exciting avenue for future work is the potential for generating models of past](#)  
401 [climate-associated variation with historical samples. Beyond validation,](#) there is even greater  
402 uncertainty on how to apply [offset estimates](#) in real-world fisheries management and marine  
403 conservation scenarios. [To this end, we provide a ‘standard operating procedure’ for marine](#)  
404 [managers, outlining how to generate offset estimates and modify workflows in the face of](#)  
405 [budgetary and time constraints. Genomic offset has the potential to transform marine](#)  
406 [management and is highly complementary to other genetic and non-genetic approaches to](#)  
407 [conserving vital marine resources.](#)

408

## 409 Conflict of Interest Statement

410 The authors declare that they have no conflicts of interest.

## 411 Data Availability

412 Data sharing not applicable – no new data generated in this manuscript.

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For Review Only

1 **Predicting the future of our oceans – evaluating genomic forecasting approaches in**  
 2 **marine species**

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7 **Running head:** Genomic forecasting in marine species

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## 38 1. Abstract

39 Climate change is restructuring biodiversity on multiple scales and there is a pressing need  
40 to understand the downstream ecological and genomic consequences of this change.  
41 Recent advancements in the field of eco-evolutionary genomics have sought to include  
42 evolutionary processes in forecasting species' responses to climate change (e.g. genomic  
43 offset), but to date, much of this work has focused on terrestrial species. Coastal and  
44 offshore species, and the fisheries they support, may be even more vulnerable to climate  
45 change than their terrestrial counterparts, warranting a critical appraisal of these approaches  
46 in marine systems. First, we synthesize knowledge about the genomic basis of adaptation in  
47 marine species, and then we discuss the few examples where genomic forecasting has been  
48 applied in marine systems. Next, we identify the key challenges in validating genomic offset  
49 estimates in marine species, and we advocate for the inclusion of historical sampling data  
50 and hindcasting in the validation phase. Lastly, we describe a workflow to guide marine  
51 managers in incorporating these predictions into the decision-making process.

## 52 2. Introduction

53 Climate change results in severe environmental change, with recent years being the  
54 warmest on record throughout the industrial period (Cheng et al. 2023). The global increase  
55 in average temperature is accompanied by a suite of environmental changes including  
56 increases in the frequency and intensity of extreme weather events, regional temperatures,  
57 atmospheric water vapour, and ocean heat, as well as decreases in pH, dissolved oxygen,  
58 and land and sea ice cover. For marine ecosystems, increased glacial runoff and rising sea  
59 temperatures pose significant challenges (He & Sillman 2019). The consequences of these  
60 impacts are evidenced by distributional shifts in many taxa (e.g., Poloczanska et al. 2013),  
61 with populations at the trailing edge declining and populations at the leading edge shifting  
62 poleward or into deeper waters (Polyakov et al. 2020; Pinsky et al. 2020). In fact, marine  
63 species and the fisheries they sustain appear to be more vulnerable to climate change than  
64 their terrestrial counterparts (Pinsky 2021). Given the global reliance on marine resources,  
65 these changes will undoubtedly impact food security and economic stability (Payne et al.  
66 2021). Consequently, there is a need to 'future-proof' marine ecosystems and conservation  
67 areas through proactive management based on a sound understanding of the ecological and  
68 genetic impacts of climate change (Tittensor et al. 2019).

69 There is a pressing necessity to predict climate change impacts in marine species  
70 and ecosystems to inform conservation planning and strategies. These predictions are  
71 particularly relevant to global fisheries and aquaculture, which provide a major source of  
72 nutrition to developed and developing countries (Bene et al. 2016). For instance, ocean  
73 warming has been linked to significant decreases in production capacity and shifts in the  
74 distribution of fisheries-targeted species (e.g., tuna, Monllor-Hurtado et al. 2017). Predicting  
75 range shifts in marine taxa remains a significant challenge and ultimately requires  
76 information on existing ranges, predictions of future environments, capacity for adaptive and  
77 plastic responses to environmental change, dispersal potential, and ecosystem structure and  
78 function. Marine species' ranges largely conform to their thermal limits (Sunday et al. 2012)  
79 and therefore even small changes in the thermal profile of a given marine region can have  
80 measurable consequences on population survival and subsequent extirpation.

81 A growing body of research has focused on developing tools to predict the impacts of  
82 climate change on wild populations. Ecological niche modelling - akin to species distribution  
83 modelling (SDM) - has been used in the last 20 years to map the probability of occurrence of  
84 a species across a landscape (Kearney & Porter 2009). However, traditional SDMs do not  
85 consider adaptive responses of populations to environmental change, for instance through  
86 multigenerational selection of advantageous genomic variants (e.g., standing genetic  
87 variation), or through the expression of epigenetic variants leading to acclimation via  
88 phenotypic plasticity. More recently, genomic offset - also termed genomic vulnerability (Bay

89 et al. 2018) - has been applied to both terrestrial and marine taxa to predict potential future  
90 maladaptation driven by climate change (e.g., Fitzpatrick & Keller 2015; Laruson et al. 2022;  
91 Layton and Bradbury 2021). This approach maps the contemporary spatial turnover of  
92 adaptive alleles onto current environmental conditions and then calculates the offset  
93 between present and future climate-associated genomic composition as a measure of  
94 maladaptation to climate change. In other words, genomic offset is an estimate of the  
95 change in genomic composition that would be required to track predicted climate change.  
96 Despite some limitations and challenges, including validation and management buy-in  
97 (Rellstab et al. 2021), the approach seems to accurately estimate climate change  
98 vulnerability when compared to experimental predictions (e.g., Fitzpatrick et al. 2021).  
99 Bernatchez et al. (2023) provide a comprehensive overview of this method, among others, in  
100 their recent review of genomics-based monitoring approaches, but to date, no study has  
101 assessed these methods in specific ecological contexts. Given the potential of genomic  
102 offset estimates to inform climate change predictions, and the observation that marine  
103 species are already being impacted by climate change, an evaluation of the method's  
104 applicability to marine species is warranted.

105 There are several reasons why estimating genomic offset can be useful for managing  
106 and conserving marine ecosystems and species. The poikilothermic nature of most marine  
107 fish, invertebrates, and macrophytes means that temperature is often a dominant selective  
108 pressure driving adaptive genetic diversity across populations. The low genetic structure and  
109 generally large effective population sizes ( $N_e$ ) often observed within marine species  
110 (Bradbury et al. 2008) means that the influence of genetic drift is typically minimal compared  
111 with that of natural selection. Moreover, many marine species occupy large latitudinal ranges  
112 and genomic approaches have repeatedly demonstrated putative adaptation across these  
113 variable environments. Taken together, our ability to resolve the genomic basis of climate-  
114 associated adaptation may be elevated in the marine environment compared with terrestrial,  
115 which can translate into improved power to predict population-level responses or  
116 vulnerability in these systems.

117 In this opinion piece, we review the literature on the genomic basis of climate  
118 adaptation in marine species (section 3), evaluate current examples of genomic offset  
119 estimates in marine systems (section 4), assess the potential for validation of these  
120 estimates (section 5), and finally we discuss the utility of these estimates in informing  
121 fisheries policy (section 6). Here, we argue that the wealth of data available from long-term  
122 monitoring programs in exploited marine species provides an unprecedented opportunity for  
123 validating offset estimates in an otherwise logistically challenging environment. We also  
124 argue that implementing offset estimates in marine management will enable a more  
125 comprehensive assessment of the impacts of climate change on exploitation.

### 126 **3. Genomic basis of adaptation in marine species**

127 Accurate prediction of potential maladaptation requires an understanding of how  
128 species are adapted to their environments. The number of potential drivers of adaptation in  
129 the marine environment is broad and includes numerous environmental variables such as  
130 temperature, salinity, dissolved oxygen, pH, and depth. Although theory would predict that  
131 extensive gene flow facilitated by long pelagic larval durations in marine species would  
132 erode and prevent local adaptation, recent studies employing genome-wide data have  
133 provided strong evidence for climate-associated adaptation in several marine taxa (e.g.  
134 Drinan et al. 2018; Vranken et al. 2021). For some species with high connectivity and gene  
135 flow, like Atlantic cod (*Gadus morhua*), herring (*Clupea harengus*), horse mackerel  
136 (*Trachurus trachurus*), and northern sand lance (*Ammodytes dubius*), a few "large effect"  
137 chromosomal rearrangements seem to explain most of the climate-associated genomic  
138 variation (e.g., Barth et al. 2017; Kess et al. 2020; Fuentes-Pardo et al. 2023a). For  
139 example, a large 10Mb inversion on chromosome 21 discriminates northern and southern  
140 populations of horse mackerel in Europe (Fuentes-Pardo et al. 2023a). In other cases, a

141 signature of local adaptation is restricted to many regions of “small effect” in the genome,  
142 requiring dense genomic data for detection, as seen in Arctic charr (*S. alpinus*), Atlantic  
143 silversides (*Menidia menidia*) and the Baltic copepod (*Eurytemora affinis*) (Wilder et al. 2020;  
144 Kess et al. 2021; Stern et al. 2022). Here, adaptive SNPs are dispersed across most of the  
145 genome, rather than being concentrated in one particular region, constituting a signature of  
146 polygenic adaptation. The genomic underpinnings of local adaptation can vary not only  
147 across species but also across environmental gradients, and this is especially complex in  
148 marine systems where species are distributed across both geographic and bathymetric  
149 clines.

150 Genomic signatures of thermal adaptation have repeatedly been reported and  
151 appear to be more prevalent in marine systems than in terrestrial or freshwater systems  
152 (Sasaki et al. 2022). For example, temperature-driven structure has been observed in sea  
153 scallop (*Placopecten magellanicus*) (Van Wyngaarden et al. 2017), northern shrimp  
154 (*Pandalus borealis*) (Stanley et al. 2018), capelin (*Mallotus villosus*) (Cayuela et al 2021),  
155 and Atlantic herring (*Clupea harengus*) (Fuentes-Pardo et al 2023b). Extreme thermal  
156 events can also result in a reshuffling of genetic clusters leading to local adaptation. For  
157 example, Coleman et al. (2020) demonstrated that an extreme marine heatwave caused a  
158 significant poleward shift in populations of kelp forests along the coast of western Australia,  
159 whereby ‘cool water’ alleles were replaced by ‘warm water’ alleles, resulting in a genetic  
160 tropicalisation of the populations. While within a species the same adaptive alleles can be  
161 selected multiple times in distinct geographic areas, resulting in parallel evolution of thermal  
162 adaptation (Bradbury et al. 2010), the universality of the molecular processes involved in  
163 thermal adaptation is largely unknown in marine systems, partly due to the lack of genomic  
164 resources and functional validation of the markers under selection in published studies.

165 Climate change projections not only indicate a rapid increase in ocean temperature in  
166 the next century but also lower salinity in relation to glacier melting and higher precipitation  
167 in some regions, like the northern hemisphere (Luo et al. 2016). Additionally, many marine  
168 species use a variety of habitats throughout their life cycle, some spanning freshwater and  
169 estuarine environments and thereby experiencing steep salinity clines. A significant body of  
170 work supports salinity adaptation in marine organisms (Johannesson et al. 2020), particularly  
171 in the Baltic Sea. For instance, whole genome sequencing revealed hundreds of regions  
172 across the genome of Atlantic herring (*C. harengus*) that showed significant differentiation  
173 between Baltic and Atlantic populations (Han et al. 2020). Equivalent comparisons of Baltic  
174 and Atlantic populations have yielded similar results in other species such as Atlantic cod (*G.*  
175 *morhua*) (Berg et al. 2015), sand goby (*Pomatoschistus minutus*) (Leder et al. 2021), and  
176 European plaice (*Pleuronectes platessa*) (Le Moan et al. 2021), indicating adaptation to low  
177 salinity levels. Within the Baltic, different species of mussels have also shown salinity-related  
178 adaptation between western and eastern regions (Knöbel et al. 2021). Recently, Stern et al.  
179 (2022) showed experimental and genomic evidence of Baltic copepod (*E. affinis*) rapidly  
180 adapting to decreasing salinity. Similar to thermal adaptation, species can adapt to salinity  
181 changes through either parallel or convergent evolution (Le Moan et al. 2021), involving  
182 either few genetic variants of large effect or many loci of small effect (e.g., Berg et al. 2015;  
183 Le Moan, et al. 2021).

184  
185 Additionally, it is increasingly clear that the basis of local adaptation in marine taxa  
186 extends beyond SNPs to large-scale chromosomal rearrangements, copy number variants  
187 (CNVs), and epigenetic variation. For instance, environmental adaptation in American  
188 lobster (*Homarus americanus*) was driven almost entirely by CNVs with little to no signal in  
189 SNP data (Dorant et al. 2020). In contrast, Layton et al. (2021) reported similar spatial trends  
190 in genomic offset calculated from CNV and SNP datasets in Arctic Charr populations from  
191 eastern Canada. In three-spined stickleback, differentially methylated regions (DMRs) were  
192 more significantly associated with environmental variation (salinity) than outlier SNPs (Ruiz-  
193 Arenas et al. 2017). Given these findings, Layton and Bradbury (2022) suggest a revised



194 offset approach incorporating normalized read counts and methylation scores alongside  
 195 allele frequencies which might better reflect overall (genetic + epigenetic) adaptive  
 196 processes, thereby improving prediction accuracy. Despite a complex landscape of adaptive  
 197 genomic variation in marine species, only a few studies have leveraged this information for  
 198 estimating genomic offset in the marine environment.

199

#### 200 **4. Prediction of climate change impacts using genomic tools in marine** 201 **taxa**

202 As discussed above, local adaptation to ocean climate is widespread (at least at  
 203 regional scales) across marine species in various taxonomic groups and ecological contexts.  
 204 However, climate change is expected to disrupt local adaptation in the coming years,  
 205 resulting in potential maladaptation as the speed of change outpaces natural selection in  
 206 many species and populations (Razgour et al. 2019). The ability to resolve the genomic  
 207 basis of adaptation, in conjunction with fine-scale climate projections, presents an  
 208 opportunity to leverage these datasets to forecast future climate-associated genomic  
 209 composition and maladaptation. Genomic offset, defined as the difference between current  
 210 genomic composition and the predicted future composition required to maintain adaptation,  
 211 was first introduced by Fitzpatrick and Keller (2015) and later by Bay et al. (2018) and has  
 212 been used to identify populations most vulnerable to future climate change. Additionally, the  
 213 genomic offset approach can be employed across historical timescales, for instance by  
 214 calculating the difference between current genomic composition and past genomic  
 215 composition hindcasted at the last glacial maximum.

216

217 In the past few years, this method has been increasingly employed across various  
 218 terrestrial systems (e.g., Capblancq et al. 2020), with more recent work focussing on *in situ*  
 219 validation of these offset estimates (Fitzpatrick et al. 2021). To derive the offset estimate,  
 220 allele frequencies of putatively adaptive, climate-associated loci are the response variables  
 221 to environmental predictor data to model climate-associated genomic variation using any  
 222 number of modelling approaches. The most common modelling approaches include  
 223 generalized dissimilarity modelling (GDM) and gradient forest (GF)—both of which  
 224 accommodate for nonlinear associations of genomic and environmental data. The former  
 225 uses distance matrices to model climate-associated genomic variation while the latter  
 226 employs a regression-tree approach that is especially suitable in the context of steep  
 227 environmental gradients (Fitzpatrick & Keller 2015). The model is then used alongside  
 228 environmental data from both current and future time periods and across the species' range  
 229 to predict current and future adaptive indices, respectively. The difference between these  
 230 values represents offset, with larger values indicating that a population is more likely to be  
 231 maladapted to future climate. This method has typically been used in species with strong  
 232 population structure distributed across well-defined environmental gradients, but its utility  
 233 and downstream interpretation in marine species has been understudied. However, recent  
 234 work has begun to address this gap, demonstrating its potential utility in eleven species of  
 235 fish, invertebrates and marine plants (Table 1).

236 **Table 1:** List of current publications employing genomic offset estimates in marine species.  
 237 The statistical method used to generate offset estimates, and the environmental predictors  
 238 used, is also listed (RDA=redundancy analysis; GDM= generalised dissimilarity modelling;  
 239 GF=gradient forest).

Organism	Region	Method	Included Climate Variables	Validated	Reference
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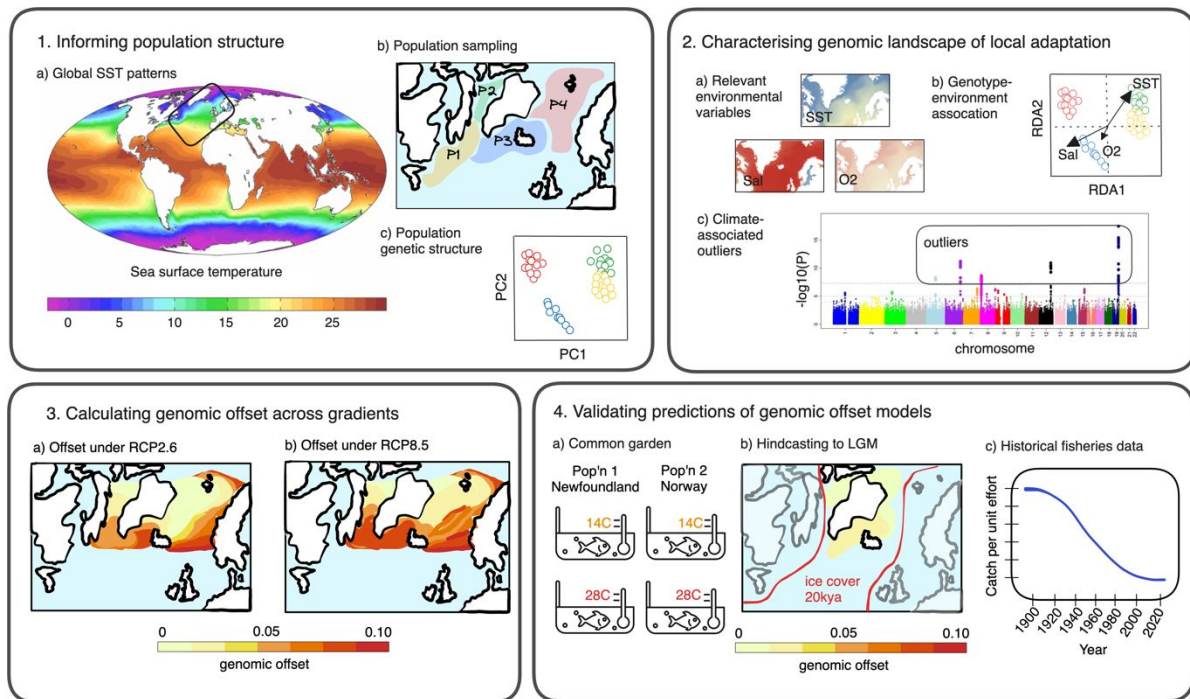
<b>Macrophytes</b>					
Eelgrass ( <i>Zostera marina</i> )	Coastal North America	RDA	Seasonal, annual bottom & surface temperature, salinity	No	Jeffery et al. (2024)
Seaweed ( <i>Phyllospora comosa</i> )	Southeastern Australia	GDM	Sea surface temperature	No	Wood et al. (2021)
Kelp ( <i>Ecklonia radiata</i> )	Western Australia	GF	Dissolved oxygen, sea surface salinity, sea surface nitrate, seawater velocity, attenuation	No	Vranken et al. (2021)
<b>Vertebrates</b>					
Arctic Charr ( <i>Salvelinus alpinus</i> )	Newfoundland/Labrador	GF	Precipitation, air temperature	No	Layton et al. (2021)
Sockeye salmon ( <i>Oncorhynchus nerka</i> )	British Columbia & Yukon	GF	Precipitation, air temperature	No	Tigano et al. (2024)
<b>Invertebrates</b>					
Multi-species: Urchin ( <i>Parechinus angulosus</i> ), crab ( <i>Cyclograpsus punctatus</i> ) & limpet ( <i>Scutellastra granularis</i> )	South Africa	GF	Sea surface temperature, sea surface salinity & air temperature	No	Nielsen et al. (2021)
Coral ( <i>Acropora digitifera</i> )	Western Australia	GF & GDM	Sea surface temperature	No	Adam et al. (2022)
Tubeworms ( <i>Galeolaria caespitosa</i> & <i>G. gemineoa</i> )	Southeast Australia	GF	Sea surface temperature	No	Gallegos et al. (2023)

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Most of these studies have focused on generating offset estimates in single species across a variety of spatial scales, with variable patterns across taxonomic groups and geographic areas. For instance, in eastern Canada, offset estimates were highest in southern populations of Arctic charr (*S. alpinus*) (Layton et al. 2021), indicative of a scenario of contraction of the southern range limit of this Arctic species. Alternatively, genomic offset

246 values were higher in northern (subarctic) populations of a widely distributed seagrass  
 247 species (*Z. marina*) across a similar area (Jeffery et al. 2024). Estimates of future offset in  
 248 *Acropora digitifera* in western Australia are more spatially complex, but populations living at  
 249 the upper thermal limits (i.e. at lower latitudes) were predicted to require less of an adaptive  
 250 shift than mid-latitude reefs (Adam et al. 2022). Similarly, Wood et al. (2021) shows a  
 251 spatially complex pattern of future offsets in a forest-forming seaweed (*P. comosa*) in  
 252 Australia, demonstrating that offset estimates do not follow a simple latitudinal cline and  
 253 rather vary with standing genetic diversity and predicted rates of climate change. Finally,  
 254 Nielsen et al. (2021) in a comparative study of three marine invertebrates, explore genomic  
 255 offset values and reveal a strong correlation among temperature and genomic variation in  
 256 some species but not others and that species-specific patterns were better predictors of  
 257 required adaptive shifts than environmental data alone. These findings suggest that broad  
 258 generalizations of climate change vulnerability in marine species, even among closely  
 259 related taxa or within similar geographic regions, might be challenging. However, they clearly  
 260 indicate that additional investigations of genomic offset in marine organisms are  
 261 necessary. This is especially true when considering validation, as no studies to date have  
 262 attempted to validate genomic offset estimates in marine species.

### 263 Generating and validating genomic offset estimates in marine environments



264

265 **Figure 1:** The first step in calculating genomic offset estimates in the marine environment is  
 266 to sample populations from across the range, ideally from steep environmental gradients, to  
 267 inform population structure in the species of interest (1a,b,c). Next, allele frequencies/read  
 268 counts/methylation scores (response) and environmental (predictor) data are used for  
 269 genotype-environment association (GEA) analyses to identify climate-associated outlier  
 270 variants (see Bernatchez et al. (2023) for a detailed overview of GEA approaches) (2a,b,c).  
 271 Allele frequencies/read counts/methylation scores from outlier variants are used alongside  
 272 current and projected future environmental data in a modelling framework to generate  
 273 genomic offset estimates (3a,b). Lastly, multiple methods can be employed to validate these  
 274 model-based offset estimates, including assessing the fitness of constituent populations in  
 275 common garden experiments (4a), generating historical offset estimates using publicly  
 276 available climate data (e.g. BioOracle) (4b), and comparing historical offset estimates with  
 277 recent/historical demographic patterns uncovered through long-term fisheries data (4c).  
 278 Abbreviations: SST, sea surface temperature; Sal, salinity; O<sub>2</sub>, dissolved oxygen.

## 279 5. Validating genomic offset in marine systems

280 Predictions of climate change vulnerability via genomic offset are correlative in nature  
281 and as such, these models can be prone to misinterpretation or errors when the underlying  
282 genomic data, climate projections, or their associations are of low resolution or inaccurate.  
283 Moreover, these models largely ignore much of the underlying complexity of real-world  
284 evolutionary scenarios including effective population size, rates of mutation and  
285 recombination (Rellstab et al. 2021). The approach assumes that there will be a non-  
286 negligible mismatch between current and future optima and that the current genotype-  
287 environment association accurately reflects spatial patterns in local adaptation, assumptions  
288 that can be impacted by demographic patterns and genetic drift (Rellstab et al. 2021;  
289 Laruson et al. 2022). For instance, spatial changes in allele frequencies may reflect neutral  
290 drift rather than selection, and this is especially likely when population size varies along  
291 environmental gradients. Laruson et al. (2022) employ simulations to demonstrate that  
292 although genomic offset is broadly correlated with population mean fitness, it could be  
293 confounded by demography, drift, genomic architecture, and the nature of the offset-fitness  
294 relationship.

295 Beyond the recent simulation study, few studies to date have attempted to validate  
296 the assumptions inherent to, or the projected vulnerabilities associated with, genomic offset  
297 calculations. In theory, validation may come from experimental studies, or comparison of  
298 predictions with existing demographic or ecological data. The only examples of experimental  
299 validation to date are from terrestrial species, where genomic offset estimates were  
300 compared to population performance measured in common garden settings—where distinct  
301 populations are grown under the same environmental conditions to identify differences in  
302 fitness (e.g. Fitzpatrick et al. 2021; Gain et al. 2023). For instance, Fitzpatrick et al. (2021)  
303 reported a negative relationship between genomic offset and common garden performance  
304 consistent with significant power of offset estimates to predict population response to climate  
305 change, exceeding that of climate differences alone. In contrast, Bay et al. (2018) used  
306 genomic offset to identify vulnerable populations of the yellow warbler (*Setophaga petechia*)  
307 and compared offset estimates to historical trends in abundance. Although they report a  
308 correlation between offset projections and demographic decline, this approach assumes that  
309 historical population trends are indicative of future trends, and it can be biased by non-  
310 selective / demographic influences on the offset prediction (Laruson et al. 2022).  
311 Interestingly, no direct attempts to validate genomic offset predictions in marine species  
312 have been published to date.

313 Although very informative and likely the gold standard, the potential for experimental  
314 validation of offset estimates through either reciprocal transplant or common garden  
315 experiments in marine species are limited by comparison with terrestrial plants or animals.  
316 This is largely due to the added complexity of these experiments in the marine environment,  
317 but some exceptions exist. For instance, Jacobs et al. (2022) reared fertilized eggs of  
318 Atlantic silversides (*Menidia menidia*) in temperature-controlled water baths and compared  
319 growth rates amongst treatments. However, long generation times in many exploited marine  
320 species (e.g. 20 years in deepwater redfish, *Sebastes mentella*, COSEWIC 2010) means  
321 that the short timescales with which common garden experiments are typically performed will  
322 provide only a snapshot of response. Alternatively, marine species, particularly exploited  
323 ones, often have extensive stock assessment and long-term monitoring programs with  
324 decades of time series data that can be used for validation in the absence of common  
325 garden experiments. Rather than comparing future estimates of climate change impact with  
326 past demographic data, time series data allows direct comparison of past demographic  
327 trends with predictions of past climate-induced maladaptation (i.e. offset). This approach,  
328 although not perfect, offers a means for validation when offset calculations are hindcast to  
329 the period over which population monitoring has occurred. Furthermore, sampling programs  
330 spanning decades present the opportunity to retrospectively test for temporal changes in

331 allele frequencies in response to climate change. Here, we can pair historical DNA (e.g. from  
332 scales or otoliths) with environmental data from the same time to estimate past climate-  
333 associated variation (e.g. Atmore et al. 2022). This dataset can then serve as the base  
334 model for computing genomic offset, both for contemporary and future scenarios. These  
335 approaches to validation, although powerful, are biased toward exploited species whose  
336 stocks are already depleted from fishing and thereby teasing apart the relative impacts of  
337 climate change and exploitation will be critical in these cases. Nonetheless, we argue that  
338 the availability of extensive population data and historical samples for many economically  
339 and ecologically relevant marine species creates an unprecedented opportunity for  
340 retrospective indirect validation in marine systems.

## 341 **6. Implementing genomic offset in marine management**

342 Validating offset estimates in the marine environment will continue to be an important  
343 avenue for future work, but the integration of these estimates in marine management is even  
344 more vital. This is because existing management approaches typically rely on SDMs, which  
345 although informative, are best used to compliment methods that explicitly consider  
346 adaptation. To first generate and integrate genomic offset estimates into marine  
347 management decisions, the following steps should be taken. First, comprehensive sampling  
348 across the range of the species of interest is needed (i.e. covering all known populations,  
349 latitudes, conservation areas, spawning areas, temperature regimes, etc.). Next, suitable  
350 genomic sampling is required to inform population structure and to produce accurate and  
351 robust allele frequencies (i.e. minimum 30 individuals per sampling location, and genomic  
352 variants through high resolution whole genome sequencing, including pool-seq, or  
353 methylation sequencing at depths >2-10X). Then, high resolution long-term climate data is  
354 needed for the study region, covering biologically relevant environmental variables and  
355 preferably validated with *in situ* measurements accounting for depth and seasonal variation.  
356 To complement this, future climate change scenario models of the same resolution as  
357 contemporary climate data are required, which often show a trade-off of model resolution  
358 and geographic scale. Selection of future emissions scenarios should be justified, aligning  
359 with relevant management priorities in a region (e.g., RCP 4.5 versus 8.5). The resulting  
360 offset estimates offer valuable insights, particularly for identifying populations or areas  
361 expected to be hotspots of future maladaptation, thereby serving as focal points for proactive  
362 management. In such cases, we recommend applying genomic offset estimates in the real-  
363 world through 'assisted evolution' or restoration through transplantation, enhancing resilience  
364 to a changing climate (e.g., Wood et al. 2021). Although straightforward in theory, this  
365 proposed workflow can be challenging to implement in practice given constraints on budget  
366 and time. For instance, generating dense genomic datasets for many individuals and  
367 populations can be expensive and thus targeting a smaller subset of climate-associated loci  
368 might be a feasible alternative. Additionally, sampling from all known populations across a  
369 species range can be logistically challenging and thus selecting a subset of populations that  
370 best represent variation (both genomic and environmental) in the system could be an  
371 alternative approach.

372 As genomic offset models are refined and applied to other taxa of conservation  
373 interest, there will be a need to integrate predictions into management and decision making.  
374 While validating genomic offset models, through experiments or observations over time,  
375 should foster trust in the method, there are consequences to inaction as well (Salafsky and  
376 Redford 2013). The standards of proof for a model or prediction can vary depending on the  
377 potential consequences of action versus inaction, and whether management or mitigation  
378 strategies are reversible. When inaction might result in long-term ecological consequences  
379 and when there is some certainty regarding a positive outcome for a population or species, a  
380 relatively low standard of proof may suffice (Salafsky and Redford 2013). In a management  
381 context, a plain-language report that states the results of the study, the caveats of the



382 genomic offset estimates, and potential consequences of action versus inaction is vital for  
383 informing decision-making processes.

## 384 7. Conclusions

385 Climate change is restructuring marine ecosystems, diminishing biodiversity and  
386 compromising ecosystem function. The global reliance on marine resources means that  
387 these changes will undoubtedly have clear repercussions on food security, economic  
388 stability, and human health (Payne et al. 2021). Our ability to mitigate these changes and  
389 “future-proof” management decisions and conservation actions through placing them in the  
390 larger context of climate change impacts could be a powerful tool. However, achieving this  
391 will depend on a thorough understanding of the basis of biological adaptation to climate and  
392 accurate predictions of the impacts of climate change on marine species.

393 Here, we reveal a growing wealth of examples of climate-associated adaptation in  
394 marine taxa, whose demonstration is only now possible with high-depth genomic sequencing  
395 and high-resolution marine climate data. Yet, there remains a general lack of application and  
396 validation of genomic offset estimates, heightening the uncertainty of these predictions.  
397 Here, we argue that future work should focus on leveraging the wealth of long-term  
398 population data available for many economically and ecologically vital marine species to  
399 validate offset estimates when more traditional approaches are logistically challenging. A  
400 particularly exciting avenue for future work is the potential for generating models of past  
401 climate-associated variation with historical samples. Beyond validation, there is even greater  
402 uncertainty on how to apply offset estimates in real-world fisheries management and marine  
403 conservation scenarios. To this end, we provide a ‘standard operating procedure’ for marine  
404 managers, outlining how to generate offset estimates and modify workflows in the face of  
405 budgetary and time constraints. Genomic offset has the potential to transform marine  
406 management and is highly complementary to other genetic and non-genetic approaches to  
407 conserving vital marine resources.

408

## 409 Conflict of Interest Statement

410 The authors declare that they have no conflicts of interest.

## 411 Data Availability

412 Data sharing not applicable – no new data generated in this manuscript.

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