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

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Abstract

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

Introduction

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

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

We selected global spatial gridded datasets on variables that characterize dimensions of the different anthropogenic drivers at some time point between 1950 and 2010 (Tables 1 and S1–S2). We focused on variables that had previously been deemed of sufficient global importance to be included in maps of environmental change for each realm[6-9]. Although the specific variables differ among realms, we aligned each variable to one of the dominant drivers that are common across both realms (Table 1). We also included several climate change metrics that were not included in some of the previous global maps[6,7]. For climate change-related variables, we used time-series data to calculate temporal trends. In most other cases, only single time-slice data were available, but trends could also be calculated for land cover variables. For simplicity, habitat conversion and exploitation were grouped together as 'human use'. We ranked and scaled the values of each variable between 0 and 1 to enable comparison. To investigate the relationships among these variables, we calculated Spearman's rank correlation coefficients (ρ) for each pair-wise combination of variables within each realm. We used a modified t-test[15] to account for spatial autocorrelation. To better understand the causes and consequences of these correlations, we examined the magnitude of the different drivers in different terrestrial biomes and marine regions and we used a clustering algorithm to classify regions of the world according to their pattern of exposure to the different drivers. Finally, we determined which regions of the world have been exposed to the highest intensities of multiple drivers.

Results

Consistent with our first hypothesis, we found that drivers of biodiversity change were more spatially coupled in the terrestrial than in the marine realm (Fig. 1). On land, 33% of the possible pair-wise relationships between variables (excluding climate change-related variables) showed positive correlation strengths of at least 0.7. Thus, terrestrial areas with high intensities of one variable also tended to have high intensities of other variables. Moreover, correlations were found between different types of drivers. High cropland cover was associated with high pollution, high accessibility, high human population density and rapid increases in urban land cover. Conversely, in the marine realm, we found fewer correlations – only 15% of the possible pair-wise relationships (excluding climate change-related variables) showed a strong positive correlation (> 0.7) – and they were mostly within, rather than between, different driver types; for instance, among different types of human use (e.g., different fishing types; Fig. 1). Oceanic regions showed fewer correlations compared to coastal regions (Fig. S3). Spatial autocorrelation was present in all variables and tended to reach greater distances in the marine human-uses and climate-change variables (Figs S4 and S5), and shorter distances in the coastal-based marine variables, but the correlations remained statistical significant (all $P<0.05$ for links in Fig. 1) after accounting for autocorrelation.

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

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

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

Discussion

Correlations among drivers have important implications because they indicate that regional biological communities are often jointly impacted by different pressures. Strong correlations are also likely to hinder attempts to disentangle the contributions of different drivers to biodiversity change. Although spatial heterogeneity at smaller spatial scales (e.g., neighboring sites with different land cover) can be used to estimate the local effect of drivers such as habitat conversion[16], correlated large-scale drivers affecting regional species pools may still influence local community dynamics[17]. Spatial relationships between different land use changes in the terrestrial realm were expected based on the land requirements to support proximal human populations[18]. In the marine realm, different human uses (i.e., fisheries) largely occur in different areas (for instance, demersal fisheries mostly occur over the continental shelf, whilst pelagic fisheries can be either continental or oceanic), explaining the weaker correlations. Coastal regions were intermediate in patterns between terrestrial and oceanic regions, suggesting that the prevalence of human presence may contribute to the differences between the two realms[19]. As we found fewer strong correlations among different driver variables in the marine realm, separating the effects of different drivers may be more feasible in marine, especially in open ocean, ecosystems.

As climate change is only weakly associated with other drivers, there is considerable opportunity to disentangle climate change impacts from those of other drivers. The weak association means that climate change affects biological communities exposed to both strong and weak intensities of other drivers. In the case when other drivers are weak, climate change has the potential to be the dominant driver of change. Even though other drivers are also spatially variable, their variability tends to be spatially correlated. Consequently, climate change impacts on species abundances, range limits and community compositions[20,21] may be easier to isolate than those of other drivers. Indeed, high-latitude regions, such as the tundra and boreal forests, with low human-use but pronounced climate change[12,22] have historically undergone less human settlement and agriculture. Warming of ocean temperatures is affected by additional factors compared with air temperatures, especially ocean currents[12,23], which likely contributes to the rapid temperature change in the Indo-Pacific, also an area of intense fishing activity[24]. Hence, locations in which climate change is the main driver of change in a community are likely to be more common in terrestrial communities.

Given the strong spatial correlations among many drivers of biodiversity change, attributing biodiversity change to drivers is likely to be most successful if focused on complexes of environmental change, rather than on each variable individually. Our classification of ATCs helps regard anthropogenic environmental change as a series of at least 11 ‘natural experiments’ across the globe. In particular, the ATCs highlight which environmental changes have the most opportunity to jointly influence communities. When multiple drivers simultaneously act on a community, they could have additive, synergistic or antagonistic effects[25-27]. The differential associations of drivers, summarized by the proposed ATCs, provide an informed baseline for further studies aiming at understanding the effects of multiple drivers on biodiversity and ecosystem services. Because drivers related to human-use, pollution and species invasions have great potential to co-occur, understanding these interactive effects has widespread importance. As climate change is occurring globally[12], interactive effects of climate change and other drivers also have the potential to be widespread. However, we find that there is greater spatial overlap between high intensities of climate change and other drivers in the marine realm. The ATCs could be further used in macroecological studies of driver impacts. For example, examination of the relationships between the ATCs and the distributions of threatened species or local/regional estimates of biodiversity change may help to identify the most harmful combination of drivers. Estimating the specific effects of individual drivers may also be aided by considering our ATCs (or driver clusters identified by a similar approach). Study regions that are most suitable to isolate the effects of a specific driver could be selected from within geographic clusters dominated by the driver of interest, to reduce the confounding effects of other drivers in the landscape. Moreover, our approach could be used to design the spatial sampling of quasi-experimental observatories in future monitoring programs. Observatories could be selected along different driver gradients (keeping all but one driver constant) or within different driver combinations. Long-term data from such observatories could greatly advance our understanding of the underlying causes of biodiversity change.

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

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

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

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

Data on global drivers of biodiversity change are still limited[34]. Further global datasets on driver variables in the ocean, such as plastic pollution, would be especially valuable, and allow deeper examination of the relationships among drivers in the marine realm. Spatially-explicit maps of the number of invasive species would also have improved our analysis. These data are now often available at national or sometimes regional scales[35] but have not been downscaled or modelled explicitly across the world. We followed the approach of Halpern et al.[8,9] and inferred the pressure from invasive species through transport connectivity for both the terrestrial and marine realm; however, our overall findings are not affected by the inclusion of this variable. For estimation of historical temporal trends in land cover between 1950-2010, we used the land use harmonization (LUH2) dataset of annual predictions of land-use states, which is based on diverse empirical data along with interpolation assumptions[36], and hence are not exact data. However, we regarded all datasets as the best current estimates of each driver-related variable. For most drivers, it is currently only possible to examine spatially-explicit trends over recent, short time-scales[7,8]. Ongoing projects, such as the Copernicus project (http://www.copernicus.eu/), will greatly increase the availability of spatiotemporally-explicit, high resolution datasets on different variables[37] in the coming years for further study of the relationships between drivers and for attribution of biodiversity change to the underlying drivers.

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

Methods

Data selection

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

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

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

Data on the spatial distribution of terrestrial biomes were taken from WWF[47] and marine regions were obtained by combining coastal region polygon data – MEOW[48] and ocean polygon data (naturalearthdata.com).

Data organization

For interpretation and presentation purposes, variables were grouped by which global driver of change they were most directly related to, i.e., climate change, habitat conversion, exploitation, pollution or species invasions. Because habitat conversion and exploitation were difficult to class separately across the terrestrial and marine realms, we combined both into a single “human use” category. There are no high-resolution spatial maps of invasive species richness; however, we used maps of human transport connectivity, based on the assumption that they are a proxy of human-mediated propagule pressure (e.g., related to human movement and trade) of alien species, which is known to be an important determinant of invasion success[49,50] and is an approach following others[8,9]. We used spatial datasets of accessibility based on transport infrastructure in the terrestrial realm and cargo volume at ports in the marine realm (Table S1)[9,46]. We also included "human population density"[42] as a separate driver accounting for the effects of human activities not falling into the other categories (e.g., tourism/recreation activities), as well as to determine the relationship of human population density with other drivers.

Data processing

For most datasets, the data were collected from one or a few years (at some point during 1990–2010) and were available as pooled data into a single time point (see Table S1 for more details). For data available as a time series (see those marked by * in Table 1), we calculated temporal trends for each raster grid as the regression coefficient of a year effect in a linear regression for 1950–2010, reflecting change during the recently defined Anthropocene that is estimated to have started in 1950[51]. Aridity trend was estimated by taking monthly and annual datasets on potential evapotranspiration and precipitation, and calculating their ratio[52], and finally the temporal trend of the annual monthly average of this ratio. Velocity of climate change was calculated following ref.[53]. We also calculated two additional climate change metrics: temperature divergence – following ideas by ref.[54], which was inferred from the t-static of the linear regression (i.e., temperature trend in °C divided by its standard error), and also trends of extreme temperatures (whichever was largest of the temporal trends in temperature of the warmest or coolest month). Missing values in some of the human activity datasets were in remote regions (e.g., very high latitudes) with likely absent or low variable values and were imputed as zero. However, datasets were also bounded to an extent of -179, 179, -58, 78 (xmin, xmax, ymin, ymax) to avoid map edge effects. Greenland was also excluded due to missing data in several of the datasets.

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

Data analysis

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

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

To compare the relative importance of different drivers for different regions of each realm, we calculated the difference between each region's average (weighting each grid cell by the coverage of each region) and the average across all regions in each realm. We did not use marine ecosystem data as used by others[9] because the ecosystems spatially overlapped in our coarse 2-D global raster grid, when, in reality, they are at different depths in the water column. We used k-medoid clustering, using the partitioning around the medoids algorithm with Manhattan distances[56], for clustering grid cells according to their extent of exposure of all variables. To make the number of variables per driver more comparable, we first used principal components analysis on drivers with multiple associated variables (climate change, human use and pollution) to produce a reduced number of variables (two axes for climate change and pollution, three axes for human use) that explained most (>75%) of the variation in each. We then applied the cluster analysis to a dataset of these PCA variables with the human population density and species invasion variables. We selected the number of clusters by comparing the changes in dissimilarly and cluster silhouette width with increasing cluster number. However, we limited the cluster number so that it was less than 10 and so that each cluster was linked to a different dominant driver variable. To slightly smooth the maps, we used a moving window to assign each cell the mode of its 3 x 3 cell neighborhood. Although, driver combinations vary in a continuous manner, we chose a clustering method that produces discrete grouping to provide the simplest description of the main groupings in the data. Finally, to identify which regions of the world were exposed to high intensities of multiple drivers, we identified and summed the number of variables for which a grid cell was in the upper 10% of values (based on all values greater than zero) of each variable.

Sensitivity analyses

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

Data availability

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

Code availability

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

https://github.com/bowlerbear/harmonizeRasters

R script for the subsequent analysis is found here:

https://github.com/bowlerbear/geographyDrivers

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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.

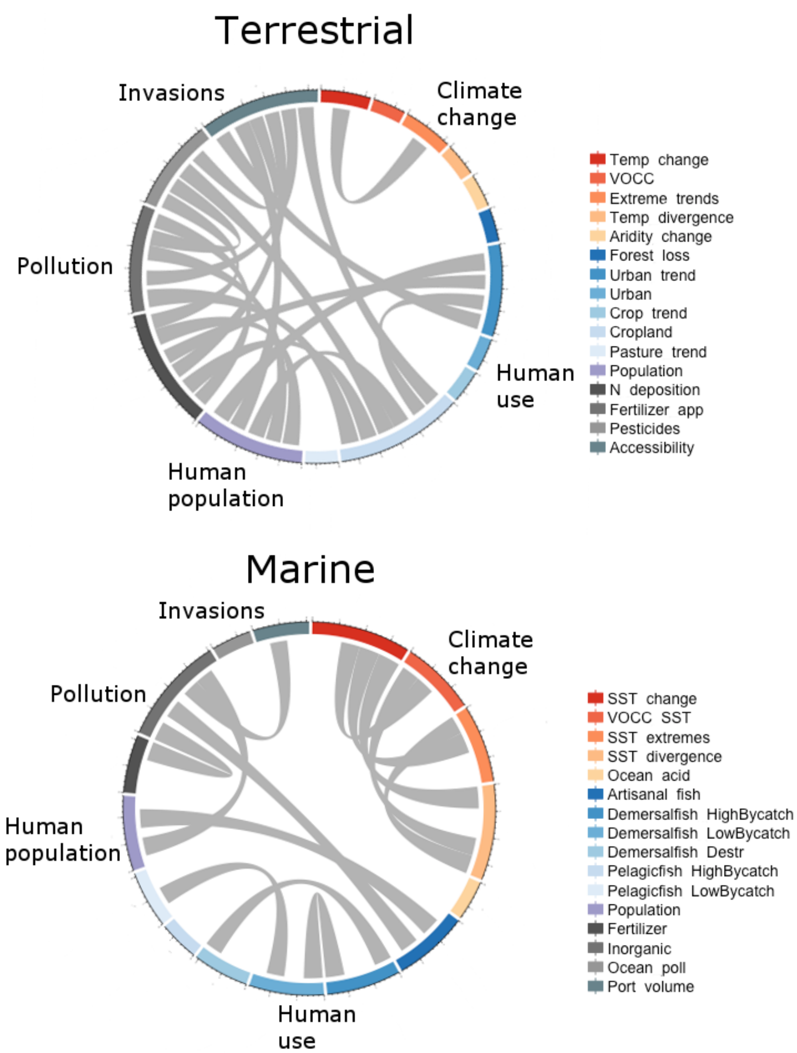

Fig. 1 Strong and positive relationships among anthropogenic drivers of biodiversity change. We find a higher number of correlations between drivers in the terrestrial versus the marine realm. Each link represents a significant and strong positive correlation (with strength >0.7) between two variables across 100 square km grids covering the world (see also Figs S1 and S2). No negative correlations were stronger than -0.7.

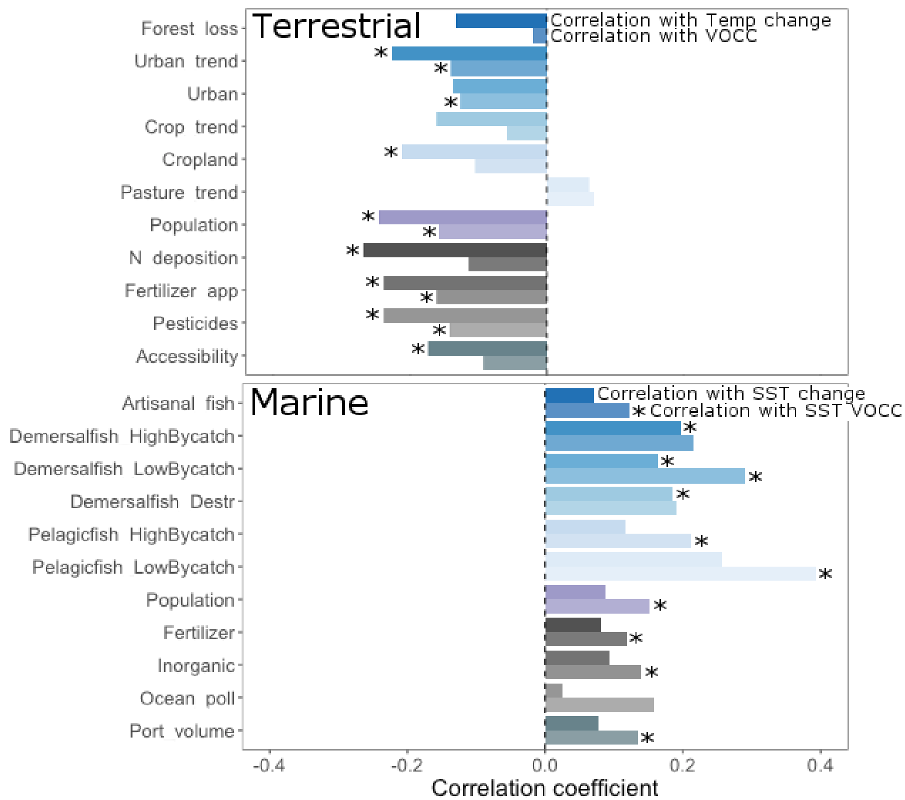

Fig. 2 Relationships between climate change and other drivers. Comparing the relationships between each variable and temperature change (air or sea surface temperature – SST) or the velocity of climate change (VOCC), we find weak negative (>-0.3) correlations in the terrestrial realm and weak positive (<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.

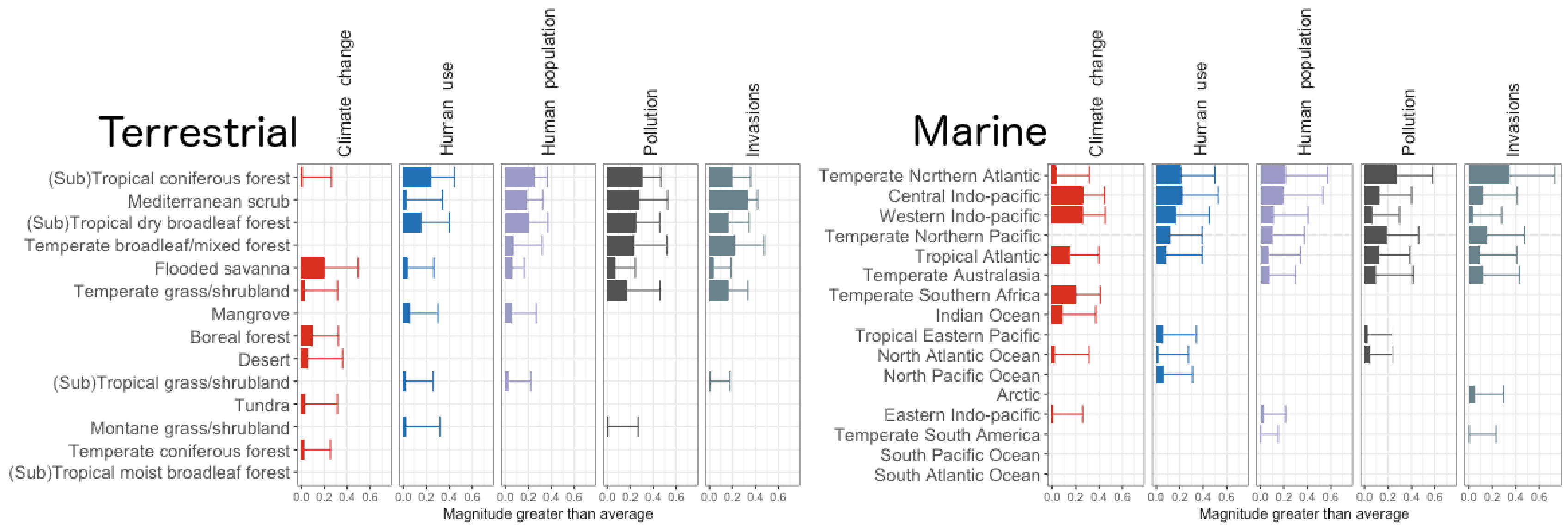

Fig. 3 Regions of the terrestrial and marine realms are exposed to distinct combinations of drivers. The bars show the dominant drivers in each terrestrial and marine region. The length of the bar represents the positive deviation (plus standard deviation) of that region's average + standard deviation (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.

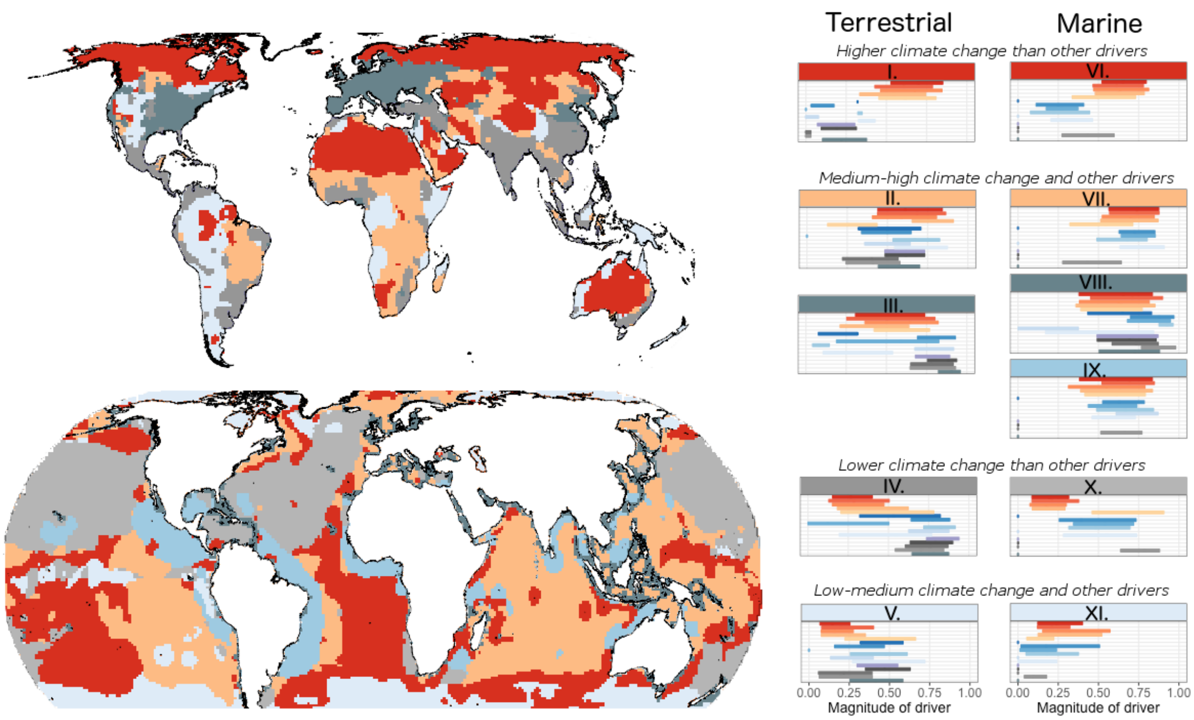

Fig. 4 Geography of the Anthropocene. Different geographic regions of the world are exposed to different Anthropogenic Threat Complexes (numbered I to XI). These regions were obtained by k-medoid clustering based on their similarity of exposure to different drivers of biodiversity change and are colored 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.

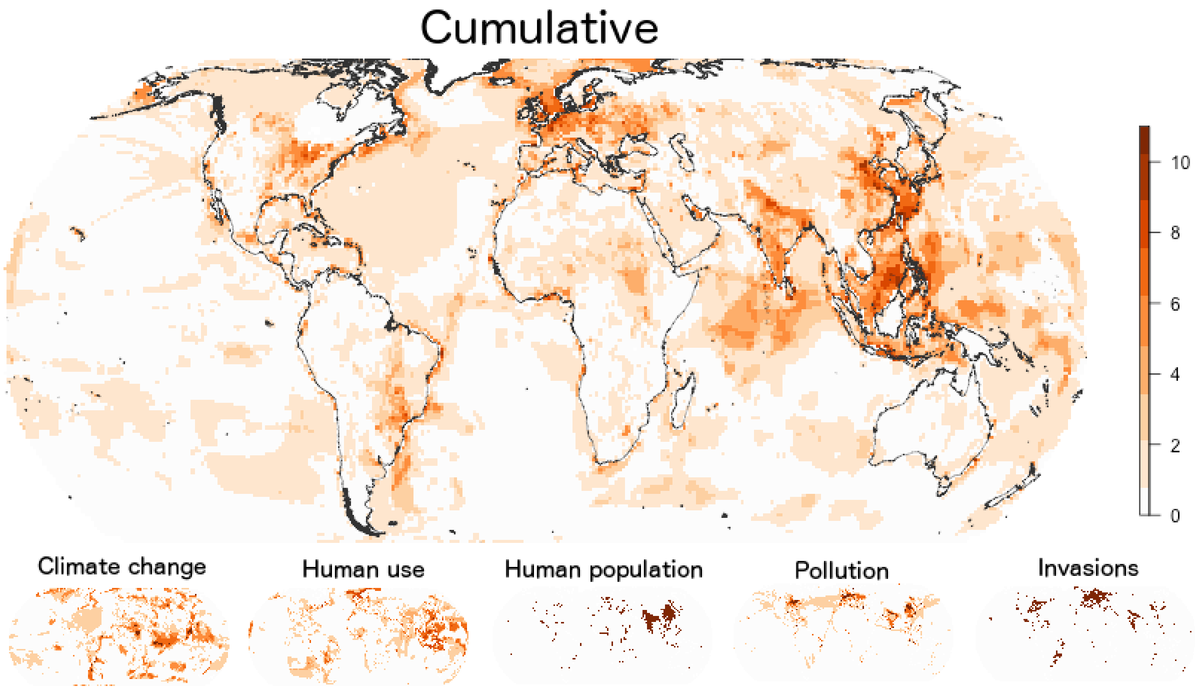

Fig. 5 Regions of the world exposed to high intensities of multiple drivers. The number of the 16 driver variables that each grid cell was in the highest 10% of values within its realm. Regions in the darkest orange are exposed to high intensities of multiple variables, while those in off-white are exposed 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	Associated variables: Marine
Climate Change	Temperature change*	Temperature change*
	Temperature divergence*	Temperature divergence*
	Change in climate extremes*	Change in climate extremes*
	Velocity of climate change*	Velocity of climate change*
	Aridity change*	Ocean acidification
Human use (land use or change, resource extraction, exploitation)	Crop cover	Destructive demersal fishing
	Crop cover trend*	Low by-catch demersal fishing
	Pasture cover trend*	High by-catch demersal fishing
	Forest loss trend*	Low by-catch pelagic fishing
	Urban cover	High by-catch pelagic fishing
	Urban cover trend*	Artisanal fishing
Human population density	Population density	Coastal population density
Pollution	Atmospheric nitrogen deposition	Ocean pollution
	Nitrogen fertilizer application	Inorganic coastal pollution
	Pesticide application	Fertilizer coastal pollution
Invasions (~ connectivity)	Travel time to major city (“Accessibility”)	Port cargo volume