

## **The geography of the Anthropocene differs between the land and the sea**

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1 **Abstract**

2 Climate change and other anthropogenic drivers of biodiversity change are unequally distributed  
3 across the world. Despite the implications for biodiversity change, it is unknown if the  
4 geographic patterns of drivers differ between the terrestrial and marine realm. Using global  
5 datasets on human population density, land and resource exploitation, pollution, species  
6 invasions, and climate change, we found stronger positive correlations among drivers in the  
7 terrestrial than in the marine realm, leading to areas of especially intense human impact on land.  
8 Climate change tended to be negatively correlated with other drivers in the terrestrial realm  
9 whereas the opposite was true in the marine realm. We show that different regions of the world  
10 are exposed to distinct ‘anthropogenic threat complexes’, comprising suites of drivers of varying  
11 intensities. Our global analysis highlights the broad conservation priorities needed to mitigate the  
12 drivers shaping biodiversity responses to anthropogenic change.

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## 17 **Introduction**

18 Human activities are reshaping biological communities and impacting ecosystem functioning  
19 across the Earth<sup>1-4</sup>. Meeting the global challenge of the conservation and sustainable use of  
20 nature requires not only quantifying biodiversity change, but also identifying the underlying  
21 causes of change<sup>5</sup>. An essential first step towards determining these causes is characterizing the  
22 exposure patterns of biological communities to environmental change. Considerable effort has  
23 been devoted to mapping the magnitude of environmental changes that are affecting biodiversity.  
24 Global maps produced by this research, such as the Human Footprint<sup>6-10</sup>, have played an  
25 important role in highlighting the geographic hotspots of biodiversity threats. However, these  
26 maps show the summed pressure of different drivers and ignore any relationships among them.  
27 Understanding the relationships among drivers is essential for disentangling the relative  
28 importance of climate change and other human drivers for biodiversity change and ecosystem  
29 services, which is a key component of both policy-oriented assessments, such as IPBES<sup>11</sup>, and  
30 conservation targets, such as Aichi Biodiversity Targets<sup>5</sup>. Moreover, studies mapping drivers of  
31 biodiversity change<sup>6-10</sup> have so far considered the terrestrial and marine realms separately.  
32 Identifying similarities and differences in anthropogenic environmental change across the world,  
33 including across realms, would contribute towards a more general understanding of the global  
34 pattern of biodiversity change as well as help identify regions over which knowledge and  
35 information could be shared and synthesized to mitigate impacts. For the first time, we examined  
36 the relationships between drivers of biodiversity change across the entire surface of the world.  
37 Based on these relationships, we defined ‘anthropogenic threat complexes’ that typify the  
38 combinations of drivers impacting different regions of the world.

39

40 We quantified the strengths of the relationships among the intensities of different variables  
41 related to the dominant direct anthropogenic drivers of biodiversity change – climate change,  
42 habitat conversion and exploitation, pollution and species invasions<sup>12-14</sup>. We conducted our  
43 analysis at the global scale to identify the most general patterns emerging across ecosystems. By  
44 employing a standardized analysis for both the terrestrial and marine realms, we could compare  
45 the patterns in each. Multiple drivers may act in the same areas due to related local or regional  
46 human activities, especially in the terrestrial realm. In contrast, climate change is expected to be  
47 distributed differently than other variables because it is an outcome of processes at regional and  
48 global scales<sup>12</sup>. Based on this, we expected the correlations among drivers to differ, with  
49 implications for the typical combinations of drivers emerging in different regions of the world.  
50 We tested two main hypotheses on these correlations: 1) the intensities of many drivers are more  
51 strongly and positively correlated in the terrestrial compared with marine realm because of closer  
52 proximate human influences and 2) climate change-related variables are spatially decoupled  
53 from variables related to human populations due to the different scale at which the underlying  
54 processes act.

55

56 We selected global spatial gridded datasets on variables that characterize dimensions of the  
57 different anthropogenic drivers at some time point between 1950 and 2010 (Tables 1 and S1–  
58 S2). We focused on variables that had previously been deemed of sufficient global importance to  
59 be included in maps of environmental change for each realm<sup>6-9</sup>. Although the specific variables  
60 differ among realms, we aligned each variable to one of the dominant drivers that are common  
61 across both realms (Table 1). We also included several climate change metrics that were not  
62 included in some of the previous global maps<sup>6,7</sup>. For climate change-related variables, we used

63 time-series data to calculate temporal trends. In most other cases, only single time-slice data  
64 were available, but trends could also be calculated for land cover variables. For simplicity,  
65 habitat conversion and exploitation were grouped together as ‘human use’. We ranked and scaled  
66 the values of each variable between 0 and 1 to enable comparison. To investigate the  
67 relationships among these variables, we calculated Spearman’s rank correlation coefficients ( $\rho$ )  
68 for each pair-wise combination of variables within each realm. We used a modified t-test<sup>15</sup> to  
69 account for spatial autocorrelation. To better understand the causes and consequences of these  
70 correlations, we examined the magnitude of the different drivers in different terrestrial biomes  
71 and marine regions and we used a clustering algorithm to classify regions of the world according  
72 to their pattern of exposure to the different drivers. Finally, we determined which regions of the  
73 world have been exposed to the highest intensities of multiple drivers.

74

## 75 **Results**

76 Consistent with our first hypothesis, we found that drivers of biodiversity change were more  
77 spatially coupled in the terrestrial than in the marine realm (Fig. 1). On land, 33% of the possible  
78 pair-wise relationships between variables (excluding climate change-related variables) showed  
79 positive correlation strengths of at least 0.7. Thus, terrestrial areas with high intensities of one  
80 variable also tended to have high intensities of other variables. Moreover, correlations were  
81 found between different types of drivers. High cropland cover was associated with high  
82 pollution, high accessibility, high human population density and rapid increases in urban land  
83 cover. Conversely, in the marine realm, we found fewer correlations – only 15% of the possible  
84 pair-wise relationships (excluding climate change-related variables) showed a strong positive  
85 correlation ( $> 0.7$ ) – and they were mostly within, rather than between, different driver types; for

86 instance, among different types of human use (e.g., different fishing types; Fig. 1). Oceanic  
87 regions showed fewer correlations compared to coastal regions (Fig. S3). Spatial autocorrelation  
88 was present in all variables and tended to reach greater distances in the marine human-uses and  
89 climate-change variables (Figs S4 and S5), and shorter distances in the coastal-based marine  
90 variables, but the correlations remained statistical significant (all  $P < 0.05$  for links in Fig. 1) after  
91 accounting for autocorrelation.

92

93 Climate change emerged from our analysis as a spatially distinct driver of biodiversity change,  
94 with contrasting relationships to other drivers in the terrestrial and marine realms. In neither  
95 realm were there strong correlations between climate change and other drivers (Fig. 1),  
96 supporting our second hypothesis based on the broader spatial scale at which carbon emissions  
97 affect climate<sup>12</sup>. However, we did find some weak correlations, with the direction of these  
98 correlations differing between realms (Fig. 2). Temperature change was negatively associated  
99 with the average intensity of other variables in the terrestrial realm ( $\rho = -0.25$ ,  $P < 0.01$ , Fig. 2),  
100 but positively associated with the average intensity of other variables in the marine realm ( $\rho =$   
101  $0.20$ ,  $P < 0.05$ ; Fig. 2). Terrestrial biomes exposed to strong climate change, such as the tundra,  
102 boreal forest and deserts, have experienced relatively low human use; while terrestrial biomes,  
103 such as tropical dry broadleaf forest, with high intensities of human use, pollution and invasions  
104 have had lower intensities of climate change (Fig. 3). In contrast, marine areas exposed to strong  
105 climate change have been also strongly exposed to other drivers (Fig. 3). The central and western  
106 Indo-Pacific emerged as regions particularly at risk by being exposed to rapid climate change as  
107 well as multiple human uses.

108

109 Using cluster analysis, we defined five terrestrial and six marine regions according to their  
110 similarity of exposure to the different driver variables (Fig. 4). These exposure patterns can be  
111 regarded as ‘anthropogenic threat complexes’ (ATC) that characterize the typical combinations  
112 of environmental change. ATCs I and VI represent terrestrial and marine areas ranked with  
113 higher exposure to climate change than to other drivers (red regions in Fig. 4), while the reverse  
114 is true for ATCs IV and X (grey regions). ATCs II and III (terrestrial) and VII and VIII (marine)  
115 are regions exposed to relatively high intensities of many variables (orange and blue-grey  
116 regions) while ATCs V and XI (light blue regions) are areas generally exposed to lower  
117 intensities of most variables.

118

119 We further used our analysis to produce a fully global map showing areas exposed to high  
120 intensities of multiple drivers (Fig. 5). This helps understand the connection between the ATCs  
121 and previous cumulative human impact maps produced separately for the terrestrial<sup>6,7</sup> and marine  
122 realms<sup>8,9</sup>. Regions with the highest cumulative intensities across all variables tended to be within  
123 ATCs III and IV (terrestrial), areas with especially high pollution, and VIII (marine), coastal  
124 areas with high intensities of almost all drivers. By contrast, regions with the lowest cumulative  
125 intensities include ATCs I and V (terrestrial) and VI and XI (marine), which have lower human  
126 uses, pollution and invasions, but still could have high exposure to climate change.

127

## 128 **Discussion**

129 Correlations among drivers have important implications because they indicate that regional  
130 biological communities are often jointly impacted by different pressures. Strong correlations are

131 also likely to hinder attempts to disentangle the contributions of different drivers to biodiversity  
132 change. Although spatial heterogeneity at smaller spatial scales (e.g., neighboring sites with  
133 different land cover) can be used to estimate the local effect of drivers such as habitat  
134 conversion<sup>16</sup>, correlated large-scale drivers affecting regional species pools may still influence  
135 local community dynamics<sup>17</sup>. Spatial relationships between different land use changes in the  
136 terrestrial realm were expected based on the land requirements to support proximal human  
137 populations<sup>18</sup>. In the marine realm, different human uses (i.e., fisheries) largely occur in different  
138 areas (for instance, demersal fisheries mostly occur over the continental shelf, whilst pelagic  
139 fisheries can be either continental or oceanic), explaining the weaker correlations. Coastal  
140 regions were intermediate in patterns between terrestrial and oceanic regions, suggesting that the  
141 prevalence of human presence may contribute to the differences between the two realms<sup>19</sup>. As  
142 we found fewer strong correlations among different driver variables in the marine realm,  
143 separating the effects of different drivers may be more feasible in marine, especially in open  
144 ocean, ecosystems.

145

146 As climate change is only weakly associated with other drivers, there is considerable opportunity  
147 to disentangle climate change impacts from those of other drivers. The weak association means  
148 that climate change affects biological communities exposed to both strong and weak intensities  
149 of other drivers. In the case when other drivers are weak, climate change has the potential to be  
150 the dominant driver of change. Even though other drivers are also spatially variable, their  
151 variability tends to be spatially correlated. Consequently, climate change impacts on species  
152 abundances, range limits and community compositions<sup>20,21</sup> may be easier to isolate than those of  
153 other drivers. Indeed, high-latitude regions, such as the tundra and boreal forests, with low

154 human-use but pronounced climate change<sup>12,22</sup> have historically undergone less human  
155 settlement and agriculture. Warming of ocean temperatures is affected by additional factors  
156 compared with air temperatures, especially ocean currents<sup>12,23</sup>, which likely contributes to the  
157 rapid temperature change in the Indo-Pacific, also an area of intense fishing activity<sup>24</sup>. Hence,  
158 locations in which climate change is the main driver of change in a community are likely to be  
159 more common in terrestrial communities.

160

161 Given the strong spatial correlations among many drivers of biodiversity change, attributing  
162 biodiversity change to drivers is likely to be most successful if focused on complexes of  
163 environmental change, rather than on each variable individually. Our classification of ATCs  
164 helps regard anthropogenic environmental change as a series of at least 11 ‘natural experiments’  
165 across the globe. In particular, the ATCs highlight which environmental changes have the most  
166 opportunity to jointly influence communities. When multiple drivers simultaneously act on a  
167 community, they could have additive, synergistic or antagonistic effects<sup>25-27</sup>. The differential  
168 associations of drivers, summarized by the proposed ATCs, provide an informed baseline for  
169 further studies aiming at understanding the effects of multiple drivers on biodiversity and  
170 ecosystem services. Because drivers related to human-use, pollution and species invasions have  
171 great potential to co-occur, understanding these interactive effects has widespread importance.  
172 As climate change is occurring globally<sup>12</sup>, interactive effects of climate change and other drivers  
173 also have the potential to be widespread. However, we find that there is greater spatial overlap  
174 between high intensities of climate change and other drivers in the marine realm. The ATCs  
175 could be further used in macroecological studies of driver impacts. For example, examination of  
176 the relationships between the ATCs and the distributions of threatened species or local/regional

177 estimates of biodiversity change may help to identify the most harmful combination of drivers.  
178 Estimating the specific effects of individual drivers may also be aided by considering our ATCs  
179 (or driver clusters identified by a similar approach). Study regions that are most suitable to  
180 isolate the effects of a specific driver could be selected from within geographic clusters  
181 dominated by the driver of interest, to reduce the confounding effects of other drivers in the  
182 landscape. Moreover, our approach could be used to design the spatial sampling of quasi-  
183 experimental observatories in future monitoring programs. Observatories could be selected along  
184 different driver gradients (keeping all but one driver constant) or within different driver  
185 combinations. Long-term data from such observatories could greatly advance our understanding  
186 of the underlying causes of biodiversity change.

187  
188 Quantifying exposure to environmental change is the first step towards understanding how life  
189 on Earth is being reshaped in the Anthropocene and more specifically for determining which  
190 species, in which places, are or will be most exposed to human activities. The impacts of  
191 different drivers on biodiversity will depend on a combination of the magnitude of exposure to  
192 drivers and species' sensitivities to environmental change<sup>28</sup>. We intentionally focused on  
193 exposure patterns so that our results are not species-specific and are therefore potentially relevant  
194 for any taxa or ecosystem. Unlike exposure, sensitivities vary among taxa according to  
195 characteristics such as their life history, traits and niche breadth among others<sup>29</sup> and therefore  
196 should be examined separately for different taxa. We also avoided making any complex  
197 assumptions about the relationships between the absolute levels of each driver variable and its  
198 impact on organisms, rather we assumed that all variables were similarly important.

199

200 Management at specific locations is clearly aided by assessing the local magnitudes of different  
201 drivers. However, there are a number of advantages of knowledge on the general patterns in how  
202 different drivers combine at larger-scales. First, these large-scale patterns allow local  
203 management to be modified according to the wider anthropogenic land- or seascape context,  
204 which affects the regional species pool and hence potentially biodiversity changes at smaller-  
205 scales<sup>17</sup>. Second, managers may only have access to partial data at local scales – the typical  
206 combinations of drivers that we identify can help managers predict the extent to which other  
207 drivers should be of concern. Finally, by characterizing regions of the world in terms of the  
208 nature of environmental change, our ATCs suggest how information and data might be pooled  
209 and synthesized across regions, and even across realms<sup>30</sup>. Regions exposed to the same ATC,  
210 regardless of location, would benefit from exchanging knowledge about prioritization strategies  
211 and management of the multiple drivers, as well as implementing cross-border strategies to  
212 minimize their impact.

213

214 Global impact assessments and mitigation policy can be better informed by explicitly  
215 incorporating the coupled and decoupled drivers of current and future biodiversity change. Our  
216 macroecological approach to mapping the drivers of biodiversity change contributes to the  
217 development of broad conservation policy targeted toward the mitigation of specific driver  
218 complexes. The main drivers affecting nature and nature's contribution to people are one of the  
219 overarching components of the IPBES framework and assessments<sup>11,31</sup> while attribution of  
220 climate change impacts is a core chapter of the IPCC report<sup>32</sup>. Our findings are especially  
221 relevant for the IPBES Global Assessment that seeks knowledge on global-level linkages.  
222 Monitoring progress towards the Aichi Biodiversity Targets and the Sustainable Development

223 Goals also requires a clear understanding of the different drivers and their inter-causal  
224 relationships<sup>5</sup>. The empirical spatial relationships among drivers indicate the strength to which  
225 they are affected by common processes and hence are likely to have inter-linked impacts. A  
226 better understanding of these associations, and their integration within biodiversity models could  
227 improve the quality of the projections made with scenarios of future global change, by  
228 considering how the full suite of drivers might change over time<sup>33</sup>.

229

230 Data on global drivers of biodiversity change are still limited<sup>34</sup>. Further global datasets on driver  
231 variables in the ocean, such as plastic pollution, would be especially valuable, and allow deeper  
232 examination of the relationships among drivers in the marine realm. Spatially-explicit maps of  
233 the number of invasive species would also have improved our analysis. These data are now often  
234 available at national or sometimes regional scales<sup>35</sup> but have not been downscaled or modelled  
235 explicitly across the world. We followed the approach of Halpern et al.<sup>8,9</sup> and inferred the  
236 pressure from invasive species through transport connectivity for both the terrestrial and marine  
237 realm; however, our overall findings are not affected by the inclusion of this variable. For  
238 estimation of historical temporal trends in land cover between 1950-2010, we used the land use  
239 harmonization (LUH2) dataset of annual predictions of land-use states, which is based on diverse  
240 empirical data along with interpolation assumptions<sup>36</sup>, and hence are not exact data. However,  
241 we regarded all datasets as the best current estimates of each driver-related variable. For most  
242 drivers, it is currently only possible to examine spatially-explicit trends over recent, short time-  
243 scales<sup>7,8</sup>. Ongoing projects, such as the Copernicus project (<http://www.copernicus.eu/>), will  
244 greatly increase the availability of spatiotemporally-explicit, high resolution datasets on different

245 variables<sup>37</sup> in the coming years for further study of the relationships between drivers and for  
246 attribution of biodiversity change to the underlying drivers.

247

248 Anthropogenic impacts are now pervasive across the globe, even reaching ecosystems that have  
249 so far avoided major exposure to the effects of direct human activity. However, their effects are  
250 not spatially homogeneous. Terrestrial and marine communities differ in their exposure to  
251 anthropogenic drivers, with greater spatial coupling of threats in the terrestrial realm, likely  
252 driven by proximate human populations. The relationships that we document here have  
253 implications for the spatial patterning of biodiversity change across the world. Especially on  
254 land, climate change can act as a lone driver of biodiversity change across more communities  
255 than other drivers. This means that its unique fingerprints may be easier to detect than those of  
256 other drivers that more often act in combination, regardless of its relative importance. A central  
257 focus of modern ecology is to understand global patterns of biodiversity change. Yet, all too  
258 often, scientists and managers are reading, citing, and focusing on system and realm-specific  
259 influences of global change drivers<sup>30</sup>. By a cross-realm approach, we hope to encourage  
260 information exchange across regions of the world that are exposed to similar suites of drivers,  
261 regardless of environmental realm, and the development of joined-up conservation policies  
262 across the terrestrial-marine interface.

263

## 264 **Methods**

265

266 *Data selection*

267 Our analysis is only made possible by the great efforts of researchers to develop and make  
268 publicly available gridded global datasets on environmental change variables<sup>10,36,38-46</sup>, especially  
269 Halpern et al. for the marine realm<sup>8,9</sup>. We selected variables that were regarded to be sufficiently  
270 global important to be included in other studies on global drivers of change<sup>6-9</sup>, even if these  
271 impacts did not cover the whole area within each realm. The terrestrial datasets came from  
272 various sources (see Tables 1 and S1 for all datasets). Most of the marine datasets came from the  
273 landmark study of Halpern et al.<sup>9</sup>. Even though a more recent set of these marine layers is  
274 available<sup>8</sup>, we used the layers from their first article<sup>9</sup> because the time-period of the data was  
275 closer to that of the other datasets (i.e., before 2010). For the terrestrial realm, we could calculate  
276 both a trend (i.e., average change in area per year) for the period 1950-2010<sup>36</sup> as well as a current  
277 value for some variables (e.g., urban and crop land cover in 2000/2001)<sup>40,41</sup>. We decided to  
278 include both in the analysis since the underlying processes generating the current area of cover  
279 may precede 1950 and therefore may have a different distribution than the recent trend in cover  
280 since 1950 (justified by the fact that they were not strongly correlated). In fact, only urban land  
281 cover trend displayed any strong correlations with the other variables in our analysis. For forest  
282 cover, only forest cover trend (i.e., loss) based on FAO wood harvest statistics<sup>36</sup> was included as  
283 an anthropogenic pressure.

284

285 Further spatial datasets that were potentially relevant but subsequently found to be highly  
286 correlated (>0.9) with another dataset, and were present over slightly smaller areas than their  
287 correlated partners, were excluded on the basis of redundancy: phosphorus fertilizer application  
288 (correlated with N fertilizer application) in the terrestrial realm, and pesticide (correlated with  
289 fertilizer) and shipping (correlated with ocean pollution) in the marine realm (see Table S1).

290 Although not correlated, we obtained similar results (in terms of relationships with other drivers)  
291 for pasture cover and pasture cover trend, so we used only the latter in our analysis to ensure an  
292 even number in the variables tested in the terrestrial and marine realms. Some datasets were not  
293 entirely independent. In both the terrestrial and marine realms, country-specific estimates of land  
294 pollution (pesticides and nitrogen fertilizer use) were downscaled by the data providers  
295 according to the distribution of cropland<sup>10,45</sup>. Also in the marine realm, national estimates of  
296 artisanal fishing had been downscaled based on assumptions regarding the distance from coastal  
297 human populations<sup>9</sup>. We regarded each dataset as the best current estimate of the spatial patterns  
298 for each variable. The Land-Use Harmonization dataset (used for trends in forest, crop, pasture  
299 and urban land-use – see Table S1)<sup>36</sup> also used human population data for downscaling but we  
300 only used this dataset to calculate trends in land-use.

301 Data on the spatial distribution of terrestrial biomes were taken from WWF<sup>47</sup> and marine regions  
302 were obtained by combining coastal region polygon data – MEOW<sup>48</sup> and ocean polygon data  
303 ([naturalearthdata.com](http://naturalearthdata.com)).

304

### 305 *Data organization*

306 For interpretation and presentation purposes, variables were grouped by which global driver of  
307 change they were most directly related to, i.e., climate change, habitat conversion, exploitation,  
308 pollution or species invasions. Because habitat conversion and exploitation were difficult to class  
309 separately across the terrestrial and marine realms, we combined both into a single “human use”  
310 category. There are no high-resolution spatial maps of invasive species richness; however, we  
311 used maps of human transport connectivity, based on the assumption that they are a proxy of  
312 human-mediated propagule pressure (e.g., related to human movement and trade) of alien

313 species, which is known to be an important determinant of invasion success<sup>49,50</sup> and is an  
314 approach following others<sup>8,9</sup>. We used spatial datasets of accessibility based on transport  
315 infrastructure in the terrestrial realm and cargo volume at ports in the marine realm (Table  
316 S1)<sup>9,46</sup>. We also included “human population density”<sup>42</sup> as a separate driver accounting for the  
317 effects of human activities not falling into the other categories (e.g., tourism/recreation  
318 activities), as well as to determine the relationship of human population density with other  
319 drivers.

320

### 321 *Data processing*

322 For most datasets, the data were collected from one or a few years (at some point during 1990–  
323 2010) and were available as pooled data into a single time point (see Table S1 for more details).  
324 For data available as a time series (see those marked by \* in Table 1), we calculated temporal  
325 trends for each raster grid as the regression coefficient of a year effect in a linear regression for  
326 1950–2010, reflecting change during the recently defined Anthropocene that is estimated to have  
327 started in 1950<sup>51</sup>. Aridity trend was estimated by taking monthly and annual datasets on potential  
328 evapotranspiration and precipitation, and calculating their ratio<sup>52</sup>, and finally the temporal trend  
329 of the annual monthly average of this ratio. Velocity of climate change was calculated following  
330 ref.<sup>53</sup>. We also calculated two additional climate change metrics: temperature divergence –  
331 following ideas by ref.<sup>54</sup>, which was inferred from the t-static of the linear regression (i.e.,  
332 temperature trend in °C divided by its standard error), and also trends of extreme temperatures  
333 (whichever was largest of the temporal trends in temperature of the warmest or coolest month).  
334 Missing values in some of the human activity datasets were in remote regions (e.g., very high  
335 latitudes) with likely absent or low variable values and were imputed as zero. However, datasets

336 were also bounded to an extent of -179, 179, -58, 78 (xmin, xmax, ymin, ymax) to avoid map  
337 edge effects. Greenland was also excluded due to missing data in several of the datasets.

338

339 Next, we harmonized each dataset to a standard global grid. The resolutions of the original  
340 datasets were approximately at a 100 km square grid (or 1°) or finer resolution, with the  
341 exception of atmospheric nitrogen deposition<sup>43</sup>. Thus, we chose to aggregate all datasets to a  
342 standard grid of 100 km square grid cells. This aggregation was done by summing the values of  
343 grid cells or by taking the median of values (in the case of trend variables, accessibility and  
344 ocean acidification). Datasets were then re-projected onto a common equal-area map projection  
345 (Eckert IV; EPSG = 54012). Because each dataset comprised data in different units, it was not  
346 possible to directly compare the absolute values among all the datasets. Instead, the values of  
347 each dataset were ranked because of the highly-skewed distributions and scaled between 0 and 1  
348 for ease of interpretation (Fig. S9 show the distributions of the original values of each variable  
349 and Fig. S10 shows global maps of the ranked and scaled data). For all datasets, larger values  
350 reflected a greater potential exposure of that variable on biodiversity. Transformations were  
351 needed in two cases to achieve this – we inverted terrestrial accessibility (i.e.,  $values^{-1}$ ) and  
352 changed the sign of the forest trend values (i.e.,  $values \times -1$ ).

353

#### 354 *Data analysis*

355 Spearman's rank correlation coefficients ( $\rho$ ) were calculated for each pair-wise combination of  
356 variables in each realm at the global-level. This statistic is robust to data processing decisions  
357 because it only uses rankings of the data values and is equivalent to the commonly used

358 Pearson's correlation on ranked data. We used Dutilleul's modified t-test to account for spatial  
359 autocorrelation in each dataset before testing the significance of the correlations<sup>15</sup>. For the  
360 marine realm, these correlations were also examined separately for grid cells whose centroid  
361 overlapped with oceanic or coastal regions. We examined Moran's I and correlograms to  
362 determine the spatial extent of autocorrelation within each variable and its statistical  
363 significance<sup>55</sup>.

364

365 To compare the relative importance of different drivers for different regions of each realm, we  
366 calculated the difference between each region's average (weighting each grid cell by the  
367 coverage of each region) and the average across all regions in each realm. We did not use marine  
368 ecosystem data as used by others<sup>9</sup> because the ecosystems spatially overlapped in our coarse 2-D  
369 global raster grid, when, in reality, they are at different depths in the water column. We used k-  
370 medoid clustering, using the partitioning around the medoids algorithm with Manhattan  
371 distances<sup>56</sup>, for clustering grid cells according to their extent of exposure of all variables. To  
372 make the number of variables per driver more comparable, we first used principal components  
373 analysis on drivers with multiple associated variables (climate change, human use and pollution)  
374 to produce a reduced number of variables (two axes for climate change and pollution, three axes  
375 for human use) that explained most (>75%) of the variation in each. We then applied the cluster  
376 analysis to a dataset of these PCA variables with the human population density and species  
377 invasion variables. We selected the number of clusters by comparing the changes in dissimilarity  
378 and cluster silhouette width with increasing cluster number. However, we limited the cluster  
379 number so that it was less than 10 and so that each cluster was linked to a different dominant  
380 driver variable. To slightly smooth the maps, we used a moving window to assign each cell the

381 mode of its 3 x 3 cell neighborhood. Although, driver combinations vary in a continuous manner,  
382 we chose a clustering method that produces discrete grouping to provide the simplest description  
383 of the main groupings in the data. Finally, to identify which regions of the world were exposed to  
384 high intensities of multiple drivers, we identified and summed the number of variables for which  
385 a grid cell was in the upper 10% of values (based on all values greater than zero) of each  
386 variable.

387

### 388 *Sensitivity analyses*

389 To examine the effect of the grain size of our global grid, we repeated the data processing steps  
390 except harmonizing the datasets to global grids of different resolutions (800, 400, 200, 100 and  
391 50 [terrestrial only] square km grid) and repeated the analysis of correlations (similar results  
392 were obtained – see Fig. S11). To check the effects of ranking the data values because of the  
393 skewed data distributions, we repeated the data processing steps by logging the values (to the  
394 base 10) rather than ranking them, after bounding values above the upper and lower 2.5% of  
395 quantiles to the values of the upper and lower 2.5% quantiles. This alternative data  
396 transformation does not affect the correlation coefficients because in any case Spearman's  
397 correlations only uses the ranks of the data. We repeated our remaining analysis with this  
398 alternative transformation, calculating the average variable intensities for different terrestrial and  
399 marine regions, and the clustering analysis (similar results were obtained – see Fig. S12 and  
400 S13).

401

### 402 *Data availability*

403 Table S1 shows the sources of each dataset and links to where each dataset can be downloaded.  
404 Datasets produced during our analysis (raster layers shown in Figures 4 and 5) are available as  
405 georeferenced TIFF files in the SOM.

406

407 *Code availability*

408

409 R script to harmonize the raster to a standard grid is found here:

410 <https://github.com/bowlerbear/harmonizeRasters>

411 R script for the subsequent analysis is found here:

412 <https://github.com/bowlerbear/geographyDrivers>

## References

- 1 Pereira, H. M. *et al.* Scenarios for Global Biodiversity in the 21st Century. *Science* **330**, 1496-1501, doi:10.1126/science.1196624 (2010).
- 2 Barnosky, A. D. *et al.* Has the Earth's sixth mass extinction already arrived? *Nature* **471**, 51-57, doi:10.1038/nature09678 (2011).
- 3 Dornelas, M. *et al.* Assemblage Time Series Reveal Biodiversity Change but Not Systematic Loss. *Science* **344**, 296-299, doi:10.1126/science.1248484 (2014).
- 4 Isbell, F. *et al.* Linking the influence and dependence of people on biodiversity across scales. *Nature* **546**, 65-72, doi:10.1038/nature22899 (2017).
- 5 Tittensor, D. P. *et al.* A mid-term analysis of progress toward international biodiversity targets. *Science* **346**, 241-244, doi:10.1126/science.1257484 (2014).
- 6 Sanderson, E. W. *et al.* The human footprint and the last of the wild. *Bioscience* **52**, 891-904, doi:10.1641/0006-3568(2002)052[0891:thfatl]2.0.co;2 (2002).
- 7 Venter, O. *et al.* Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. *Nature Communications* **7**, doi:10.1038/ncomms12558 (2016).
- 8 Halpern, B. S. *et al.* Spatial and temporal changes in cumulative human impacts on the world's ocean. *Nature Communications* **6**, doi:10.1038/ncomms8615 (2015).
- 9 Halpern, B. S. *et al.* A global map of human impact on marine ecosystems. *Science* **319**, 948-952, doi:10.1126/science.1149345 (2008).
- 10 Vorosmarty, C. J. *et al.* Global threats to human water security and river biodiversity. *Nature* **467**, 555-561, doi:10.1038/nature09440 (2010).
- 11 Diaz, S. *et al.* The IPBES Conceptual Framework - connecting nature and people. *Current Opinion in Environmental Sustainability* **14**, 1-16, doi:10.1016/j.cosust.2014.11.002 (2015).
- 12 IPCC. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press, 2013).
- 13 Butchart, S. H. M. *et al.* Global Biodiversity: Indicators of Recent Declines. *Science* **328**, 1164-1168, doi:10.1126/science.1187512 (2010).
- 14 Pereira, H. M., Navarro, L. M. & Martins, I. S. in *Annual Review of Environment and Resources, Vol 37* Vol. 37 *Annual Review of Environment and Resources* (eds A. Gadgil & D. M. Liverman) 25-+ (2012).
- 15 Dutilleul, P., Pelletier, B. & Alpargu, G. Modified F tests for assessing the multiple correlation between one spatial process and several others. *Journal of Statistical Planning and Inference* **138**, 1402-1415, doi:10.1016/j.jspi.2007.06.022 (2008).
- 16 Newbold, T. *et al.* Global effects of land use on local terrestrial biodiversity. *Nature* **520**, 45-+, doi:10.1038/nature14324 (2015).
- 17 Harrison, S. & Cornell, H. Toward a better understanding of the regional causes of local community richness. *Ecology Letters* **11**, 969-979, doi:10.1111/j.1461-0248.2008.01210.x (2008).
- 18 Ellis, E. C., Goldewijk, K. K., Siebert, S., Lightman, D. & Ramankutty, N. Anthropogenic transformation of the biomes, 1700 to 2000. *Global Ecology and Biogeography* **19**, 589-606, doi:10.1111/j.1466-8238.2010.00540.x (2010).
- 19 Halpern, B. S. *et al.* Patterns and Emerging Trends in Global Ocean Health. *Plos One* **10**, doi:10.1371/journal.pone.0117863 (2015).
- 20 Parmesan, C. & Yohe, G. A globally coherent fingerprint of climate change impacts across natural systems. *Nature* **421**, 37-42, doi:10.1038/nature01286 (2003).
- 21 Poloczanska, E. S. *et al.* Global imprint of climate change on marine life. *Nature Climate Change* **3**, 919-925, doi:10.1038/nclimate1958 (2013).
- 22 Pithan, F. & Mauritsen, T. Arctic amplification dominated by temperature feedbacks in contemporary climate models. *Nature Geoscience* **7**, 181-184, doi:10.1038/ngeo2071 (2014).
- 23 Burrows, M. T. *et al.* The Pace of Shifting Climate in Marine and Terrestrial Ecosystems. *Science* **334**, 652-655, doi:10.1126/science.1210288 (2011).
- 24 Ramirez, F., Afan, I., Davis, L. S. & Chiaradia, A. Climate impacts on global hot spots of marine biodiversity. *Science Advances* **3**, doi:10.1126/sciadv.1601198 (2017).
- 25 Hof, C., Araujo, M. B., Jetz, W. & Rahbek, C. Additive threats from pathogens, climate and land-use change for global amphibian diversity. *Nature* **480**, 516-U137, doi:10.1038/nature10650 (2011).

- 26 Garcia-Valdes, R., Svenning, J. C., Zavala, M. A., Purves, D. W. & Araujo, M. B. Evaluating the combined effects of climate and land-use change on tree species distributions. *Journal of Applied Ecology* **52**, 902-912, doi:10.1111/1365-2664.12453 (2015).
- 27 Travis, J. M. J. Climate change and habitat destruction: a deadly anthropogenic cocktail. *Proceedings of the Royal Society B-Biological Sciences* **270**, 467-473, doi:10.1098/rspb.2002.2246 (2003).
- 28 Foden, W. B. *et al.* Identifying the World's Most Climate Change Vulnerable Species: A Systematic Trait-Based Assessment of all Birds, Amphibians and Corals. *Plos One* **8**, doi:10.1371/journal.pone.0065427 (2013).
- 29 Sunday, J. M. *et al.* Species traits and climate velocity explain geographic range shifts in an ocean-warming hotspot. *Ecology Letters* **18**, 944-953, doi:10.1111/ele.12474 (2015).
- 30 Webb, T. J. Marine and terrestrial ecology: unifying concepts, revealing differences. *Trends in Ecology & Evolution* **27**, 535-541, doi:10.1016/j.tree.2012.06.002 (2012).
- 31 Kok, M. T. J. *et al.* Biodiversity and ecosystem services require IPBES to take novel approach to scenarios. *Sustainability Science* **12**, 177-181, doi:10.1007/s11625-016-0354-8 (2017).
- 32 Cramer, W. *et al.* in *Climate Change 2014 : Impacts, Adaptation, and Vulnerability* (Cambridge University Press, 2014).
- 33 Rosa, I. M. D. *et al.* Multiscale scenarios for nature futures. *Nature Ecology & Evolution* **1**, 1416-1419, doi:10.1038/s41559-017-0273-9 (2017).
- 34 Joppa, L. N. *et al.* Filling in biodiversity threat gaps. *Science* **352**, 416-418, doi:10.1126/science.aaf3565 (2016).
- 35 Dawson, W. *et al.* Global hotspots and correlates of alien species richness across taxonomic groups. *Nature Ecology & Evolution* **1**, doi:10.1038/s41559-017-0186 (2017).
- 36 Hurtt, G. C. *et al.* Harmonization of land-use scenarios for the period 1500-2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands. *Climatic Change* **109**, 117-161, doi:10.1007/s10584-011-0153-2 (2011).
- 37 Skidmore, A. K. *et al.* Agree on biodiversity metrics to track from space. *Nature* **523**, 403-405, doi:10.1038/523403a (2015).
- 38 Harris, I., Jones, P. D., Osborn, T. J. & Lister, D. H. Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *International Journal of Climatology* **34**, 623-642, doi:10.1002/joc.3711 (2014).
- 39 Rayner, N. A. *et al.* Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research-Atmospheres* **108**, doi:10.1029/2002jd002670 (2003).
- 40 Ramankutty, N., Evan, A. T., Monfreda, C. & Foley, J. A. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles* **22**, doi:10.1029/2007gb002952 (2008).
- 41 Friedl, M. A. *et al.* MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets, 2001-2012, Collection 5.1 IGBP Land Cover. (Boston University, Boston, MA, USA, 2010).
- 42 Center for International Earth Science Information Network - CIESIN - Columbia University. (NASA Socioeconomic Data and Applications Center (SEDAC), Palisades, NY, 2017).
- 43 Dentener, F. J. (Oak Ridge, Tennessee, USA, 2006).
- 44 Hurtt, G., Chini, L., Sahajpal, R. & Frohking, S. Harmonization of global land-use change and management for the period 850-2100". Geoscientific Model Development. ((in prep)).
- 45 Potter, P., Ramankutty, N., Bennett, E. M. & Donner, S. D. Characterizing the Spatial Patterns of Global Fertilizer Application and Manure Production. *Earth Interactions* **14**, 1-22 (2010).
- 46 Nelson, A. (2008).
- 47 Olson, D. M. *et al.* Terrestrial ecoregions of the worlds: A new map of life on Earth. *Bioscience* **51**, 933-938, doi:10.1641/0006-3568(2001)051[0933:teotwa]2.0.co;2 (2001).
- 48 Spalding, M. D. *et al.* Marine ecoregions of the world: A bioregionalization of coastal and shelf areas. *Bioscience* **57**, 573-583, doi:10.1641/b570707 (2007).
- 49 Seebens, H. *et al.* Global trade will accelerate plant invasions in emerging economies under climate change. *Global Change Biology* **21**, 4128-4140, doi:10.1111/gcb.13021 (2015).
- 50 Hulme, P. E. Trade, transport and trouble: managing invasive species pathways in an era of globalization. *Journal of Applied Ecology* **46**, 10-18, doi:10.1111/j.1365-2664.2008.01600.x (2009).
- 51 Waters, C. N. *et al.* The Anthropocene is functionally and stratigraphically distinct from the Holocene. *Science* **351**, 137-+, doi:10.1126/science.aad2622 (2016).

- 52 Zorner, R. J., Trabucco, A., Bossio, D. A. & Verchot, L. V. Climate change mitigation: A spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. *Agriculture Ecosystems & Environment* **126**, 67-80, doi:10.1016/j.agee.2008.01.014 (2008).
- 53 Loarie, S. R. *et al.* The velocity of climate change. *Nature* **462**, 1052-U1111, doi:10.1038/nature08649 (2009).
- 54 Nadeau, C. P. & Fuller, A. K. Accounting for multiple climate components when estimating climate change exposure and velocity. *Methods in Ecology and Evolution* **6**, 697-705, doi:10.1111/2041-210x.12360 (2015).
- 55 Bjornstad, O. N., Ims, R. A. & Lambin, X. Spatial population dynamics: analyzing patterns and processes of population synchrony. *Trends in Ecology & Evolution* **14**, 427-432, doi:10.1016/s0169-5347(99)01677-8 (1999).
- 56 cluster: Cluster Analysis Basics and Extensions (R package version 2.0.6. , 2017).

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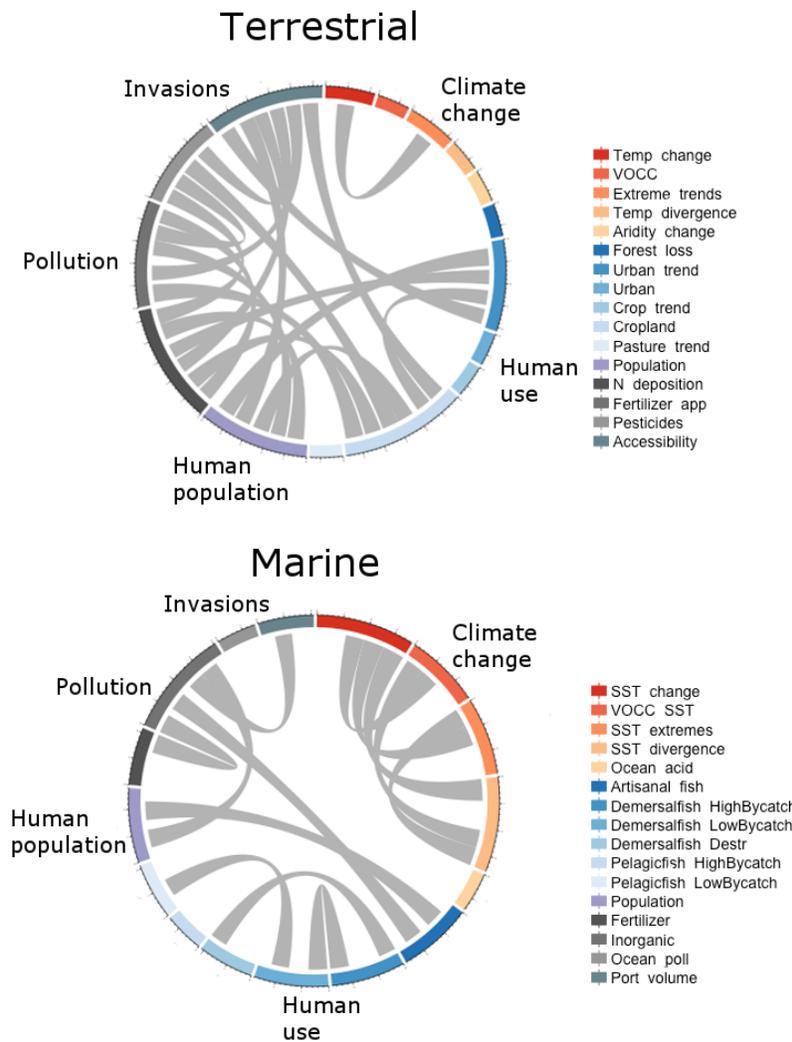
This paper arose from discussions at the sChange Workshop ([www.idiv.de/schange](http://www.idiv.de/schange)) during February 2016, which was supported by and held at sDiv, the synthesis centre of iDiv, the German Centre for Integrative Biodiversity Research Halle-Jena-Leipzig. We thank all other participants of this workshop for the stimulating discussion and compilation of data that directly fed into this project. We also thank Suzanne Fritz, Mary O'Connor and Bob O'Hara for comments on a previous version of the manuscript. DB, JSC & MW were funded by the German Research Foundation (DB: Grant no BO 1221/23-1; JSC & MW: via iDiv: FZT 118). SRS is funded by the National Science Foundation, USA (NSF 1400911). LHA was supported by Fundação para a Ciência e Tecnologia, Portugal (POPH/FSE SFRH/BD/90469/2012). ADB was supported by The Danish Council for Independent Research - Natural Sciences (DFR 4181-00565). MD is funded by the Scottish Funding Council (MASTS, grant reference HR09011) and MD & AEM by the ERC project BioTIME (250189) and BioCHANGE (727440). CW was supported by the Natural Environmental Research Council (grant number NE/L002531/1)

**Author contributions:**

DB performed the analyses and wrote the first outline of the paper with AEB. All authors designed the study and helped draft the manuscript.

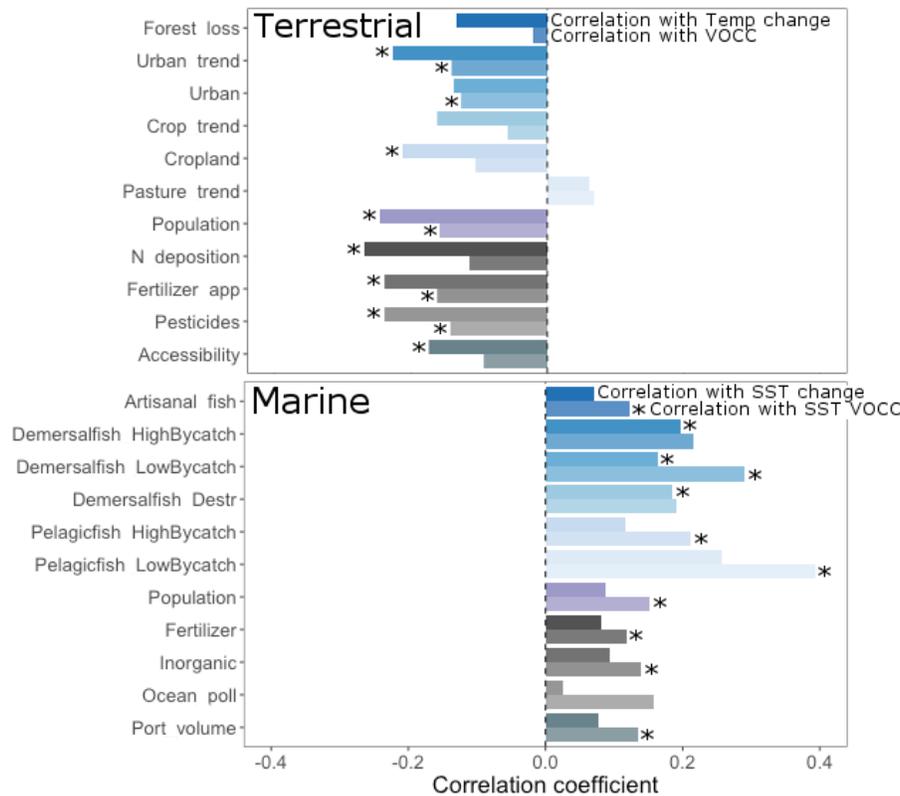
**Competing financial interests:**

The authors declare no competing financial interests.

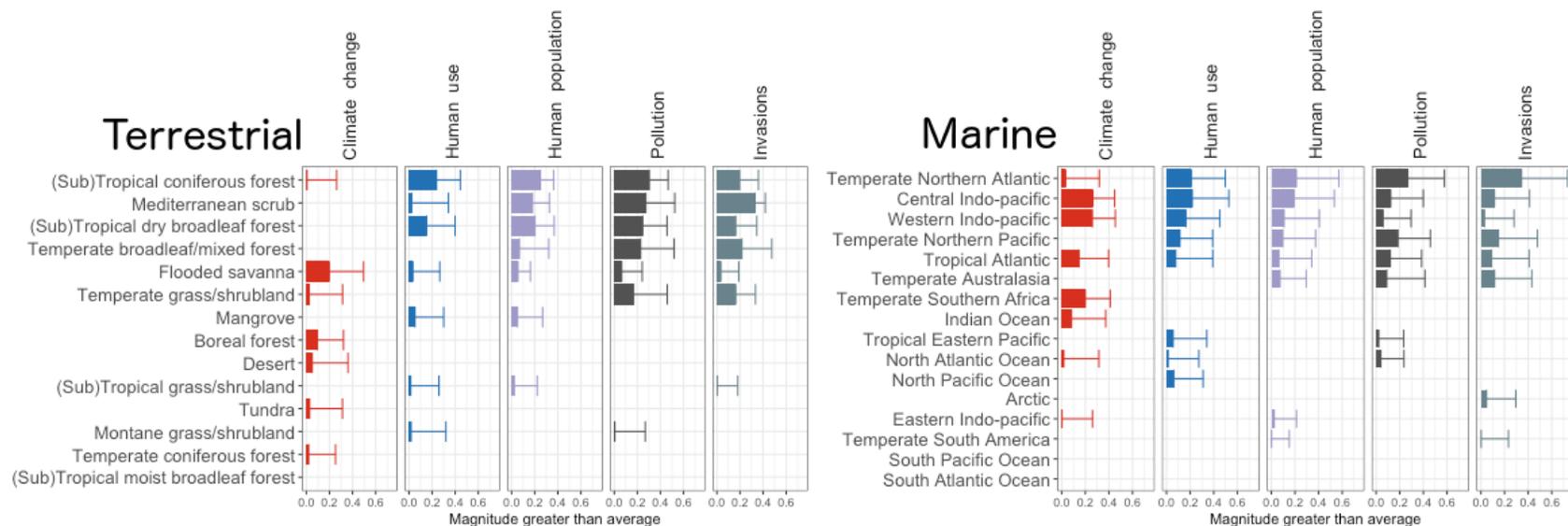


**Fig. 1 Strong and positive relationships among anthropogenic drivers of biodiversity**

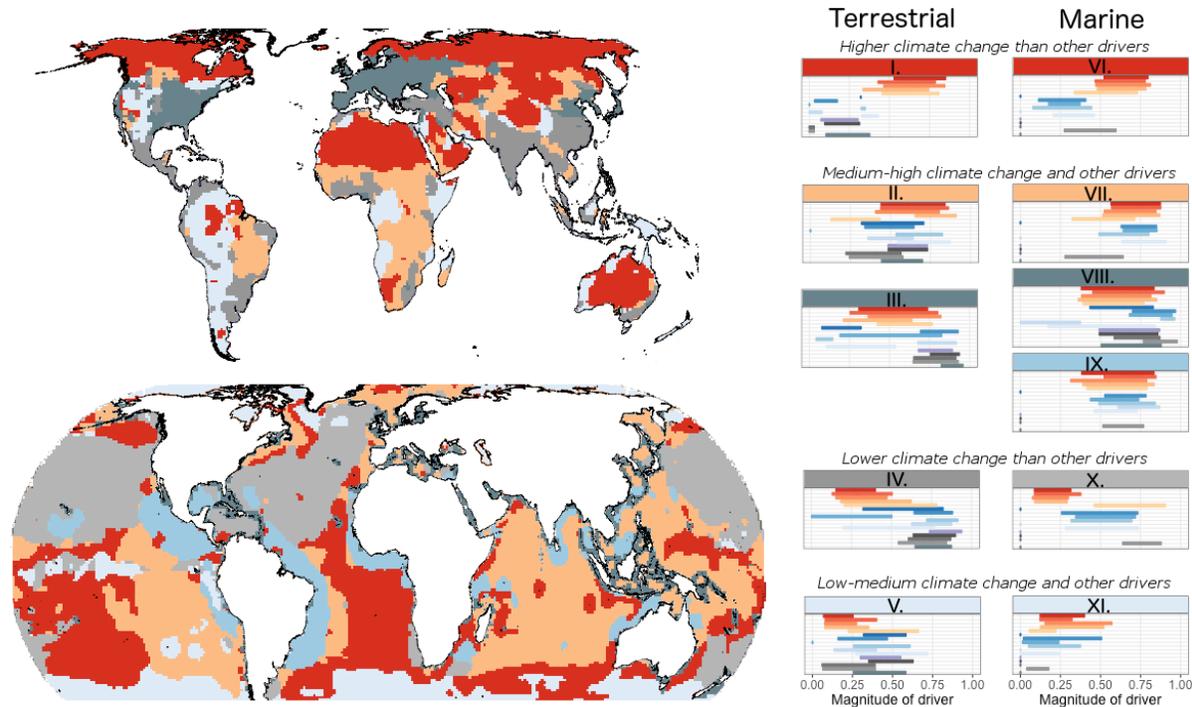
**change.** We find a higher number of correlations between drivers in the terrestrial versus the marine realm. Each link represents a significant and strong positive correlation (with strength >0.7) between two variables across 100 square km grids covering the world (see also Figs S1 and S2). No negative correlations were stronger than -0.7.



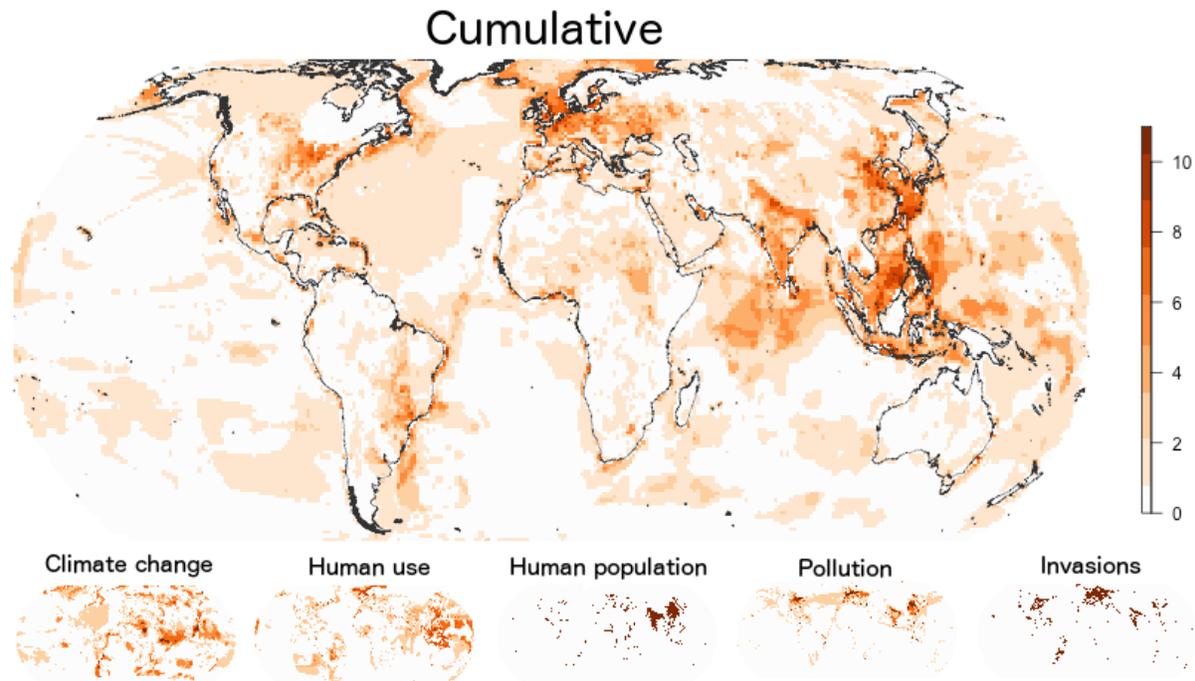
**Fig. 2 Relationships between climate change and other drivers.** Comparing the relationships between each variable and temperature change (air or sea surface temperature – SST) or the velocity of climate change (VOCC), we find weak negative ( $>-0.3$ ) correlations in the terrestrial realm and weak positive ( $<0.4$ ) correlations in the marine realm. The length of each bar shows the correlation coefficient between temperature change (upper bar) or VOCC (lower bar) and each variable. \* denotes statistical significance after accounting for spatial autocorrelation.



**Fig. 3 Regions of the terrestrial and marine realms are exposed to distinct combinations of drivers.** The bars show the dominant drivers in each terrestrial and marine region. The length of the bar represents the positive deviation (plus standard deviation) of that region's average + standard deviation (across all variables in each driver – see Table 1) from the average of all regions. Bars with negative average deviations are not shown to simplify the presentation. Regions are presented in declining order of the sum of all their bar lengths. Names of the terrestrial regions were shortened for presentation purposes. Figure S6 shows the full distributions for each individual driver variable in each region as well as gives the full names of the terrestrial regions.



**Fig. 4 Geography of the Anthropocene.** Different geographic regions of the world are exposed to different Anthropogenic Threat Complexes (numbered I to XI). These regions were obtained by k-medoid clustering based on their similarity of exposure to different drivers of biodiversity change and are colored according to one of the highest ranked variable in each complex (i.e., an most important driver in that region). The bars in the legend show the intensities (between the lower and upper quartiles) of each variable in each complex from 0 (no impact) to 1 (highest impact). Clustered regions are colored to reflect the dominant driver and are harmonized across realms to facilitate comparison. White regions were not included in the analysis of each realm. Fig. S7 provides a larger plot of the legend.



**Fig. 5 Regions of the world exposed to high intensities of multiple drivers.** The number of the 16 driver variables that each grid cell was in the highest 10% of values within its realm. Regions in the darkest orange are exposed to high intensities of multiple variables, while those in off-white are exposed to lower intensities of all (i.e., still potentially exposed to pressures but the magnitude of the pressures is not in the highest 10% of magnitude values). The same is shown for each of the separate drivers, i.e., the intensity of the color is scaled by the number of variables within each driver (Table 1) with a value in the highest 10%. Note: Greenland was not included in the analysis due to missing data in several of the datasets. Larger versions of the plots are presented in Fig. S8.

**Table 1** Anthropogenic drivers of biodiversity change and their respective variables based on available global spatial datasets (Table S1). Time-series datasets are indicated by \*. Variables in the same line do not necessarily represent the equivalent variable in each realm.

Anthropogenic driver of biodiversity change	Associated variables	
	Terrestrial	Marine
<b>Climate Change</b>	Temperature change* Temperature divergence* Change in climate extremes* Velocity of climate change* Aridity change*	Temperature change* Temperature divergence* Change in climate extremes* Velocity of climate change* Ocean acidification
<b>Human use (land use or change, resource extraction, exploitation)</b>	Crop cover Crop cover trend* Pasture cover trend* Forest loss trend* Urban cover Urban cover trend*	Destructive demersal fishing Low by-catch demersal fishing High by-catch demersal fishing Low by-catch pelagic fishing High by-catch pelagic fishing Artisanal fishing
<b>Human population density</b>	Population density	Coastal population density
<b>Pollution</b>	Atmospheric nitrogen deposition Nitrogen fertilizer application Pesticide application	Ocean pollution Inorganic coastal pollution Fertilizer coastal pollution
<b>Invasions (~ connectivity)</b>	Travel time to major city ("Accessibility")	Port cargo volume