

Impediments to Understanding Seagrasses' Response to Global Change

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ABSTRACT

Uncertainties from sampling biases present challenges to ecologists and evolutionary biologists in understanding species sensitivity to anthropogenic climate change. Here, we synthesize possible impediments that can constrain research to assess present and future seagrass response from climate change. First, our knowledge of seagrass occurrence information is prevalent with biases, gaps and uncertainties that can influence inferences on species response to global change. Second, research on seagrass diversity has been focused on species-level metrics that can be measured with data from the present - but rarely accounting for the shared phylogenetic relationships and evolutionary distinctiveness of species despite species evolved and diversified from shared ancestors. Third, compared to the mass production of species occurrence records, computational tools that can analyze these datasets in a reasonable amount of time are almost non-existent or do not scale well in terms of computer time and memory. These impediments mean that scientists must work with incomplete information and often unrepresentative data to predict how seagrass diversity might change in the future. We discuss these shortfalls and provide a framework for overcoming the impediments and diminishing the knowledge gaps they generate.

INTRODUCTION

Human activities, through fossil fuel emissions and widespread deforestation, have contributed to increased global temperature above pre-industrial levels (IPCC 2018). As a consequence, global increases in temperature and atmospheric carbon dioxide can influence species by altering their growth rates, physiological functions, sexual reproduction, distribution, community composition, and primary productivity (Campbell et al., 2006; Short & Neckles 1999). Such changes in environmental climate outside species' tolerable thresholds will cause some species to relocate in order to stay within their tolerance zones (Bradshaw & Holzapfel 2001; Parmesan, 2006; Miller-Rushing & Primack 2008; Anderson et al., 2012; MacLean et al., 2018). For instance, species on land generally ascend to higher elevations or latitudes as temperatures warm, but may run out of room, which can lead to local extirpation (Parmesan et al., 1999; Freeman et al., 2018). The sensitivity and responsivity of seagrasses or other marine species, whose distributional ranges lie at the land-sea margin and with very different evolutionary histories may show different responses to climate change.

46 Seagrasses are a major vascular plant clade of about 70 species belonging to the Alismatales, an
47 order that includes ~4000 other non-marine species (Berry 2019). They are widely distributed
48 across marine coastlines or estuarine environments, often growing submerged in marine water
49 (Hemminga & Duarte 2000). Seagrasses display a wide variety of morphological diversity
50 including turtlegrass (*Thalassia testudinum*) which forms long and jointed rhizomes, rhizome
51 matts in *Posidonia*, ribbonlike leaves in eelgrass (*Zostera marina*), and paddle-shaped leaves in
52 paddle grass (*Halophila decipiens*) (Figure 1). They play key ecosystem roles including primary
53 productivity, nutrient cycling, and carbon sequestration (Hemminga & Duarte 2000; Duarte
54 2002; Les et al., 2002; Orth et al., 2006; McGlathery et al., 2007; Nordlund et al., 2018).
55 Seagrass meadows are an important nursery ground for many invertebrates and fishes (Beck et
56 al., 2001), and directly provide food for marine herbivores including manatees, dugongs, and
57 green sea turtles (Green & Short 2003; Larkum et al., 2006). As threats from global climate
58 change intensify, the impacts across seagrass communities are mixed. Some studies have found a
59 decline in seagrass habitats especially in Australasia with decline rates of about 110 km² per year
60 (Waycott et al., 2009). This pattern is not true in North America and Europe where seagrass
61 communities are no longer in decline, but in fact show positive trajectories in some cases (de los
62 Santos et al., 2019), perhaps as a result of the proliferation of seagrass monitoring and
63 conservation programs such as Seagrass-Watch (<https://www.seagrasswatch.org/>) and
64 SeagrassSpotter (<https://seagrassspotter.org/>). Indeed, the vulnerability to the impacts of climate
65 change on seagrass communities may be scale or context dependent (Day et al., 2008).

66
67 A number of studies indicate that global climate change can impact seagrass communities in a
68 variety of ways. Short & Neckles (1999) reviewed the potential effects of climate change on
69 seagrass growth rates, reproduction and spatial distributions; Duarte et al. (2018) explored
70 relationships between climate change and phenotypic variation in seagrasses (including
71 physiological variation, propagation success, and herbivore resistance); whereas Erry et al.
72 (2019) used a mesocosm experiment to assess response of a multi-trophic seagrass ecosystem to
73 several global change factors. The findings overwhelmingly demonstrated that these factors in
74 unison could lead to deleterious effects on seagrass ecosystems if they are unable to rapidly
75 adapt to changes in climate. Similar trends have been observed for specific seagrass locations
76 e.g., Great Barrier Reef (Waycott et al., 2007), Mediterranean (Pergent et al., 2014), tropical
77 Pacific Ocean (Waycott et al., 2011), and Western Australia (Arias-Ortiz et al., 2018; Strydom et
78 al., 2020); or in selected species (e.g., Chefaoui et al., 2018). Other threats to seagrass
79 populations can be attributed to overexploitation, physical modification, nutrient and sediment
80 pollution, and introduction and spread of invasive species (Zieman 1976; Ralph et al., 2006;
81 Moksnes et al., 2008; Bryars et al., 2011; Dewsbury et al., 2016). By contrast, research to
82 elucidate effects of global climate change on seagrass meadows and how to improve the
83 prediction of future risks under varying scenarios of climate change have received less attention
84 (Pernetta et al., 1994; Bijlsma et al., 1995; Short & Neckles 1999).

85
86 Here, we argue that the extension of research agenda to assess seagrasses' response to climate
87 change may be constrained by at least three factors. First, our knowledge of seagrass occurrence
88 information is widespread with biases, gaps and uncertainties that can influence downstream
89 inferences. Second, most of the research on seagrass diversity has been focused on species-level
90 metrics (e.g., species richness, endemism or threat) that can be measured with data from the
91 present - but rarely accounting for the shared phylogenetic relationships and evolutionary

92 distinctiveness of species. Species are not independent units but are lineages that evolve and
93 diversify from shared ancestors (Diniz-Filho et al., 2013). Third, compared to the mass
94 production of species occurrence records, computational tools that can analyze these datasets in a
95 reasonable amount of time are almost non-existent or do not scale well in terms of computer time
96 and memory. These impediments mean that scientists must work with incomplete information
97 and often unrepresentative data to predict how seagrass diversity might change in the future.
98 These shortfalls need be carefully recognized and remedied. The objectives of this review are
99 therefore to first identify the knowledge gaps to understanding seagrasses' response to climate
100 change, and secondly propose strategies and tools to overcome these impediments.
101

102 **KNOWLEDGE GAPS IN SEAGRASS SAMPLING PRACTICES**

103 Global change has become a central focus of modern ecology. Yet, our knowledge of how
104 anthropogenic drivers affect seagrass evolutionary diversity is limited by a lack of biological
105 data spanning the Anthropocene that equally represents all seagrass species. We define the
106 Anthropocene as a period of profound human impact on biodiversity, characterized by
107 widespread migration by humans as initiated by the Columbian Exchange circa 1492 (Nunn &
108 Qian 2010). The vast amounts of specimens of seagrasses deposited in herbaria can serve as a
109 historical lens into the ecological processes by which present-day seagrass diversity arose, are
110 maintained, and may evolve in the future. However, occurrence records archived in herbaria and
111 museums are non-randomly collected over space and time, and thus present biases and
112 uncertainties that can complicate ecological inferences (e.g., Boakes et al., 2010; Meyer et al.,
113 2016; Daru et al., 2018; Dias Tarli et al., 2018). As a consequence, the use of occurrence records
114 has not fully permeated the field of global change biology. The gap between specimen
115 availability and use is widening as hundreds of thousands of specimens are being mobilized
116 through massive digitization efforts worldwide. We argue that sampling uncertainties in seagrass
117 occurrence records can manifest in at least three ways: geographic, taxonomic, and temporal
118 uncertainties (Figure 2). We distinguish between the uncertainties and describe how these
119 limitations can inhibit progress in understanding seagrass response to global change.
120

121 ***Uncertainties in geographic sampling***

122 Geographic bias is the disproportionate sampling of a species in some regions of its range
123 relative to others (Meyer et al., 2016; Stropp et al., 2016; Daru et al., 2018; Menegotto & Rangel
124 2019). Seagrass geographic data is commonly available as point records or polygons. Point
125 records are commonly derived from major data hubs such as the Global Biodiversity Information
126 Facility (GBIF; Edwards, Lane, & Nielsen 2000), United Nations Environment World
127 Conservation Monitoring Centre (UNEP-WCMC & Short 2020) or Ocean Biodiversity
128 Information Facility (OBIS) whereas polygons are derived from the International Union for the
129 Conservation of Nature's (IUCN) spatial database and United Nations Environment World
130 Conservation Monitoring Centre (Green & Short 2003; UNEP-WCMC & Short 2020). Despite
131 the fundamental importance of occurrence data for species distribution modeling, the sampling
132 of seagrasses across most of their ranges are underrepresented in collections (Green & Short
133 2003). For instance, extensive spatial gaps exist across regions that harbor high concentrations of
134 seagrass diversity, especially in Western and Central Indo-Pacific, whereas Europe and North
135 America are well sampled (Figure 3) (see Methods and Source Data file in Supplementary
136 Material for details). This pattern is consistent with previous studies. For example, Waycott et al.
137 (2009) found wide sampling gaps in West Africa, northeast South America, and the northwest

138 Pacific area of the United States, most of which correspond to seagrass areas of endemism.
139 Moreover, since biogeographic patterns are scale dependent, varying along spatial grains,
140 geographic extents and taxonomic treatments (Jarzyna et al., 2018; Daru et al., 2020), the extent
141 to which geographic uncertainties in seagrass sampling vary with spatial extent, grain size and
142 taxonomic treatment remains poorly explored. However, it has been predicted that as grain size
143 decreases, the knowledge gap in geographic sampling correspondingly increases (Hortal et al.,
144 2015).

145
146 The mismatch between observed seagrass diversity and maps of survey efforts can be attributed
147 to several factors: 1) knowing data exists in the first place and where it is, 2) harvesting data
148 collected in native languages not common to science, 3) getting permission to access data
149 collected under commercial license or from uncooperative governments, 4) validating data both
150 spatially and taxonomically, 5) the difficulty in sampling specimens especially species in remote
151 and inaccessible waters e.g., *Halophila decipiens* occurring >70 m deep in the Central Indo-
152 Pacific (Short et al., 2007) or large parts of Northern Australia that are only accessible by
153 helicopter, 6) lack of reliable research infrastructure e.g., West Papua and Papua New Guinea, 7)
154 un-inhabited reef lagoons in large parts of the tropics and Western Pacific, 8) the cost of
155 gathering long-term data (Wolfe et al., 1987), 9) perhaps a reversing trend of seagrass loss in
156 Europe, North America, and subtropical Atlantic, e.g., increasing population trends in
157 *Cymodocea nodosa* (Schäfer et al., 2021), *Zostera marina* and *Zostera noltei* (de los Santos et
158 al., 2019; Guerrero-Meseguer et al., 2021), and 10) budget constraints for seagrass research. If
159 seagrass species observations are made near accessible areas e.g., seaports, harbors or marine
160 research stations, their application in analysis of species distribution modeling can compromise
161 model performance (Kadmon et al., 2004; Lobo & Tognelli 2011; Bystriakova et al., 2012;
162 Kramer-Schadt et al., 2013; Varela et al., 2014). In practice, this means that most observations
163 only reflect the climate space of accessible areas, and correspondingly areas of human activities
164 where surface temperatures are higher than in surrounding natural areas (Kalnay & Cai 2003).
165 Additionally, regions known to contain seagrass meadows (e.g., Canada, Indonesia, and Russia)
166 have inadequately mapped distributions, while other currently mapped regions most likely only
167 represent a small portion of seagrass diversity (McKenzie et al., 2020). Targeting the places that
168 are underrepresented in future collecting expeditions could remedy these limitations and aid in
169 evaluating how species are responding to recent and future environmental change across biomes.
170

171 ***Uncertainties in temporal sampling***

172 The sampling of seagrasses can manifest as temporal bias—the unbalanced collecting of
173 specimens in some years or parts of a given year. This can influence conclusions drawn from
174 analyses of such nonrandomly sampled collections records (Syfert et al., 2013). Temporal data is
175 increasingly used in a wide range of applications in ecology and evolutionary studies including
176 tracking changes in phenology – the timing of seasonal events such as flowering, leafing and
177 fruiting – and monitoring the spread of invasive species (Iler et al., 2013; Veeneklaas et al.,
178 2013; Meerdink et al., 2019). Yet, while there is general agreement that climate change can
179 influence phenological patterns by disrupting the timing of life cycle events and consequently
180 drive changes in fitness and population demography (Ovaskainen et al., 2013; CaraDonna et al.,
181 2014; Thackeray et al., 2016; Kharouba & Wolkovich 2020), most have been observed in
182 terrestrial species and to a lesser extent in marine flowering plants. In a meta-analysis of GBIF
183 occurrence records over the course of 250 years (1770-2020) to understand the nature and

184 evolution of seagrass sampling, sparser records were observed in earlier years and high
185 collection densities between the 1900s and present-day (Figure 4). Although over the 250-year
186 time span, occurrence data was absent for a total of 131 years. Seasonally, seagrass specimens
187 were overwhelmingly biased toward spring and summer months (regardless of hemisphere
188 location) for most marine ecoregions including Temperate Southern Africa, Temperate
189 Australasia, Temperate Northern Pacific, and Temperate Northern Atlantic (Figure 5; see
190 Methods and Source Data file in Supplementary Material). Interestingly, these periods are
191 spanned by comprehensive time series data of ocean climate including sea temperature and
192 salinity (Benway et al., 2019). This means that the time series of changes in seagrass
193 communities across years or seasons are fewer than the available climate records (cf. Duarte et
194 al., 1992). As a consequence, the nonrandom sampling of seagrasses in some years or parts of a
195 year could mean that occurrence records are not reliable sources of phenological change driven
196 by climate or population demography. If seagrasses are collected only when it is climatically
197 convenient coupled with lack of reproductive structures on most specimens (Pearson et al.,
198 2020), botanists may miss important phenological events such as winter bud formation, which
199 protects the embryonic shoot of species during development and elongation (van der Schoot et
200 al., 2013). Similarly, climate change can influence population demography through range change
201 (Hunter et al., 2010; Dalglish et al., 2011; Hugo 2011; Gaillard et al., 2013; Selwood et al.,
202 2015) or facilitate the spread of invasive species (Hellmann et al., 2008; Clements & Ditomaso
203 2011; Vicente et al., 2013; Hou et al., 2014; Thapa et al., 2018). However, the skewed sampling
204 of seagrass occurrence data suggests that the data is insufficient to track demographic changes or
205 monitor spread of invasive species. We recognize that several aspects can influence seagrass
206 sampling across years or seasons. For instance, some seagrass species are annuals, completing
207 their life cycle within one growing season (e.g., *Halophila decipiens*). Other reasons include
208 inaccessibility to most sites in the West Indo-Pacific during monsoon times, resulting in
209 overrepresentation of specimens during maximum growing season/flowering season.
210

211 *Uncertainties in taxonomic sampling*

212 The sampling and collection of seagrass data may be disproportionately higher in some taxa over
213 others (Hortal et al., 2008). Taxonomic uncertainty can manifest as phylogenetic bias and be
214 assessed by testing for phylogenetic signal in collection frequency. A strong phylogenetic signal
215 – closely related species share similar collecting frequency – would suggest phylogenetic bias in
216 collections (Daru et al., 2018). Phylogenetic bias can hamper prospects of identifying species
217 that are climate change indicators and those most likely to be affected by future climate change,
218 especially given that species' response to climate change tends to be phylogenetically
219 nonrandom (Willis et al., 2008; Davis et al., 2010; Davies et al., 2013). A phylogenetic analysis
220 of long-term monitoring data in Concord Massachusetts, for instance, revealed a strong
221 association between change in abundance with flowering time response such that the response
222 traits are shared among closely related plant species (Willis et al., 2008). However,
223 taxonomically nonrandom collection may mask such patterns and therefore bias conclusions of
224 seagrass response to climate change. These data limitations may result from a research focus on
225 specific seagrasses lineages over other groups or simply lack of data on some species. For
226 example, Coyer et al. (2013) estimated divergence times in 20 species in the family Zosteraceae
227 at 14.4 Ma, whereas Dilipan et al. (2018) assessed phylogenetic relationships by focusing on
228 only family Hydrocharitaceae. Not only do these clade-based approaches point to different
229 divergence times, but the phylogenetic reconstructions also used different gene regions with

230 likely different rates of evolution. Seagrass occurrence data on GBIF tends to display a weak
231 phylogenetic signal in the tendency of closely related species to be sampled similarly; with an
232 average of ~9 specimens per species representing most *Halophila*, and ~6-9 specimens per
233 species representing most *Zostera*, whereas *Halodule* and *Posidonia* had far fewer records
234 (Figure 6; see Methods and Source Data file in Supplementary Material for details).

235
236 Another factor that can induce taxonomic bias is the lack of comprehensive phylogeny for
237 seagrass species. Inferring evolutionary patterns based only on phylogeny of the taxa within the
238 community of interest without fully accounting for the overall phylogenetic diversity of the
239 entire lineage can potentially lead to spurious results (Park et al., 2018). The available DNA
240 sequences of seagrasses in GenBank/EBI are sufficient to construct a molecular phylogenetic
241 tree for only 55 (of 72) species (Daru & le Roux 2016). The 17 species without available DNA
242 sequences are often manually grafted to the molecular tree in a multichotomy to the node of their
243 close relatives using a Bayesian framework (Thomas et al., 2013). Such incomplete sampling or
244 misplaced taxa on the phylogeny can influence the final tree topology and compromise rates of
245 evolution (Nee et al., 1994, FitzJohn et al., 2009), especially when biases are also geographically
246 nonrandom (Daru et al., 2018). Even with complete DNA sequences for all seagrass species,
247 there are large uncertainties in the estimation of divergence times, and unknown evolutionary
248 models linking phylogenies to underlying ecological traits and life history variation (Diniz-Filho
249 et al., 2013). Moreover, the polyphyletic nature of seagrasses, drawing from several lineages
250 within the Alismatales, might also compound our understanding of phylogenetic sampling
251 biases.

252
253 The aforementioned sampling uncertainties can combine with each other in several ways.
254 Taxonomic uncertainty can influence all other uncertainties because it reflects knowledge gaps
255 on the fundamental unit of ecology and evolutionary biology. Geographic uncertainty is strongly
256 influenced by temporal uncertainty as limited accumulation of data over time can alter accurate
257 estimations of species' range size or population demographic history (Pybus et al., 2000,
258 Drummond et al., 2005). Similarly, geographic uncertainty can compromise estimates of species'
259 phenological response to climate change or demographic change, owing to lack of geographical
260 coverage in many regions (Poelen et al., 2014). Ultimately, these sampling uncertainties are
261 human artefacts such that any personal preferences, biases, and proclivities of collectors can
262 greatly skew our understanding of seagrass diversity.

263
264 **GAPS IN KNOWLEDGE OF SEAGRASS EVOLUTIONARY DIVERSITY**
265 Understanding what drives variation in the distribution of biodiversity can provide insights into
266 the ecological and historical processes underlying community assembly (Cavender-Bares et al.,
267 2009) and for prioritizing conservation (Kreft & Jetz 2010; Holt et al., 2013; Daru & le Roux
268 2016). However, data gaps in the sampling of seagrasses (as outlined above) can influence
269 estimates of broad-scale patterns and underlying processes (e.g., extinction, speciation and niche
270 conservatism). Traditionally, identifying broad-scale patterns in seagrasses has been based on
271 species-level metrics (e.g., species richness, and endemism) (Short et al., 2007; Mtwana et al.,
272 2016; Duffy et al., 2019). Although indispensable in providing baseline biodiversity knowledge,
273 these metrics alone fail to detect the substantial evolutionary and conservation implications
274 captured by the shared phylogenetic relationships and evolutionary distinctiveness of species
275 (Mace et al., 2003; Redding & Mooers 2006; Cadotte 2013). Recent approaches harmonized

metrics that consider evolutionary components, for example, phylogenetic diversity (Faith 1992), evolutionary distinctiveness (Redding & Mooers 2006), phylogenetic endemism (Rosauer et al., 2009), or a combination of these metrics. As pressures from climate change induced by anthropogenic activity mount, we will eventually observe range shifts and losses that can erase unique evolutionary history (Waycott et al., 2009). There is some evidence that evolutionarily distinct temperate seagrass assemblages might be disproportionately at risk of extinction (Daru et al., 2017), which could elevate losses of phylogenetic diversity (Redding et al., 2008). However, the associated directionality of species' responses to climate change and impact on phylogenetic diversity under a scenario of nonrandom extinction is unclear (Purvis et al., 2000). This means that as global temperatures increase, tropical seagrass species might be capable of expanding their distributions (Beca-Carretero et al., 2020) into regions traditionally utilized only by temperate seagrass species. This can induce selection pressures on temperate species that can result in the loss of distinct evolutionary diversity of seagrasses as the available climate space for temperate species is reduced by warming temperatures. Such pressures would inhibit our ability to understand the evolutionary history of seagrasses, as evolutionarily distinct species are lost or greatly reduced.

The global decline of seagrasses along a latitudinal gradient is imbalanced, with greater declines documented in temperate than tropical regions, requiring urgent conservation action (Hauxwell et al., 2001; Orth et al., 2006; Moksnes et al., 2008; Bryars et al., 2011; Erry et al., 2019). The recent finding that temperate seagrass assemblages tend to be those that are most evolutionarily unique also warrants concern given that their extinction would result in a greater loss of phylogenetic diversity (Daru et al., 2017). In this regard, the familial membership of threatened seagrass species across marine ecoregions (see Methods and Source Data file in Supplementary Material) showed a tendency of threatened species in the Temperate Northern Pacific and Tropical Eastern Pacific clustering within similar families (Figure 7). This phylogenetic and taxonomic structuring suggests that evolutionary history is an important predictor of species decline, possibly reflecting a non-random pattern of extinction risk (Purvis et al., 2000). Van Allen et al. (2012) demonstrated the importance of life-history traits for predicting how natural assemblages are likely to be impacted by anthropogenic and climatic disturbances using modeled declines in population growth rates under simulated stochastic disturbance. With regard to species extinctions and extinction risk, an important link has been identified between the loss of species and the loss of unique evolutionary history (NRC-US, 2008). Furthermore, the extinction of evolutionarily distinct or paleoendemic species can elevate losses of evolutionary history (Veron et al., 2015). These patterns might be indicative that seagrasses are characterized by species that subtend longer phylogenetic branches perhaps representing once diverse clades that have been lost through historical extinctions.

As seagrasses are increasingly threatened along their taxonomic structure spanning several marine ecoregions, we argue that seagrass extinctions are unlikely to be random. Previously, Short et al. (2011) determined that roughly 14% of seagrass species were at an elevated risk of extinction based on the IUCN's Red List of Threatened Species criteria. Currently, the IUCN indicates that 31% (22 out of 72) of seagrass species are in global decline, and 22% lack information for proper assessment of conservation status (IUCN, 2020). Therefore, the question of why some species persist while others decline across regions will require an understanding of the shared evolutionary history underlying changes in species richness and composition

322 (Waycott 1999; Arnaud-Haond et al., 2010; Massa et al., 2013). With many species' ranges
323 greatly reduced or unknown, it is even more challenging to track patterns in seagrass population
324 successes or failures that could be indicative of their resilience to climate change. In the absence
325 of these key insights for the adaptive potential of seagrass species, we are unable to fully predict
326 how individual species of seagrasses will respond to drastic, widespread environmental changes.
327

328 In order to facilitate effective conservation action, it is important to accurately determine which
329 species are currently at the greatest risk for extinction, and which species will be at risk in the
330 future. One successful approach has been to collect expert opinion data to prioritize seagrass
331 management actions at regional scales (Grech et al., 2012) for species that may be unequally
332 impacted. To this end, phylogenetic information can be very useful for predicting vulnerabilities
333 at individual or familial levels (Gallagher et al., 2015). For example, families with a high
334 proportion of species in global decline include Zosteraceae, Hydrocharitaceae, Posidoniaceae,
335 and Cymodoceaceae; with Zosteraceae contributing about half of the total number of species in
336 decline (Figure 8). Therefore, Zosteraceae and other evolutionarily similar families may possess
337 a phylogenetic signal for extinction pressures. Families with seagrasses having unknown
338 population trends include Hydrocharitaceae, Cymodoceaceae, Ruppiaceae, Posidoniaceae, and
339 Zosteraceae according to the IUCN (see Methods and Source Data file in Supplementary
340 Material for details). These groups are of high conservation concern given that species associated
341 with these families may be currently threatened or already in decline without notice. Such
342 population trends, or lack thereof, imply that certain species of seagrasses may be too heavily
343 impacted in the future to prevent complete losses or extinctions given the rapid pace of climatic
344 change.
345

346 **SHORTFALLS IN COMPUTATIONAL TOOLS FOR ASSESSING SPECIES 347 RESPONSE TO CLIMATE CHANGE**

348 It is possible that the aforementioned impediments can be solved by increasing biological
349 knowledge and computational capacity. However, compared to the mass production of
350 occurrence records and climate data, tools that can analyze these datasets in a reasonable amount
351 of time are almost non-existent or do not scale well in terms of computer time, memory, or other
352 resources. This is particularly true for seagrasses that have wide geographic ranges, colonizing
353 every coastline. As a consequence, ecologists and conservationists wishing to address questions
354 related to seagrass response to climate change may be deterred by lack of analytical tools.
355

356 The occurrence data typically used for species distribution modeling is generated from massive
357 digitization of museum records and citizen science campaigns (e.g., Seagrass-Watch,
358 <https://www.seagrasswatch.org/>) and are often available as point records; whereas global
359 oceanographic variables are measured by instruments on satellites daily (NOAA Climate.gov,
360 2020), which increase the size of the dataset many-folds. This exponential increase in species
361 occurrences and oceanographic information inflate the size of running time for modeling
362 algorithms (Farley et al., 2018; Allen et al., 2019), and consequently increases the challenges for
363 visualizing downstream patterns. In Figure 9, the number of seagrass occurrence records in GBIF
364 has increased over time. Where there used to be access to only a few dozen records, the rapid
365 expansion of biodiversity occurrence data has now made it common for there to be a few
366 thousand records per species (see Source Data file in Supplementary Material). This poses
367 computational challenges for researchers. For analysis of species distribution modeling under

368 different representative concentration pathway scenarios, for instance, researchers rapidly run
369 into a spatial scale exponentiation problem. At a spatial resolution of 0.5 degrees (equivalent to
370 ~50 km at the equator) covering the geographic ranges of seagrasses, there are 201,600 possible
371 pixels for the algorithm to evaluate from. Computing probabilities across a 201,600-possibility
372 data frame is a challenge. Such large-scale analysis can easily reach thousands of bytes and
373 analysis using current tools would be prohibitively expensive computationally.
374

375 Presently, the software that can facilitate analysis of species distribution modeling of seagrasses
376 includes *maxent* (Steven et al., 2017), *dismo* (Hijmans et al., 2011), *biomod2* (Thuiller et al.,
377 2014), *esdm* (Woodman et al., 2019), ModEco (Guo & Liu 2010), SDMtoolbox 2.0 (Brown et
378 al., 2017), ArcGIS and ARCMAP. Several of these packages contain some statistical capabilities
379 by integrating occurrence information and climate data. For instance, *biomod2* facilitates species
380 distribution modeling by averaging across different methods including generalized additive
381 models, generalized linear models, generalized boosting trees, maximum entropy, and random
382 forest (Thuiller et al., 2014). However, these packages differ in their inferences, and analytical
383 and computational capacity to process the massively mobilized occurrence records spanning tens
384 of thousands of pixels across the globe (depending on the measurement scale). Some of these
385 packages are developed for use in command-line while others are graphical user-interface (GUI).
386 Most packages are developed to address a specific biological question and may have restricted
387 analytical options that can limit computational flexibility. Ultimately, scientists wishing to
388 address more complex hypotheses will have to use a compilation of multiple computational
389 workflows.
390

391 More recent approaches to scale existing software to handle the exponential growth of
392 biodiversity datasets include developing parallel algorithms (McCallum 2011) and using modern
393 computational architectures, such as multicore systems, graphics processing units, and
394 supercomputers (Maruyama et al., 2011). The advantages of these methods are that they provide
395 reproducible source codes. However, they might require the user to have a good background in
396 high performance computing. These limitations should not detract from exploring other
397 outstanding questions that remained to be addressed with the available tools: 1) What are the
398 effects of reduced area and increased isolation of marine habitats? 2) Where will seagrass species
399 disperse to under alternative scenarios of climate change? and 3) How have anthropogenic
400 activities e.g., marine pollution, sedimentation, and coastal urbanization changed the geography
401 of seagrasses?
402

403 **OVERCOMING THE IMPEDIMENTS**

404 Seagrass occurrence records are increasingly being utilized in biogeographical investigations and
405 prioritizing conservation (Valle et al., 2014; Chefaoui et al., 2018; Jayathilake & Costello 2018;
406 Beca-Carretero et al., 2020; Heck et al., 2020). As possible solutions for the geographic
407 uncertainty, we suggest enhanced funding for local, regional, and global inventories such as
408 SeagrassNet for seagrass habitats in the Western Pacific (Short et al., 2006), Seagrass-Watch in
409 Australasia (McKenzie et al., 2000, 2009), ResilienSEA (<http://resiliensea.org/>) in West Africa,
410 Texas Seagrass Monitoring program (<http://www.texasseagrass.org/>), SeagrassSpotter
411 (<https://seagrassspotter.org/>) a global tool for locating seagrasses, or Zostera Experimental
412 Network (<http://zensecience.org>) for eelgrass (*Zostera marina*). Overcoming gaps in geographic
413 sampling can also include collectors using best practices for collecting and vouchering

414 specimens such as capturing accurate geolocations. It could also require the digitization and
415 mobilization of vouchered seagrass specimens stored in herbaria and museums across the world.
416 The iNaturalist project is a platform for sharing species observations along with geographic
417 coordinates for terrestrial organisms and can be leveraged for filling in the data gaps in seagrass
418 sampling. Kew's Plants of the World Online portal (POWO) provides distribution information
419 on the seed-bearing plants of the world based on level 3 of the Taxonomic Diversity Working
420 Group distribution scheme which corresponds to country borders (POWO 2019) and can be
421 extended to cover seagrasses as well. High resolution cameras attached to unmanned aerial
422 vehicles can be deployed to survey seagrasses in remote and inaccessible waters; however,
423 special permits can often be required to access some sites (Johnston 2019).

424 Species distribution models – the statistical estimation of species geographic distributions based
425 on only some known occurrences and environmental conditions (Peterson et al., 2011) – can also
426 provide an unbiased and easily interpretable estimate of improving representativeness and
427 coverage of seagrass distributions. For example, a recent species distribution model predicts
428 more than two-fold increase in the potential global distribution of seagrasses (Jayathilake &
429 Costello 2018). However, the accuracy of this prediction has attracted particular scrutiny because
430 of inconsistent measures and widespread sampling gaps in seagrass occurrence records
431 (McKenzie et al., 2020). Additionally, modeling approaches can contribute other useful
432 measurements of seagrass meadows such as assessing ecosystem services as well as estimating
433 broad-scale seagrass resources as was exemplified by Collier et al. (2021) who used historical
434 data to accurately predict the below-ground biomass of five seagrass species. Because
435 geographic scale is an important consideration in ecological analyses (Jarzyna & Jetz 2018; Daru
436 et al. 2020), a multi-scale approach varying along spatial extents (local, regional and global) and
437 grain resolutions should be considered in assessing seagrass response to global change and
438 model testing. Temporal uncertainty can be diminished by carrying out new field surveys that are
439 more consistent and evenly distributed across seasons and years. Collectors should use best
440 practices such as capturing and documenting accurate dates of collection. For the taxonomic
441 uncertainty: increased support for marine plant taxonomy and advances in taxonomic
442 publications could minimize biases. Next-generation DNA sequencing combined with
443 bioinformatics (Taberlet et al., 2012) will help diminish taxonomic uncertainty such as
444 sequencing old herbarium specimens of very rare species such as *Halodule bermudensis*. The
445 rapid growth of large databases such as GenBank (<http://www.ncbi.nlm.nih.gov/genbank>),
446 SeagrassDB (Sablok et al., 2018), and Treebase (<http://www.treebase.org>), allows researchers to
447 download available phylogenies or DNA sequences to build their own (Morell 1996; Piel et al.,
448 2000; Page et al., 2007). Taxonomic bias can also be reduced by targeting future collecting in
449 poorly sampled clades.

450
451 Improvement of analytical and computational tools is an important priority for handling the
452 analyses for large-scale comparative analyses of seagrass species. For instance, the US National
453 Science Foundation-funded software *BiotaPhy* facilitates integration, data collection and analysis
454 by connecting to existing data repositories such as the Open Tree of Life, iDigBio, and
455 Lifemapper (BiotaPhy 2020), whereas the open-source package *sampbias* allows quantification
456 of geographic sampling biases in species distribution data (Zizka et al., 2020). The R software
457 package *phyloregion* – designed for biogeographic regionalization and macroecology – can
458 overcome some computational challenges (Daru et al., 2020). It contains tools for

460 biogeographical regionalization, macroecology, conservation, and visualizing biodiversity
461 patterns, and has potential application in diverse fields including evolution, microbial diversity,
462 systematics, ecology, phylogenetics, and many others (Daru et al., 2020). We expect that the
463 proliferation of more open-source analytical tools to greatly facilitate comprehensive
464 understanding of seagrass sensitivity to ecological change driven by anthropogenic causes.
465

466 **CONCLUDING REMARKS**

467 Here, we outlined impediments that limit progress in understanding seagrass sensitivity to global
468 change induced by human activities. These knowledge gaps are interconnected and represent
469 only few of the possible issues related to research in seagrass diversity and evolution. Taxonomic
470 uncertainty can influence all other types of uncertainties as it reflects knowledge gaps on the
471 fundamental unit of ecology and evolutionary biology. The geographic and temporal
472 uncertainties are strongly related and capture knowledge gaps about species distributions in
473 space and time, respectively. Even when the aforementioned impediments are resolved, many of
474 the critical questions about seagrass sensitivity to global change, can be out of reach for scientists
475 without the right analytical tools. The recent development of efficient and replicable
476 computational tools, massive mobilization of natural history collections, and increased funding
477 for seagrass research could remedy these shortcomings. Most of the management tools designed
478 for use in developed countries can be extended to remote areas in developing countries where
479 most seagrass diversity resides e.g., the Central Indo-Pacific. Although research on a single
480 taxon or selected taxa is useful to a certain extent, species are lineages that evolve and diversify
481 from shared ancestors, suggesting an integrative approach that accounts for their shared
482 phylogenetic relationships.
483

484 485 **AUTHOR CONTRIBUTIONS**

486 BHD conceived and designed the study. BMR ran the analyses with help from BHD. BMR wrote
487 the paper with substantial contributions from BHD. Both authors approved the submitted
488 version.
489

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495 **SUPPLEMENTARY MATERIAL**

496 Supplementary Methods can be found in the online version of this article.
497
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500 **REFERENCES**

501

502 Allen, J. M., Folk, R. A., Soltis, P. S., Soltis, D. E., & Guralnick, R. P. (2019).
503 Biodiversity synthesis across the green branches of the tree of life. *Nature Plants* 5, 11-13,
504 <https://doi.org/10.1038/s41477-018-0322-7>

505 Anderson, J. T., Panetta, A. M., & Mitchell-Olds, T. (2012). Evolutionary and ecological
506 responses to anthropogenic climate change. *Plant Physiology*, 160, 1728-1740.
507 <https://doi.org/10.1104/pp.112.206219>

508 Arias-Ortiz, A., Serrano, O., Masqué, P., Lavery, P. S., Mueller, U., Kendrick, G. A., ... Duarte,
509 C. M. (2018). A marine heatwave drives massive losses from the world's largest seagrass carbon
510 stocks. *Nature Climate Change*, 8(4), 338–344. <https://doi.org/10.1038/s41558-018-0096-y>

511 Arnaud-Haond, S., Marbà, N., Diaz-Almela, E. et al. (2010). Comparative analysis of stability—
512 genetic diversity in seagrass (*Posidonia oceanica*) meadows yields unexpected results. *Estuaries
513 and Coasts* 33, 878-889. <https://doi.org/10.1007/s12237-009-9238-9>

514 Beca-Carretero, P., Teichberg, M., Winters, G., Procaccini, G., & Reuter, H. (2020). Projected
515 rapid habitat expansion of tropical seagrass species in the mediterranean sea as climate change
516 progresses. *Frontiers in Plant Science*, 11, 1762. <https://doi.org/10.3389/fpls.2020.555376>

517 Beck, M., Jr, K., Able, K., Childers, D., Eggleston, D., Gillanders, B., ... Weinstein, M. (2001).
518 The identification, conservation, and management of estuarine and marine nurseries for fish and
519 invertebrates. *BioScience*, 51, 633-641. [https://doi.org/10.1641/0006-3568\(2001\)051\[0633:TICAMO\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2001)051[0633:TICAMO]2.0.CO;2)

520

521 Benway, H. M., Lorenzoni, L., White, A. E., Fiedler, B., Levine, N. M., Nicholson, D. P., ...
522 Letelier, R. M. (2019). Ocean time series observations of changing marine ecosystems: an era of
523 integration, synthesis, and societal applications. *Frontiers in Marine Science*, 6, 393.
524 <https://doi.org/10.3389/fmars.2019.00393>

525 Berry, P. E. (2019, February). Alismatales. Retrieved November 27, 2020, from
526 <https://www.britannica.com/plant/Alismatales>

527 Bijlsma, L., Ehler, C., Klein, R., Kulshrestha, S., Mclean, R., Mimura, N., ... Warrick, R. (1995).
528 Coastal zones and small islands (pp. 289-324).

529 BiotaPhy (2020). BiotaPhy Project, <https://biotaphy.github.io/>

530 Boakes, E. H., McGowan, P. J. K., Fuller, R. A., Chang-qing, D., Clark, N. E., O'Connor, K., &
531 Mace, G. M. (2010). Distorted views of biodiversity: spatial and temporal bias in species
532 occurrence data. *PLOS Biology*, 8, 1-11. <https://doi.org/10.1371/journal.pbio.1000385>

533 Bradshaw, W. E., & Holzapfel, C. M. (2001). Genetic shift in photoperiodic response correlated
534 with global warming. *Proceedings of the National Academy of Sciences*, 98, 14509-14511.
535 <https://doi.org/10.1073/pnas.241391498>

536 Brown, J., Bennett, J., & French, C. (2017). SDMtoolbox 2.0: The next generation Python-based
537 GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *PeerJ*,
538 5, e4095. <https://doi.org/10.7717/peerj.4095>

539 Bryars, S., Collings, G., Miller, D. (2011). Nutrient exposure causes epiphytic changes
540 and coincident declines in two temperate Australian seagrasses. *Marine Ecology Progress Series*,
541 441, 89-103. <https://doi.org/10.3354/meps09384>

542 Bystríková, N., Peregrym, M., Erkens, R., Bezsmertná, O., & Schneider, H. (2012). Sampling
543 bias in geographic and environmental space and its effect on the predictive power of species
544 distribution models. *Systematics and Biodiversity*, 10.
545 <https://doi.org/10.1080/14772000.2012.705357>

546 Cadotte, M. W. (2013). Experimental evidence that evolutionarily diverse assemblages result in
547 higher productivity. *Proceedings of the National Academy of Sciences of the United States of
548 America*, 110, 8996. <https://doi.org/10.1073/pnas.1301685110>
549

550 Campbell, S. J., McKenzie, L. J., & Kerville, S. P. (2006). Photosynthetic responses of seven
551 tropical seagrasses to elevated seawater temperature. *Journal of Experimental Marine Biology
552 and Ecology*, 330, 455-468. <http://dx.doi.org/10.1016/j.jembe.2005.09.017>
553

554 CaraDonna, P. J., Iler, A. M., & Inouye, D. W. (2014). Shifts in flowering phenology reshape a
555 subalpine plant community. *Proceedings of the National Academy of Sciences of the United
556 States of America*, 111, 4916-4921. <https://doi.org/10.1073/pnas.1323073111>

557 Cavender-Bares, J., Kozak, K., Fine, P., & Kembel, S. (2009). The merging of community
558 ecology and phylogenetic biology. *Ecology Letters*, 12, 693-715. [https://doi.org/10.1111/j.1461-0248.2009.01314.x](https://doi.org/10.1111/j.1461-
559 0248.2009.01314.x)

560 Chefaoui, R. M., Duarte, C. M., & Serrão, E. A. (2018). Dramatic loss of seagrass habitat under
561 projected climate change in the Mediterranean Sea. *Global Change Biology*, 24, 4919-4928.
562 <https://doi.org/10.1111/gcb.14401>
563

564 Clements, D. R., Ditomaso, A. (2011). Climate change and weed adaptation: can evolution of
565 invasive plants lead to greater range expansion than forecasted? *Weed Research*, 51, 227-240.
566 <https://doi.org/10.1111/j.1365-3180.2011.00850.x>

567 Collier, C. J., Langlois, L. M., McMahon, K. M., Udy, J., Rasheed, M., Lawrence, E., ...
568 McKenzie, L. J. (2021). What lies beneath: Predicting seagrass below-ground biomass from
569 above-ground biomass, environmental conditions and seagrass community composition.
570 *Ecological Indicators*, 121, 107156.
571 <https://doi.org/https://doi.org/10.1016/j.ecolind.2020.107156>

572
573 Coyer, J. A., Hoarau, G., Kuo, J., Tronholm, A., Veldsink, J., & Olsen, J. L. (2013). Phylogeny
574 and temporal divergence of the seagrass family Zosteraceae using one nuclear and three
575 chloroplast loci. *Systematics and biodiversity*, 11, 271-284.
576 <https://doi.org/10.1111/j.1477-2000.2013.821187>
577
578 Dalgleish, H. J., Koons, D. N., Hooten, M. B., Moffet, C. A., & Adler, P. B. (2011). Climate
579 influences the demography of three dominant sagebrush steppe plants. *Ecology*, 92, 75-85.
580 <https://doi.org/10.1890/10-0780.1>

581 Daru, B. H., & le Roux, P. C. (2016). Marine protected areas are insufficient to conserve global
582 marine plant diversity. *Global Ecology and Biogeography*, 25, 324-334.
583 <https://doi.org/10.1111/geb.12412>

584 Daru, B. H., Holt, B. G., Lessard, J.-P., Yessoufou, K., & Davies, T. J. (2017). Phylogenetic
585 regionalization of marine plants reveals close evolutionary affinities among disjunct temperate
586 assemblages. *Biological Conservation*, 213, 351-356.
587 <https://doi.org/10.1016/j.biocon.2016.08.022>
588
589 Daru, B. H., Park, D. S., Primack, R. B., Willis, C. G., Barrington, D. S., Whitfeld, T. J. S., ...
590 Davis, C. C. (2018). Widespread sampling biases in herbaria revealed from large-scale
591 digitization. *New Phytologist*, 217, 939-955. <https://doi.org/10.1111/nph.14855>
592
593 Daru, B. H., Farooq, H., Antonelli, A. & Faurby, S. (2020). Endemism patterns are scale
594 dependent. *Nature Communications*, 11, 2115. <https://doi.org/10.1038/s41467-020-15921-6>
595
596 Daru, B.H., Karunarathne P. & Schliep K. (2020). phyloregion: R package for biogeographic
597 regionalization and macroecology. *Methods in Ecology and Evolution* 11, 1483-1491.
598 <https://doi.org/10.1111/2041-210X.13478>
599
600 Davis, C. C., Willis, C. G., Primack, R. B., & Miller-Rushing, A. J. (2010). The importance of
601 phylogeny to the study of phenological response to global climate change. *Philosophical
602 transactions of the Royal Society of London. Series B, Biological sciences*, 365, 3201-3213.
603 <https://doi.org/10.1098/rstb.2010.0130>

604 Davies, T. J., Wolkovich, E. M., Kraft, N. J. B., Salamin, N., Allen, J. M., Ault, T. R., ...
605 Travers, S. E. (2013). Phylogenetic conservatism in plant phenology. *Journal of Ecology*, 101,
606 1520-1530. <https://doi.org/10.1111/j.1365-2745.12154>

607 Day, J. W., Christian, R. R., Boesch, D. M., Yáñez-Arancibia, A., Morris, J., Twilley, R. R.,
608 Naylor, L. and Schaffner, L., (2008). Consequences of climate change on the ecogeomorphology
609 of coastal wetlands. *Estuaries and Coasts*, 31, 477-491.
610
611 Dewsbury, B. M., Bhat, M., & Fourqurean, J. W. (2016). A review of seagrass economic
612 valuations: Gaps and progress in valuation approaches. *Ecosystem Services*, 18, 68-77.
613 <https://doi.org/10.1016/j.ecoser.2016.02.010>

614 Dias Tarli, V., Grandcolas, P., & Pellens, R. (2018). The informative value of museum
615 collections for ecology and conservation: A comparison with target sampling in the Brazilian
616 Atlantic forest. *PLOS ONE*, 13, 1-17. <https://doi.org/10.1371/journal.pone.0205710>

617 Dilipan, E., Lucas, C., Papenbrock, J., & Thangaradjou, T. (2018). Tracking the Phylogeny of
618 Seagrasses: Inferred from 18S rRNA Gene and Ancestral State Reconstruction of Morphological
619 Data. *Proceedings of the National Academy of Sciences, India Section B: Biological Sciences*,
620 88, 497-504. <https://doi.org/10.1007/s40011-016-0780-5>

621 Diniz-Filho, J. A. F., Loyola, R. D., Raia, P., Mooers, A. O., & Bini, L. M. (2013). Darwinian
622 shortfalls in biodiversity conservation. *Trends in Ecology & Evolution*, 28, 689-695.
623 <https://doi.org/10.1016/j.tree.2013.09.003>

624 Drummond, A. J., Rambaut, A., Shapiro, B., & Pybus, O. G. (2005). Bayesian coalescent
625 inference of past population dynamics from molecular sequences. *Molecular Biology and
626 Evolution*, 22, 1185-1192. <https://doi.org/10.1093/molbev/msi103>

627 Duarte, C. M. (1992). Nutrient concentration of aquatic plants: Patterns across species.
628 *Limnology and Oceanography*, 37, 882-889.
629 <https://doi.org/https://doi.org/10.4319/lo.1992.37.4.0882>

630 Duarte, C. (2002). The future of seagrass meadows. *Environmental Conservation*, 29, 192-206.
631 [doi:10.1017/S0376892902000127](https://doi.org/10.1017/S0376892902000127)

632

633 Duarte, B., Martins, I., Rosa, R., Matos, A. R., Roleda, M. Y., Reusch, T. B. H., ... Jueterbock,
634 A. (2018). Climate change impacts on seagrass meadows and macroalgal forests: An integrative
635 perspective on acclimation and adaptation potential. *Frontiers in Marine Science*, 5.
636 <https://doi.org/10.3389/fmars.2018.00190>

637 Duffy, J. E., Benedetti-Cecchi, L., Trinanes, J., Muller-Karger, F. E., Ambo-Rappe, R., Boström,
638 C., ... Yaakub, S. M. (2019). Toward a coordinated global observing system for seagrasses and
639 marine macroalgae. *Frontiers in Marine Science*, 6, 317.
640 <https://doi.org/10.3389/fmars.2019.00317>

641 Edwards, J., Lane, M. A., & Nielsen, E. (2000). Interoperability of biodiversity databases:
642 biodiversity information on every desktop. *Science (New York, N.Y.)*, 289, 2312-2314.

643 Erry, D. I. P., Taveley, T. H. S., Eyanova, D. I. D., Aden, S. U. B., Upont, S. A. M. D., & Al, P.
644 E. T. (2019). Global environmental changes negatively impact temperate seagrass ecosystems.
645 *Ecosphere*, 10, e02986. <https://doi.org/https://doi.org/10.1002/ecs2.2986>

646 Faith, D. P. (1992). Conservation evaluation and phylogenetic diversity. *Biological
647 Conservation*, 61, 1-10. [https://doi.org/https://doi.org/10.1016/0006-3207\(92\)91201-3](https://doi.org/https://doi.org/10.1016/0006-3207(92)91201-3)

648 Farley, S. S., Dawson, A., Goring, S. J., & Williams, J. W. (2018). Situating ecology as a big-
649 data science: current advances, challenges, and solutions. *BioScience* 68, 563-576,
650 <https://doi.org/10.1093/biosci/biy068>

651

652 FitzJohn, R. G., Maddison, W. P., & Otto, S. P. (2009). Estimating trait-dependent speciation
653 and extinction rates from incompletely resolved phylogenies. *Systematic biology*, 58, 595-611.
654 <https://doi.org/10.1093/sysbio/syp067>

655 Freeman, B. G., Scholer, M. N., Ruiz-Gutierrez, V., & Fitzpatrick, J. W. (2018). Climate change
656 causes upslope shifts and mountaintop extirpations in a tropical bird community. *Proceedings of
657 the National Academy of Sciences*, 115, 11982-11987. <https://doi.org/10.1073/pnas.1804224115>

658 GBIF.org (17 January 2020) GBIF Occurrence Download <https://doi.org/10.15468/dl.t7xgct>

659 Gaillard, J.-M., Mark Hewison, A. J., Klein, F., Plard, F., Douhard, M., Davison, R., &
660 Bonenfant, C. (2013). How does climate change influence demographic processes of widespread
661 species? Lessons from the comparative analysis of contrasted populations of roe deer. *Ecology
662 Letters*, 16, 48-57. <https://doi.org/https://doi.org/10.1111/ele.12059>

663 Gallagher, A. J., Hammerschlag, N., Cooke, S. J., Costa, D. P., & Irschick, D. J. (2015).
664 Evolutionary theory as a tool for predicting extinction risk. *Trends in Ecology & Evolution*, 30,
665 61-65. <https://doi.org/10.1016/j.tree.2014.12.001>

666

667 Grech, A., Chartrand, K., Erfstemeijer, P., Fonseca, M., McKenzie, L., Rasheed, M., ... Coles, R.
668 (2012). A comparison of threats, vulnerabilities and management approaches in global seagrass
669 bioregions. *Environmental Research Letters*, 7. <https://doi.org/10.1088/1748-9326/7/2/024006>

670 Green E. P, Short F.T. (2003). World atlas of seagrasses. Prepared by UNEP World
671 Conservation Monitoring Centre. Berkeley (California, USA): University of California. 332 pp.
672 URL: <https://archive.org/details/worldatlasofseag03gree>

673 Guerrero-Meseguer, L., L., Veiga, P., & Rubal, M., Sampaio. (2021). Resurgence of *Zostera*
674 marina in the Ria de Aveiro lagoon, Portugal. *Aquatic Botany*, 169, 103338.
675 <https://doi.org/10.1016/j.aquabot.2020.103338>

676 Guo, Q., & Liu, Y. (2010). ModEco: An integrated software package for ecological niche
677 modeling. *Ecography*, 33, 637-642. <https://doi.org/10.1111/j.1600-0587.2010.06416.x>

678 Hauxwell, J., Cebrián, J., Furlong, C., & Valiela, I. (2001). Macroalgal canopies contribute to
679 eelgrass (*Zostera marina*) decline in temperate estuarine ecosystems. *Ecology* 82, 1007-1022.
680 [https://doi.org/https://doi.org/10.1890/0012-9658\(2001\)082\[1007:MCCTEZ\]2.0.CO;2](https://doi.org/https://doi.org/10.1890/0012-9658(2001)082[1007:MCCTEZ]2.0.CO;2)

681 Heck, K. L., Samsonova, M., Poore, A. G. B., & Hyndes, G. A. (2020). Global patterns in
682 seagrass herbivory: Why, despite existing evidence, there are solid arguments in favor of
683 latitudinal gradients in seagrass herbivory. *Estuaries and Coasts*. <https://doi.org/10.1007/s12237-020-00833-x>

685 Hellmann, J.J., Byers, J.E., Bierwagen, B.G. and Dukes, J.S. (2008). Five potential consequences
686 of climate change for invasive species. *conservation biology*. 22, 534-543.
687 <https://doi.org/10.1111/j.1523-1739.2008.00951.x>
688

689 Hemminga, M., & Duarte, C. (2000). *Seagrass Ecology*. Cambridge: Cambridge University
690 Press. doi:10.1017/CBO9780511525551
691

692 Hijmans, R. J., Phillips, S., Leathwick, J. and Elith, J. (2011), Package ‘dismo’. Available online
693 at: <http://cran.r-project.org/web/packages/dismo/index.html>.
694

695 Holt, B., Lessard, J.-P., Borregaard, M., Fritz, S., Araújo, M., Dimitrov, D., ... Rahbek, C.
696 (2013). An update of wallace’s zoogeographic regions of the world. *Science*, 339, 74-78.
697 <https://doi.org/10.1126/science.1228282>

698

699 Hortal, J. (2008). Uncertainty and the measurement of terrestrial biodiversity gradients. *Journal
700 of Biogeography*, 35, 1335-1336. <https://doi.org/https://doi.org/10.1111/j.1365-2699.2008.01955.x>

701

702 Hortal, J., de Bello, F., Diniz-Filho, J. A. F., Lewinsohn, T. M., Lobo, J. M., & Ladle, R. J.
703 (2015). Seven shortfalls that beset large-scale knowledge of biodiversity. *Annual Review of
Ecology, Evolution, and Systematics*, 46, 523-549. <https://doi.org/10.1146/annurev-ecolsys-112414-054400>

704

705 Hugo, G. (2011). Future demographic change and its interactions with migration and climate
706 change. *Global Environmental Change*, 21, S21-S33.
<https://doi.org/https://doi.org/10.1016/j.gloenvcha.2011.09.008>

707

708 Hunter, C.M., Caswell, H., Runge, M.C., Regehr, E.V., Amstrup, S.C. and Stirling, I. (2010),
709 Climate change threatens polar bear populations: a stochastic demographic analysis. *Ecology*, 91,
710 2883-2897. <https://doi.org/10.1890/09-1641.1>

711

712 Hou, QQ., Chen, BM., Peng, SL. *et al.* (2014). Effects of extreme temperature on seedling
713 establishment of nonnative invasive plants. *Biological Invasions* 16, 2049-2061.
<https://doi.org/10.1007/s10530-014-0647-8>

714

715 Iler, A.M., Høye, T.T., Inouye, D.W. and Schmidt, N.M. (2013), Long-term trends mask
716 variation in the direction and magnitude of short-term phenological shifts. *American Journal of
717 Botany*, 100, 1398-1406. <https://doi.org/10.3732/ajb.1200490>

718

719 IPCC. (2018). Summary for policymakers of IPCC special report on global warming of 1.5°C
720 approved by governments. (2018, October 8). Retrieved December 03, 2020, from
721 [warming-of-1-5c-approved-by-governments/](https://www.ipcc.ch/2018/10/08/summary-for-policymakers-of-ipcc-special-report-on-global-
722 warming-of-1-5c-approved-by-governments/)

723

724 IUCN 2020. *The IUCN Red List of Threatened Species. Version 2020-2.*
<https://www.iucnredlist.org>. Downloaded on 03 August 2020.

725 Jarzyna, M. A., & Jetz, W. (2018). Taxonomic and functional diversity change is scale
726 dependent. *Nature Communications*, 9, 2565. <https://doi.org/10.1038/s41467-018-04889-z>

727 Jayathilake, D. R. M., & Costello, M. J. (2018). A modelled global distribution of the seagrass
728 biome. *Biological Conservation*, 226, 120-126.
729 <https://doi.org/https://doi.org/10.1016/j.biocon.2018.07.009>

730 Johnston, D. W. (2019). Unoccupied aircraft systems in marine science and conservation. *Annual
731 Review of Marine Science*, 11, 439-463. <https://doi.org/10.1146/annurev-marine-010318-095323>

732 Kadmon, R., Farber, O., & Danin, A. (2004). Effect of roadside bias on the accuracy of
733 predictive maps produced by bioclimatic models. *Ecological Applications*, 14, 401-413.
734 <https://doi.org/10.1890/02-5364>

735 Kalnay, E., & Cai, M. (2003). Impact of urbanization and land-use change on climate. *Nature*
736 423, 528-531. <https://doi.org/10.1038/nature01675>

737

738 Kharouba, H. M., Wolkovich, E. M. (2020). Disconnects between ecological theory and data in
739 phenological mismatch research. *Nature Climate Change*, 10, 406-415.
740 <https://doi.org/10.1038/s41558-020-0752-x>

741 Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V., ...
742 Wilting, A. (2013). The importance of correcting for sampling bias in MaxEnt species
743 distribution models. *Diversity and Distributions*, 19, 1366-1379.
744 <https://doi.org/https://doi.org/10.1111/ddi.12096>

745 Kreft, H., & Jetz, W. (2010). A framework for delineating biogeographical regions based on
746 species distributions. *Journal of Biogeography*, 37, 2029-2053.
747 <https://doi.org/https://doi.org/10.1111/j.1365-2699.2010.02375.x>

748 Larkum, W. D., Orth, R. J., Duarte, C. M., eds (2006). *Seagrasses: Biology, Ecology and
749 Conservation*. Dordrecht (The Netherlands), Springer.

750

751 Les, D. H., Moody, M. L., Jacobs, S. W. L., & Bayer, R. J. (2002). Systematics of seagrasses
752 (Zosteraceae) in Australia and New Zealand. *Systematic Botany*, 27, 468-484. Retrieved from
753 <https://doi.org/10.1043/0363-6445-27.3.468>

754 Lobo, J., & Tognelli, M. (2011). Exploring the effects of quantity and location of pseudo-
755 absences and sampling biases on the performance of distribution models with limited point
756 occurrence data. *Journal for Nature Conservation*, 19. <https://doi.org/10.1016/j.jnc.2010.03.002>

757 Mace, G. M., Gittleman, J. L., & Purvis, A. (2003). Preserving the Tree of Life. *Science* 300,
758 1707. <https://doi.org/10.1126/science.1085510>

759

760 MacLean, S. A., Rios Dominguez, A. F., de Valpine, P., Beissinger, S. R. (2018). A century of
761 climate and land-use change cause species turnover without loss of beta diversity in California's
762 Central Valley. *Global Change Biology*, 24, 5882- 5894. <https://doi.org/10.1111/gcb.14458>

763 Maruyama, N., Nomura, T., Sato, K., & Matsuoka, S. (2011). Physis: an implicitly parallel
764 programming model for stencil computations on large-scale GPU-accelerated supercomputers. In
765 *Proceedings of 2011 International Conference for High Performance Computing, Networking,*
766 *Storage and Analysis*. New York, NY, USA: Association for Computing Machinery.
767 <https://doi.org/10.1145/2063384.2063398>

768 Massa, S. I., Paulino, C. M., Serrão, E. A. *et al.* (2013). Entangled effects of allelic and clonal
769 (genotypic) richness in the resistance and resilience of experimental populations of the seagrass
770 *Zostera noltii* to diatom invasion. *BMC Ecology* 13, 39. <https://doi.org/10.1186/1472-6785-13-39>

771 772 McCallum, E., & Weston, S. (2011). *Parallel R*. O'Reilly Media, Inc.

773 McGlathery, K. J., Sundbäck, K., & Anderson, I. (2007). Eutrophication in shallow coastal bays
774 and lagoons: The role of plants in the coastal filter. *Marine Ecology-Progress Series*, 348, 1-18.
775 <https://doi.org/10.3354/meps07132>

776 777 McKenzie, L. J., Long, L., Coles, R. G., & Roder, C. A. (2000). Seagrass-Watch: Community
778 based monitoring of seagrass resources. *Biologia Marina Mediterranea*, 7, 393-396.

779 780 McKenzie, L. J., Yoshida, R. L., Mellors, J. E., & Coles, R. G. (2009). Seagrass-watch. In
781 Proceedings of a Workshop for Monitoring Seagrass Habitats in Indonesia. The Nature
Conservancy, Coral Triangle Center, Sanur, Bali (ID), 9th Mei.

782 783 McKenzie, L., Nordlund, L., Jones, B., Cullen-Unsworth, L., Roelfsema, C., & Unsworth, R.
784 (2020). The global distribution of seagrass meadows. *Environmental Research Letters*, 15.
<https://doi.org/10.1088/1748-9326/ab7d06>

785 786 Meerdink, S. K., Roberts, D. A., Roth, K. L., King, J. Y., Gader, P. D., & Koltunov, A. (2019).
787 Classifying California plant species temporally using airborne hyperspectral imagery. *Remote
Sensing of Environment*, 232. <https://doi.org/https://doi.org/10.1016/j.rse.2019.111308>

788 789 Menegotto, A., Rangel, T., Schrader, J., Weigelt, P., & Kreft, H. (2019). A global test of the
790 subsidized island biogeography hypothesis. *Global Ecology and Biogeography*, 29.
<https://doi.org/10.1111/geb.13032>

791 792 Meyer, C., Weigelt, P., & Kreft, H. (2016). Multidimensional biases, gaps and uncertainties in
793 global plant occurrence information. *Ecology Letters*, 19, 992-1006.
<https://doi.org/10.1111/ele.12624>

794 795 Miller-Rushing, A. J., & Primack, R. B. (2008). Global warming and flowering times in
796 Thoreau's concord: A Community Perspective. *Ecology*, 89, 332-341.
<https://doi.org/https://doi.org/10.1890/07-0068.1>

797 Moksnes, P., Gullstro, M., Tryman, K., & Baden, S. (2008). Trophic cascades in a temperate
798 seagrass community. *Oikos*, 117, 763-777. <https://doi.org/10.1111/j.2008.0030-1299.16521.x>
799

800 Morell, V. (1996). TreeBASE: the roots of phylogeny. *Science*, 273, 569.
801

802 Mtwana Nordlund, L., Koch, E. W., Barbier, E. B., & Creed, J. C. (2016). Seagrass ecosystem
803 services and their variability across genera and geographical regions. *PLOS ONE*, 11.
804 <https://doi.org/10.1371/journal.pone.0163091>
805

806 National Research Council (NRC-US); Avise JC, Hubbell S.P., Ayala F.J., editors. (2008). In the
807 Light of Evolution: Volume II: Biodiversity and Extinction. Washington (DC): National
808 Academies Press (US); 9, Extinction as the Loss of Evolutionary History. Available from:
809 <https://www.ncbi.nlm.nih.gov/books/NBK214889/>
810

811 Nee, S., May, R. M., & Harvey, P. H. (1994). The reconstructed evolutionary process.
812 *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, 344,
813 305-311. <https://doi.org/10.1098/rstb.1994.0068>

814 NOAA Climate.gov: Science & information for a climate-smart nation. (2020, December 01).
815 Retrieved December 03, 2020, from <https://www.climate.gov/>

816 Nordlund, L. M., Jackson, E. L., Nakaoka, M., Samper-Villarreal, J., Beca-Carretero, P., &
817 Creed, J. C. (2018). Seagrass ecosystem services – What's next? *Marine Pollution Bulletin*, 134,
818 145-151. <https://doi.org/https://doi.org/10.1016/j.marpolbul.2017.09.014>

819 Nunn, N., & Qian, N. (2010). The Columbian Exchange: A History of Disease, Food, and Ideas.
820 *Journal of Economic Perspectives*, 24, 163–188. <https://doi.org/10.1257/jep.24.2.163>

821 Orth, R., Harwell, M., & Inglis, G. (2006). Ecology of seagrass seeds and seagrass dispersal
822 processes. In *Seagrasses: Biology, Ecology and Conservation* (pp. 111-133).
823 https://doi.org/10.1007/1-4020-2983-7_5

824 Orth, R. J., Carruthers, T. J. B., Dennison, W. C., Duarte, C. M., Fourqurean, J. W., Heck, K. L.,
825 ... Williams, S. L. (2006). A global crisis for seagrass ecosystems. *BioScience*, 56, 987-996.
826 [https://doi.org/10.1641/0006-3568\(2006\)56\[987:AGCFSE\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2006)56[987:AGCFSE]2.0.CO;2)

827 Ovaskainen, O., Skorokhodova, S., Yakovleva, M., Sukhov, A., Kutenkov, A., Kutenkova, N.,
828 ... Delgado, M. del M. (2013). Community-level phenological response to climate change.
829 *Proceedings of the National Academy of Sciences*, 110. <https://doi.org/10.1073/pnas.1305533110>

830 Page, R. D. (2007). TBMap: a taxonomic perspective on the phylogenetic database TreeBASE.
831 *Bmc Bioinformatics*, 8, 158. <https://doi.org/10.1186/1471-2105-8-158>

832 Park, D. S., Worthington, S., & Xi, Z. (2018). Taxon sampling effects on the quantification and
833 comparison of community phylogenetic diversity. *Molecular Ecology*, 27, 1296-1308.
834 <https://doi.org/https://doi.org/10.1111/mec.14520>

835 Parmesan, C., Ryrholm, N., Stefanescu, C. et al. (1999). Poleward shifts in geographical ranges
836 of butterfly species associated with regional warming. *Nature*, 399, 579-583.
837 <https://doi.org/10.1038/21181>

838 Parmesan, C. (2006). Ecological and evolutionary responses to recent climate change. *Annual
839 Review of Ecology, Evolution, and Systematics*, 37, 637-669.
840 <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>

841 Pearson, K. D., Nelson, G., Aronson, M. F. J., Bonnet, P., Brenskelle, L., Davis, C. C., ... Soltis,
842 P. S. (2020). Machine learning using digitized herbarium specimens to advance phenological
843 research. *BioScience*, 70, 610-620. <https://doi.org/10.1093/biosci/biaa044>

844 Pergent, G., Bazairi, H., Bianchi, C., Boudouresque, C., Buia, M., Calvo, S., ... Verlaque, M.
845 (2014). Climate change and Mediterranean seagrass meadows: A synopsis for environmental
846 managers. *Mediterranean Marine Science*, 15, 462-473. <https://doi.org/10.12681/mms.621>

847 Pernetta, J. C., Leemans, R., Elder, D., Humphrey, S., Brouns, J. J. (1994). Impacts of climate
848 change on ecosystems and species: Marine and coastal ecosystems, eds Pernetta JC, Leemans R,
849 Elder D, Humphrey S (International Union for Conservation of Nature, Gland, Switzerland), 2,
850 59-72. <https://portals.iucn.org/library/sites/library/files/documents/1994-028.pdf>

851

852 Peterson A. T., Soberón J., Pearson R. G., Anderson R. P., Martínez-Meyer E., Nakamura M.,
853 Araújo M. B. (2011). *Monographs in population biology*, 49. Princeton, NJ: Princeton University
854 Press.

855

856 Piel, W. H., Donoghue, M. J., Sanderson, M. J., & Netherlands, L. (2000). TreeBASE: a
857 database of phylogenetic information. In *Proceedings of the 2nd International Workshop of
858 Species 2000*.

859 Poelen, J. H., Simons, J. D., & Mungall, C. J. (2014). Global biotic interactions: An open
860 infrastructure to share and analyze species-interaction datasets. *Ecological Informatics*, 24, 148-
861 159. <https://doi.org/https://doi.org/10.1016/j.ecoinf.2014.08.005>

862 Poloczanska, E. S., Burrows, M. T., Brown, C. J., García Molinos, J., Halpern, B. S., Hoegh-
863 Guldberg, O., ... Sydeman, W. J. (2016). Responses of Marine Organisms to Climate Change
864 across Oceans. *Frontiers in Marine Science*, 3, 62. <https://doi.org/10.3389/fmars.2016.00062>

865 POWO (2019). "Plants of the World Online. Facilitated by the Royal Botanic Gardens, Kew.
866 Published on the Internet; <http://www.plantsoftheworldonline.org/> Retrieved 07 December
867 2020."

868

869 Purvis, A., Agapow, P.-M., Gittleman, J. L., & Mace, G. M. (2000). Nonrandom extinction and
870 the loss of evolutionary history. *Science*, 288, 328-330.
871 <https://doi.org/10.1126/science.288.5464.328>

872 Pybus, O. G., Rambaut, A., & Harvey, P. H. (2000). An integrated framework for the inference
873 of viral population history from reconstructed genealogies. *Genetics*, 155, 1429-1437. Retrieved
874 from <https://www.genetics.org/content/155/3/1429>

875 R Core Team (2020). R: A language and environment for statistical computing. R Foundation for
876 Statistical Computing, Vienna, Austria. URL: <https://www.R-project.org/>
877

878 Ralph, P., Tomasko, D., Moore, K., Seddon, S., Macinnis-Ng, C., Larkum, A., ... Duarte, C.
879 (2006). Human impacts on seagrasses: eutrophication, sedimentation, and contamination. In
880 *Seagrasses: Biology, Ecology and Conservation*, 567-593. https://doi.org/10.1007/1-4020-2983-7_24
881

882 Redding, D. W., & Mooers, A. Ø. (2006). Incorporating evolutionary measures into conservation
883 prioritization. *Conservation Biology* 20, 1670-1678. <https://doi.org/10.1111/j.1523-1739.2006.00555.x>
884

885 Redding, D., Hartmann, K., Mimoto, A., Bokal, D., Devos, M., & Mooers, A. (2008).
886 Evolutionarily distinct species capture more phylogenetic diversity than expected. *Journal of
887 Theoretical Biology*, 251, 606-615. <https://doi.org/10.1016/j.jtbi.2007.12.006>
888

889 Rosauer, D. A. N., Laffan, S. W., Crisp, M. D., Donnellan, S. C., & Cook, L. G. (2009).
890 Phylogenetic endemism: a new approach for identifying geographical concentrations of
891 evolutionary history. *Molecular Ecology*, 18, 4061-4072. <https://doi.org/10.1111/j.1365-294X.2009.04311.x>
892

893 Sablok, G., Hayward, R. J., Davey, P. A., Santos, R. P., Schliep, M., Larkum, A., ... Ralph, P. J.
894 (2018). SeagrassDB: An open-source transcriptomics landscape for phylogenetically profiled
895 seagrasses and aquatic plants. *Scientific Reports*, 8(1), 2749. <https://doi.org/10.1038/s41598-017-18782-0>
896

897 de los Santos, C. B., Krause-Jensen, D., Alcoverro, T., Marbà, N., Duarte, C. M., van Katwijk,
898 M. M., ... Santos, R. (2019). Recent trend reversal for declining European seagrass meadows.
899 *Nature Communications*, 10, 3356. <https://doi.org/10.1038/s41467-019-11340-4>

900 Selwood, K.E., McGeoch, M.A. and Mac Nally, R. (2015), The effects of climate change and
901 land-use change on demographic rates and population viability. *Biological Reviews*, 90, 837-
902 853. <https://doi.org/10.1111/brv.12136>
903

904 Schäfer, S., Monteiro, J., Castro, N., Gizzi, F., Henriques, F., Ramalhosa, P., ... & Canning-
905 Clode, J. (2021). Lost and found: A new hope for the seagrass *Cymodocea nodosa* in the marine
906 ecosystem of a subtropical Atlantic Island. *Regional Studies in Marine Science*, 41, 101575.
907 <https://doi.org/10.1016/j.rsma.2020.101575>

908 van der Schoot, C., Paul, L., & Rinne, P. (2013). The embryonic shoot: A lifeline through winter.
909 *Journal of Experimental Botany*, 65. <https://doi.org/10.1093/jxb/ert413>

910 Short, F. T., & Neckles, H. A. (1999). The effects of global climate change on seagrasses.
911 *Aquatic Botany*, 63, 169-196. [https://doi.org/https://doi.org/10.1016/S0304-3770\(98\)00117-X](https://doi.org/10.1016/S0304-3770(98)00117-X)
912

913 Short, F., Koch, E., Creed, J., Magalhães, K., Fernandez, E., & Gaeckle, J. (2006). SeagrassNet
914 monitoring across the Americas: Case studies of seagrass decline. *Marine Ecology*, 27, 277-289.
915 <https://doi.org/10.1111/j.1439-0485.2006.00095.x>
916

917 Short, F., Carruthers, T., Dennison, W., & Waycott, M. (2007). Global seagrass distribution and
918 diversity: A bioregional model. *Journal of Experimental Marine Biology and Ecology*, 350, 3-20.
919 <https://doi.org/10.1016/j.jembe.2007.06.012>
920

921 Short, F. T., Polidoro, B., Livingstone, S. R., Carpenter, K. E., Bandeira, S., Bujang, J. S., ...
922 Zieman, J. C. (2011). Extinction risk assessment of the world's seagrass species. *Biological
923 Conservation*, 144, 1961-1971. <https://doi.org/https://doi.org/10.1016/j.biocon.2011.04.010>
924

925 Steven J. Phillips, Miroslav Dudík, Robert E. Schapire. (2017). MaxEnt software for modeling
926 species niches and distributions (Version 3.4.1). Available from url:
927 http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 2020-12-1.

928 Stropp, J., Ladle, R. J., M. Malhado, A. C., Hortal, J., Gaffuri, J., H. Temperley, W., ... Mayaux,
929 P. (2016). Mapping ignorance: 300 years of collecting flowering plants in Africa. *Global
930 Ecology and Biogeography*, 25, 1085-1096. <https://doi.org/https://doi.org/10.1111/geb.12468>

931 Strydom, S., Murray, K., Wilson, S., Huntley, B., Rule, M., Heithaus, M., ... Zdunic, K. (2020).
932 Too hot to handle: Unprecedented seagrass death driven by marine heatwave in a World Heritage
933 Area. *Global Change Biology*, 26, 3525–3538. <https://doi.org/https://doi.org/10.1111/gcb.15065>

934 Syfert M. M., Smith M. J., Coomes D. A. (2013). The effects of sampling bias and model
935 complexity on the predictive performance of MaxEnt species distribution models. *PLOS ONE*, 8.
936 <https://doi.org/10.1371/journal.pone.0055158>
937

938 Taberlet, P., Coissac, E., Pompanon, F., Brochmann, C., & Willerslev E. (2012). Towards next-
939 generation biodiversity assessment using DNA metabarcoding. *Molecular ecology* (21), 2045-
940 2050. <https://doi.org/10.1111/j.1365-294X.2012.05470.x>
941

942 Thackeray, S. J., Henrys, P. A., Hemming, D., Bell, J. R., Botham, M. S., Burthe, S., Helaouet,
943 P., Johns, D. G., Jones, I. D., Leech, D. I., Mackay, E. B., Massimino, D., Atkinson, S., Bacon,
944 P. J., Brereton, T. M., Carvalho, L., Clutton-Brock, T. H., Duck, C., Edwards, M., Elliott, J. M.,
945 ... Wanless, S. (2016). Phenological sensitivity to climate across taxa and trophic levels. *Nature*,
946 535, 241-245. <https://doi.org/10.1038/nature18608>

947 Thapa, S., Chitale, V., Rijal, S. J., Bisht, N., & Shrestha, B. B. (2018). Understanding the
948 dynamics in distribution of invasive alien plant species under predicted climate change in
949 Western Himalaya. *PLOS ONE*, 13, 1-16. <https://doi.org/10.1371/journal.pone.0195752>

950 Thomas, J., Lonsdale, J., Salvatore, M., Phillips, R., Lo, E., Shad, S., ... Moore, H. F. (2013).
951 The Genotype-Tissue Expression (GTEx) project. *Nature Genetics*, 45, 580-585.
952 <https://doi.org/10.1038/ng.2653>

953 Thuiller, W., Georges, D., & Engler, R. (2014). biomod2: Ensemble platform for species
954 distribution modelling, 2.
955 https://www.researchgate.net/publication/309762991_biomod2_Ensemble_Platform_for_Species
956 _Distribution_Modeling

957 UNEP-WCMC, Short F. T. (2020). Global distribution of seagrasses (version 7.0). Seventh
958 update to the data layer used in Green and Short (2003). Cambridge (UK): UN Environment
959 World Conservation Monitoring Centre. URL: <http://data.unep-wcmc.org/datasets/7>

960 Valle, M., Chust, G., del Campo, A., Wisz, M. S., Olsen, S. M., Garmendia, J. M., & Borja, Á.
961 (2014). Projecting future distribution of the seagrass *Zostera noltii* under global warming and sea
962 level rise. *Biological Conservation*, 170, 74-85.
963 <https://doi.org/https://doi.org/10.1016/j.biocon.2013.12.017>

964 Van Allen, B. G., Dunham, A. E., Asquith, C. M., & Rudolf, V. H. (2012). Life history predicts
965 risk of species decline in a stochastic world. *Proceedings. Biological sciences*, 279, 2691-2697.
966 <https://doi.org/10.1098/rspb.2012.0185>

967 Varela, S., Anderson, R. P., García-Valdés, R., & Fernández-González, F. (2014). Environmental
968 filters reduce the effects of sampling bias and improve predictions of ecological niche models.
969 *Ecography*, 37, 1084-1091. <https://doi.org/https://doi.org/10.1111/j.1600-0587.2013.00441.x>

970 Veeneklaas, R. M., Dijkema, K. S., Hecker, N. and Bakker, J. P. (2013), Spatio-temporal
971 dynamics of the invasive plant species *Elytrigia atherica* on natural salt marshes. *Applied
972 Vegetation Science*, 16, 205-216. <https://doi.org/10.1111/j.1654-109X.2012.01228.x>

973 Veron, S., Davies, T., Cadotte, M., Clergeau, P., & Pavoine, S. (2015). Predicting loss of
974 evolutionary history: Where are we? *Biological Reviews of the Cambridge Philosophical Society*,
975 92. <https://doi.org/10.1111/brv.12228>

976 Vicente, J. R., Fernandes, R. F., Randin, C. F., Broennimann, O., Gonçalves, J., Marcos, B., ...
977 Honrado, J. P. (2013). Will climate change drive alien invasive plants into areas of high
978 protection value? An improved model-based regional assessment to prioritise the management of
979 invasions. *Journal of Environmental Management*, 131, 185-195.
980 <https://doi.org/https://doi.org/10.1016/j.jenvman.2013.09.032>

981 Waycott, M. (1999). Genetic factors in the conservation of seagrasses. *Pacific Conservation
982 Biology*, 5, 269-276. Retrieved from <https://doi.org/10.1071/PC000269>
983

984 Waycott, M., Collier, C., McMahon, K., Ralph, P., McKenzie, L., Udy, J., & Grech, A. (2007).
985 *Vulnerability of seagrasses in the Great Barrier Reef to climate change* (pp. 193-236). Great
986 Barrier Reef Marine Park Authority and Australian Greenhouse Office.

987 http://www.gbrmpa.gov.au/corp_site/info_services/publications/misc_pub/climate_change_vulnerability_assessment/climate_change_vulnerability_assessment

988

989

990 Waycott, M., Duarte, C. M., Carruthers, T. J. B., Orth, R. J., Dennison, W. C., Olyarnik, S., ...

991 Williams, S. L. (2009). Accelerating loss of seagrasses across the globe threatens coastal

992 ecosystems. *Proceedings of the National Academy of Sciences*, 106, 12377-12381.

993 <https://doi.org/10.1073/pnas.0905620106>

994

995 Waycott, M., McKenzie, L. J., Mellors, J. E., Ellison, J. C., Sheaves, M. T., Collier, C., &

996 Schwarz, A. M. (2011). Vulnerability of mangroves, seagrasses and intertidal flats in the tropical

997 Pacific to climate change. <https://hdl.handle.net/20.500.12348/1069>

998

999 Willis, J. K., Chambers, D. P., & Nerem, R. S. (2008). Assessing the globally averaged sea level

1000 budget on seasonal to interannual timescales. *Journal of Geophysical Research: Oceans*, 113. <https://doi.org/https://doi.org/10.1029/2007JC004517>

1001

1002 Willis, C. G., Ruhfel, B., Primack, R. B., Miller-Rushing, A. J., & Davis, C. C. (2008). Phylogenetic patterns of species loss in Thoreau's woods are driven by climate change.

1003 *Proceedings of the National Academy of Sciences of the United States of America*, 105, 17029-

1004 17033. <https://doi.org/10.1073/pnas.0806446105>

1005 Wolfe, K. H., Li, W. H., & Sharp, P. (1987). Rates of nucleotide substitution vary greatly among

1006 plant mitochondrial, chloroplast and nuclear DNA. *Proceedings of the National Academy of*

1007 *Sciences of the United States of America*, 84, 9054-9058.

1008 <https://doi.org/10.1073/pnas.84.24.9054>

1009

1010 Woodman, S. M., Forney, K. A., Becker, E. A., et al. (2019). esdm: A tool for creating and

1011 exploring ensembles of predictions from species distribution and abundance models. *Methods in*

1012 *Ecology and Evolution*, 10, 1923-1933. <https://doi.org/10.1111/2041-210X.13283>

1013 Zieman, J. C. (1976). The ecological effects of physical damage from motorboats on turtle grass

1014 beds in Southern Florida. *Aquatic Botany*, 2, 127-139.

1015 [https://doi.org/https://doi.org/10.1016/0304-3770\(76\)90015-2](https://doi.org/https://doi.org/10.1016/0304-3770(76)90015-2)

1016

1017 Zizka, A., Antonelli, A. and Silvestro, D. (2020). sampbias, a method for quantifying geographic

1018 sampling biases in species distribution data. *Ecography*. <https://doi.org/10.1111/ecog.05102>

1019 **FIGURE LEGENDS:**

1020 **Fig. 1 Morphological diversity of selected species of seagrasses.** (A) *Thalassia testudinum*
1021 (turtle grass) bed with view of jointed rhizomes, San Salvador Island, Bahamas. (B) *Posidonia*
1022 *oceanica* (Neptune grass) meadow with view of rhizome matts, Portofino, Italy. (C) *Zostera*
1023 *marina* (eelgrass) with ribbon-like blades. (D) *Halophila decipiens* (paddle grass) with paddle-
1024 shaped blades. (<https://commons.wikimedia.org> and <https://calphotos.berkeley.edu/>).

1025
1026 **Fig. 2 Interactions between sampling uncertainties indicating the extent of influence of each**
1027 **uncertainty on the others.** Taxonomic uncertainty affects all other uncertainties whereas arrows
1028 indicate direction of influence between the other two. However, all three types of uncertainty
1029 ultimately reflect the personal preferences, biases, and proclivities of collectors.

1030 **Fig. 3 Gaps in geographic sampling of seagrasses.** (A) Seagrass occurrence records showed
1031 strong density of sampling in temperate regions, while sampling within the tropics was generally
1032 low. (B) Geographic distribution of seagrass known species richness based on expert delineated
1033 polygons. Source data are provided as a Source Data file.

1034
1035 **Fig. 4 Temporal sampling of seagrasses reveal drastic increases midway throughout the**
1036 **18th century.** Temporal data from seagrass records over the course of three centuries (roughly
1037 1700-2000) display dense amount of sampling records accumulating after 1850. Each dot
1038 represents an occurrence record of a seagrass in Julian day of year format, with the color gradient
1039 representing recent years with colder color tones, and older years represented by warmer color
1040 tones. These data also support the previously identified global trend of increased sampling
1041 occurring predominantly within the summer months (early June through early October). Source
1042 data are provided as a Source Data file.

1043
1044 **Fig. 5 Temporal trends in seagrass sampling are not consistent across seasons within**
1045 **marine ecoregions of the world (MEOWs).** Temporal data from seagrass occurrence records
1046 were converted into Julian day of year format in order to analyze trends in the monthly sampling
1047 of seagrasses for all MEOWs. The blue line around each temporal sampling plot represents
1048 seagrass sampling density in monthly intervals over an extensive time period (1770-2019), with
1049 corresponding temporal sampling plot for each MEOW. Seagrass sampling rates increase during
1050 summer seasons associated with northern and southern hemispheres. The central plot provides a
1051 reference for the geographic location of each MEOW included in the analysis. Source data are
1052 provided as a Source Data file.

1053
1054 **Fig. 6 Phylogenetic bias in seagrass sampling.** Phylogenetic distribution of the number of
1055 specimens sampled per seagrass species to assess the tendency of closely related species to be
1056 similarly collected. No statistically significant phylogenetic signals were detected, although there
1057 was slight favoring for sampling of the *Thalassia*, *Enhalus*, and *Halophila* genera over other
1058 seagrass genera. Source data are provided as a Source Data file.

1059
1060 **Fig. 7 Correlations of family ranks possessing threatened seagrass species across marine**
1061 **ecoregions of the world (MEOWs).** The pairwise correlational analysis assigned values based
1062 on the level of overlap of seagrass families across MEOWs that possessed seagrass species
1063 classified as threatened by the International Union for Conservation of Nature. Low correlation

1064 values were generally reported between temperate and tropical MEOWs, indicating that the
1065 threatened seagrass species in these regions are unique to those areas. Source data are provided
1066 as a Source Data file.

1067
1068 **Fig. 8 Taxonomic distribution of extinction risk in seagrass.** Population status of seagrasses
1069 were assessed using the classifications set forth by the International Union for Conservation of
1070 Nature. Proportion of threatened species was assessed as number of threatened species in a
1071 family divided by the total number of species assessed within that family. When comparing the
1072 proportions of threatened species per family to the calculated 95% confidence interval, 3 families
1073 were significant: Zosteraceae, Posidoniaceae, and Hydrocharitaceae. Source data are provided as
1074 a Source Data file.

1075
1076 **Fig. 9 Temporal change in the amount of seagrass occurrence records over time.** Seagrass
1077 point records downloaded from GBIF were mapped over time based on the chronological date
1078 listed in the occurrence data for each record to demonstrate that seagrass occurrences have
1079 greatly increased within recent decades. This indicates that analyses with these data will be
1080 computationally expensive. Source data are provided as a Source Data file.