nature ecology & evolution

ARTICLES
https://doi.org/10.1038/s41559-021-01528-7

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Areas of global importance for conserving terrestrial biodiversity, carbon and water

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To meet the ambitious objectives of biodiversity and climate conventions, the international community requires clarity on how these objectives can be operationalized spatially and how multiple targets can be pursued concurrently. To support goal setting and the implementation of international strategies and action plans, spatial guidance is needed to identify which land areas have the potential to generate the greatest synergies between conserving biodiversity and nature's contributions to people. Here we present results from a joint optimization that minimizes the number of threatened species, maximizes carbon retention and water quality regulation, and ranks terrestrial conservation priorities globally. We found that selecting the top-ranked 30% and 50% of terrestrial land area would conserve respectively 60.7% and 85.3% of the estimated total carbon stock and 66% and 89.8% of all clean water, in addition to meeting conservation targets for 57.9% and 79% of all species considered. Our data and prioritization further suggest that adequately conserving all species considered (vertebrates and plants) would require giving conservation attention to ~70% of the terrestrial land surface. If priority was given to biodiversity only, managing 30% of optimally located land area for conservation may be sufficient to meet conservation targets for 81.3% of the terrestrial plant and vertebrate species considered. Our results provide a global assessment of where land could be optimally managed for conservation. We discuss how such a spatial prioritization framework can support the implementation of the biodiversity and climate conventions.

Biodiversity and nature's contributions to people (NCP) are in peril, requiring increasing conservation efforts to avert further decline[1,2]. Existing global biodiversity conservation targets were not met by 2020 (ref. [3]), and the world is falling short of mobilizing the full climate mitigation potential of nature-based solutions, which could provide around a third of the mitigation target specified under the Paris Agreement[4]. A new Global Biodiversity Framework is scheduled to be adopted in 2022 by the Convention on Biological Diversity (CBD) in Kunming, China[5], and there are growing calls to integrate nature-based solutions into climate mitigation strategies[6].

Targets for site-based conservation actions (hereafter 'area-based conservation targets') are given particular emphasis in the draft Global Biodiversity Framework[5]. Target 3 calls for the protection and conservation of at least "30 percent globally of land areas [...], especially areas of particular importance for biodiversity and its contribution to people, are conserved". This target somewhat integrates calls made by conservation advocates to conserve 30% of land and the oceans[7] with proposals that emphasize targeting conservation outcomes rather than conservation area. This is to ensure that, by 2030, areas of global conservation importance for biodiversity are maintained or restored[8].

The Sustainable Development Goals and decisions under the United Nations Framework Convention on Climate Change and CBD emphasize that habitat conservation and restoration should contribute simultaneously to biodiversity conservation and climate change mitigation[5]. In particular, the draft Target 8 of the Global Biodiversity Framework post-2020 calls for "contribute to [climate change] mitigation and adaptation through ecosystem-based approaches [...] and avoid all negative impacts on biodiversity." Recent global-scale spatial analyses of conservation priorities for biodiversity and carbon have overlaid areas of value for both features, effectively treating the two goals as being pursued separately (for example, see refs. [7,9]). However, multicriteria spatial optimization

A full list of affiliations appears at the end of the paper.

approaches applied to conservation and restoration prioritization have shown that carbon sequestration could be doubled, and the number of prevented extinctions tripled, if priority areas were jointly identified[10,11]. As yet, there are no comparable optimization analyses that identify areas of global terrestrial conservation importance for biodiversity and NCP.

A number of recent studies have attempted to map spatial conservation priorities on land[12], relying on spatial conservation prioritization (SCP) methods[13–16]. However, these approaches are limited in that they (1) have restricted geographic extent[17] or focus on only a subset of global biodiversity, notably lacking reptiles, invertebrates and plant species, which show considerable variation in areas of conservation importance compared with other taxa[18,19]; (2) focus on species representation, which is not directly correlated with reducing extinction risk, as per international biodiversity targets, and often ignore other dimensions of biodiversity (for example, evolutionary distinctiveness)[20,21]; (3) do not investigate the extent to which synergies between biodiversity and NCP, such as carbon sequestration or clean water regulation[22], can be maximized[17]; and (4) use a priori defined measures of importance (such as intactness[23,24]) or arbitrary area-based conservation targets (such as 30% or 50% of the Earth[7,25]) instead of objectively delineating the potential value for biodiversity and NCP across the whole world irrespective of such constraints.

The aim of this study is to identify areas of global conservation importance for biodiversity (here focusing on species conservation) jointly with two NCP: carbon storage and water quality regulation. Ensuring that the highest-ranked areas retain their present conservation value in the next decade would greatly contribute to achieving global species conservation targets, harnessing the climate change mitigation potential of natural ecosystems and maintaining their water quality regulation potential.

We define 'conservation management' as any set of site-based actions appropriate for the local context (considering pressures, tenure, land use and so on) that is commensurate with retaining the potential value of these areas for the features of conservation interest (for example, species, habitat types, soil or biomass carbon and clean water). For instance, conservation management may equate to monitoring and surveillance (when the present conditions and ongoing and projected pressures do not require active management), establishing legal protection, establishing other area-based conservation measures such as community-managed forests[26] or implementing incentives such as payment for ecosystem services. We make no assumptions about the type of local management required, its feasibility and costs, or the counterfactual outcome with an alternative form of management; therefore, our prioritization is based on the upper limit of the value of these areas for achieving global conservation targets.

We obtained fine-scale range maps for the world's terrestrial vertebrates as well as the largest sample of vascular plant range data ever considered in global species-level analysis, comprising ~41% of all accepted plant species names. To capture intraspecific variation, we considered each part of a species range occurring in geographically separate biomes as a separate feature with its own target, thus splitting each species into as many biodiversity features as the biomes in which the species occurs. We set species targets to conserving the minimum amount of species' habitat necessary to qualify it for the conservation status 'Least Concern' following IUCN Red List criteria[15,27]. For NCP, we used the latest global spatial data on above- and below-ground biomass carbon and vulnerable soil carbon, as well as the volume of potential clean water by river basin. We aimed to maximize the amount of NCPs conserved and biodiversity targets achieved within a given 'area budget', for example, 30% of land managed for conservation. We applied a multicriteria spatial optimization framework to investigate synergies between these features and explore how priority ranks change depending on how much weight is given to biodiversity, carbon sequestration or water quality regulation. We investigated the impact of accounting for vascular plants on the geography of global conservation priorities. We also tested the implications of setting biome-specific species targets, as opposed to the more common approach of setting global species targets. Finally, we examined whether the highest ranks vary if species evolutionary distinctiveness and threat status were considered.

Results

We found large potential synergies between managing land for biodiversity conservation, storing soil and biomass carbon, and maintaining clean water quality regulation. Managing the top-ranked 10% of land—that is, those areas with the highest priority—to achieve these objectives simultaneously (Fig. 1 and Extended Data Fig. 1) has the potential to achieve conservation targets for 42.5% of all species considered, including about 33.7% of all known plant species, as well as conserving 26% of the total carbon and 22.1% of the potential clean water globally. Areas with the greatest global biodiversity importance notably include the mountain ranges of the world, large parts of Mediterranean biomes and Southeast Asia (Extended Data Fig. 2a). Overall, these areas were comparable to previous expert-based delineations of conservation hotspots[28], while also highlighting additional areas of conservation importance for biodiversity, such as western central Africa, Papua New Guinea, the western Tibetan Plateau and the East Australian rainforest (Extended Data Fig. 2a). Eastern Canada, the Congo Basin and Papua New Guinea were among the top-ranked 10% areas for global carbon storage (Extended Data Figs. 2b and 3a), while the eastern United States, the Congo, European Russia and eastern India were among the areas with the greatest conservation importance for water quality regulation (Extended Data Figs. 2c and 3b). Overall, when jointly optimizing for biodiversity, carbon and water, the top-ranked areas were distributed across all continents, latitudes and biomes (see Supplementary Information for the averaged priority ranks per country).

Synergies and trade-offs depend on the relative preference given to conservation of terrestrial biodiversity, carbon storage and water quality regulation (Fig. 2a). We explored an array of conservation variants with a range of possible outcomes. At one extreme, priority is equally given to conserving biodiversity and carbon (Fig. 2b). At the other extreme are variants that prioritize conserving only biodiversity and water (Fig. 2c). Intermediate options include giving equal weighting to all three features; this weighting scheme yielded the best outcome in terms of numbers of species targets achieved (Fig. 2a) and in terms of average target shortfall across species and NCPs (Extended Data Fig. 4) and was therefore chosen to visualize spatial priorities (Fig. 1). Similar to earlier assessments[9,29,30], we found synergies between the conservation of biodiversity and carbon storage (Fig. 2b and Extended Data Fig. 4). Additionally, we discovered similar synergies for biodiversity and water quality regulation (Fig. 2c and Extended Data Fig. 4). Trade-offs between biodiversity versus carbon and water were dependent on conservation preferences (relative weights in the optimization analyses) and were particularly high when less than 50% preference was given to either NCP relative to species conservation (Fig. 2 and Extended Data Fig. 4).

Conserving the top-ranked 10% of land areas for biodiversity and carbon only (equally weighted) can protect up to 22.8% of the global total carbon (biomass carbon and vulnerable soil carbon) and 27% of all species, while maintaining 16% of all global water quality regulation as a co-benefit (Fig. 2b). In contrast, conserving the top-ranked 10% of land for biodiversity and water only (equally weighted) can protect 20% of water and 24.7% of all species (Fig. 2a), while maintaining 15% of carbon as a co-benefit (Fig. 2c). The implications of assigning different relative preferences to conserving NCP magnify with increasing amounts of land area

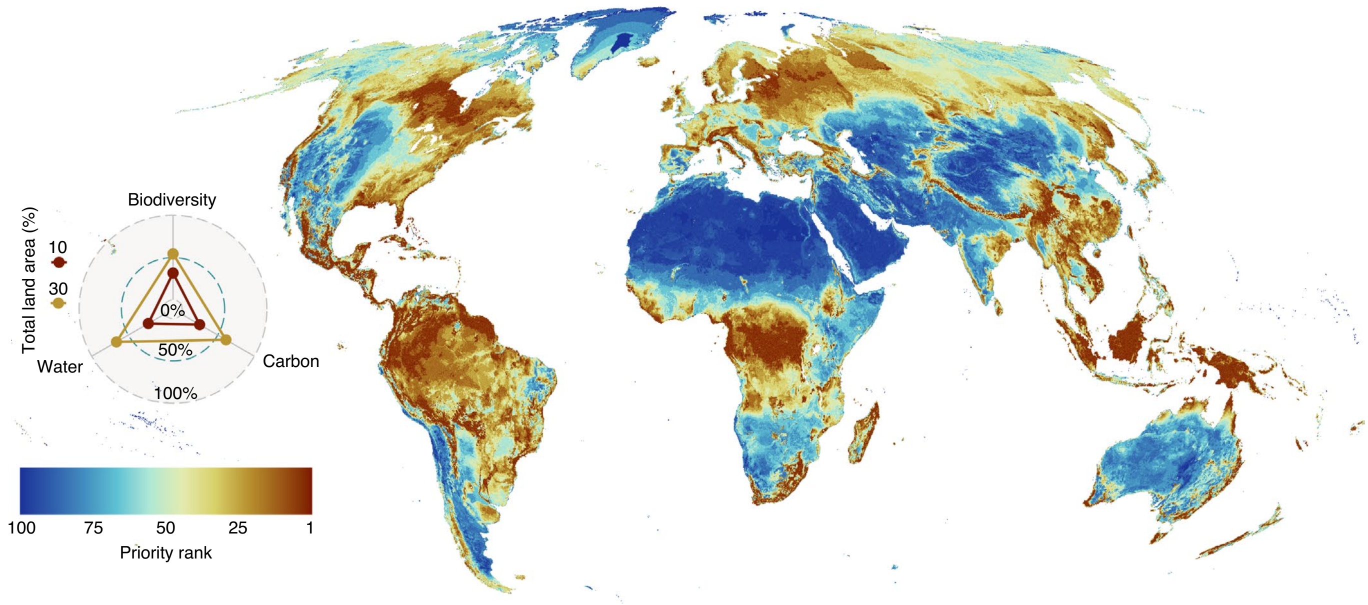

Fig. 1 | Global areas of conservation importance for terrestrial biodiversity, carbon and water. All features were jointly optimized with equal weighting given to each feature (the central point in the series of segments in Fig. 2) and ranked by the most (1–10) to least (90–100) valuable areas to conserve globally. The triangle plot shows the extent to which protecting the top-ranked 10% and 30% of global land areas (the dark brown and yellow areas on the map) contributes to minimize the number of threatened species, storing carbon and ensuring clean water. The percentages in the triangle plot refer to the proportion of all species targets reached (Fig. 3) or the average shortfall of carbon and water. The map is at 10 km resolution in a Mollweide projection. A map highlighting the uncertainty in priority ranks is shown in Extended Data Fig. 1.

managed for conservation. The range of carbon conserved is 15% to 25% when conserving 10% of land and 47.1% to 61.4% when conserving 30%. The range of clean water conserved is 16% to 21.5% when conserving 10% of land and 50% to 65.4% when conserving 30% (Fig. 2a). Our results suggest that there is ample scope for achieving co-benefits from conserving these three features, if explicit targets for each are considered, areas of conservation value for each feature are identified through multicriteria spatial optimization and the range of relative preference given to each feature is comprehensively explored.

The amount of land necessary to exclusively protect global biodiversity continues to be debated[15,31,32]. When splitting conservation targets across each biome, in the absence of any socio-economic constraints or costs and ignoring NCP such as water and carbon, bringing all vertebrate and plant species considered to a non-threatened conservation status would require at least ~70% of global land area to be managed for conservation (Fig. 3a). This is robust to the number of species included in the analyses, provided that they are a representative subset (Methods).

Optimally placing areas managed for conservation on 30% of the world's land area is already sufficient to conserve 81.3% of all species considered in this analysis (disregarding the additional contribution of existing protected areas and ignoring socio-economic constraints and costs and other NCP). Across the remaining species, the average target shortfall (Methods) was 4.4%. Currently protected areas are potentially sufficient to achieve conservation targets for 11.6% of the species analysed (Fig. 3b and Extended Data Fig. 6). However, multicriteria spatial planning aided with explicit targets and optimization algorithms could build on the highly inefficient set of existing protected areas to reach a global 30% coverage and achieve conservation targets for an additional 71.6% while leaving the average shortfall for the remaining species at 7.2% (Fig. 3b). There is thus an efficiency gap of ~10% between redesigning global conservation efforts and optimally building on existing efforts. While we do not recommend de-designations owing to other factors behind protected area establishment not considered in this analysis, the critical state of the world biodiversity suggests that ad hoc conservation efforts are no longer an option, and target-based conservation planning, using methods like ours, should be applied at all levels if we are to reverse global biodiversity trends.

When jointly optimizing for biodiversity, carbon and water (Fig. 3a), we found that selecting the top-ranked 30% and 50% of terrestrial land areas (which are popular proposals for area-based conservation targets[7]) would conserve 60.7% and 85.3% of the estimated total carbon stock and 66% and 89.8% of water quality regulation, in addition to achieving conservation targets for 57.9% and 79% of all species considered, with a remaining average shortfall of 14.1% and 6.9% (Fig. 3b).

When optimizing conservation efforts for biodiversity only, we found that the groups that benefited the most (that is, had the most rapid target accumulation curves) were amphibian and plant species (Fig. 3c,d) and threatened species (Fig. 3e,f). For plant species, this is consistent with previous work on the spatial aggregation of centres of plant diversity and endemicity[33]. Threatened species tend to have smaller range sizes and smaller absolute area targets than other groups and are inherently prioritized with budgets ≤30% of land area.

When assigning global-level rather than biome-level targets for each species, we found that current protected areas conserve 16.2% of all species. However, an optimally placed 30% of land area achieved a similar level of biodiversity performance to the biome-level analysis: conserving 76.6% of all species with an average target shortfall across the remainder of species of 5.3% (Extended Data Fig. 5). The differences in accumulation curves among taxonomic groups were generally larger if species ranges were not split by biome, especially so for threatened species, indicating that fragmented parts of their range probably occur across multiple biomes (Extended Data Fig. 5).

Our analysis included a representative subset of plant range data totalling ~41% of described vascular plant species[33] (Fig. 4). Incorporating data on plants resulted in spatial shifts in areas of importance for conservation compared with analyses where plants

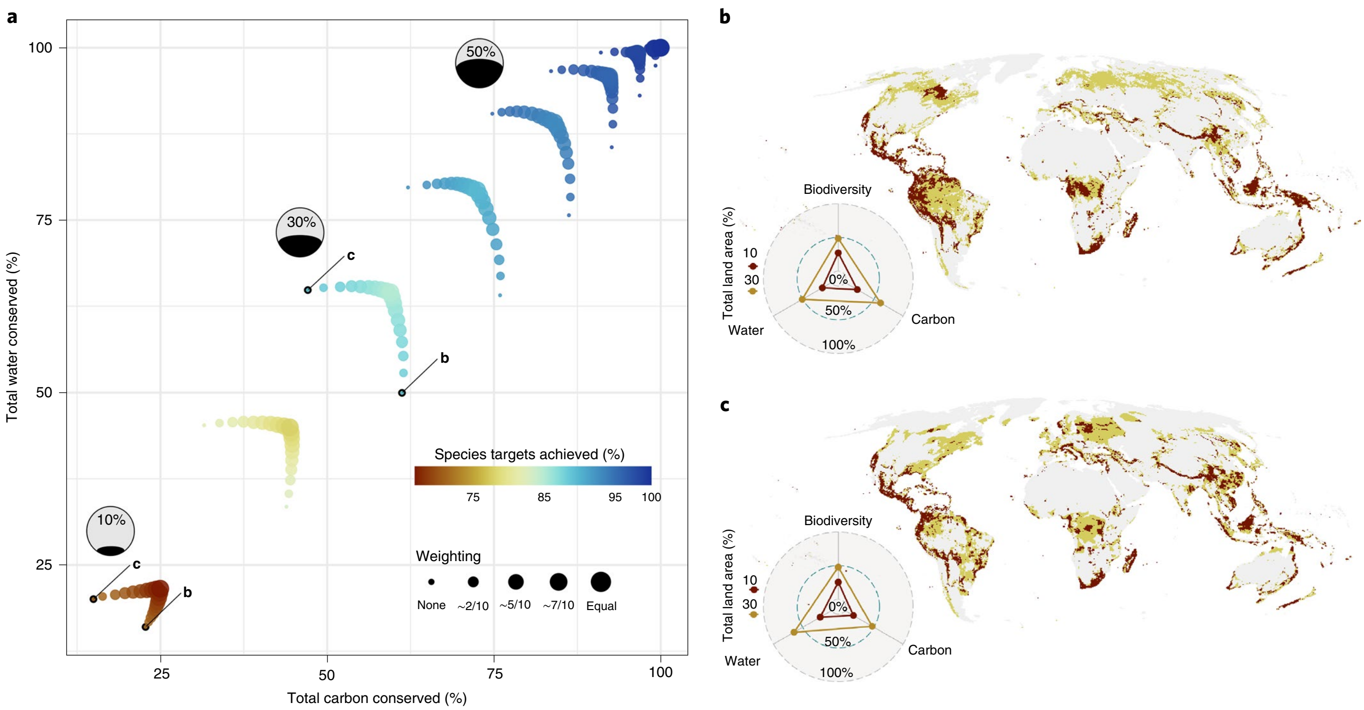

Fig. 2 | Implications of different relative weights given to carbon or water over achieving species conservation targets. a–c, Each boomerang-shaped segment of dots represents a series of conservation prioritization variants with a common area budget (from 10% of land areas at bottom left to 100% at top right; visually indicated are 10%, 30% and 50% solutions in the form of partially filled circles, extreme weightings for carbon (**b**) and water (**c**) are highlighted). The axes indicate the proportion of all carbon and water quality regulation features conserved, the colours represent the proportion of species with sufficient habitat conserved to be considered non-threatened according to IUCN Red List criteria (but see Methods) and the point size indicates the difference in weighting given to carbon or water relative to biodiversity, ranking from none to equal weighting (Methods). A detailed view on curves of relative shortfall for 10%, 30% and 50% is provided in Extended Data Fig. 4. **b**,**c**, Global areas of conservation importance if 10% (dark brown) or 30% (yellow) of land area is managed for conservation while preferring carbon protection over water (**b**) or water protection over carbon (**c**).

are ignored, particularly in the western United States, west-central and South Africa, southwest Australia, central Brazil, northern Europe and the central Asian steppes and mountains (Fig. 4a). Overall, we found that montane and temperate forest and shrubland biomes gained relative importance when considering plants, whereas tropical biomes, flooded grasslands and mangroves lost relative importance (Fig. 4b). The inclusion of plants, however, reduced the number of conservation targets achieved across vertebrate species (−11.2% at a 10% area budget; the average across all budgets was −4.75%; Fig. 4c).

Areas of conservation importance can vary spatially if species are given different weights—for instance, prioritizing the protection of threatened or more evolutionarily distinct species[20,21]. We tested the sensitivity of conservation priorities to different weighting schemes for vertebrate species by weighting species targets shortfall by current International Union for Conservation of Nature (IUCN) Red List threat category or evolutionary distinctiveness. We found that doing so has only small inefficiency implications compared with prioritization without these weights: 0.7% fewer species conservation targets are achieved when prioritizing threatened vertebrate species and 1.7% fewer when prioritizing evolutionarily distinct vertebrate species under a 10% of land area budget. Yet, the overall spatial patterns of the top-ranked 10% of land areas of conservation importance were comparable, with only minor differences, notably highlighting the importance of New Zealand and the Brazilian Amazon for conserving threatened vertebrate species, and the Mediterranean Basin, the northwestern United States, Florida and fringes of the Amazon Basin for conserving evolutionarily distinct vertebrate species (Extended Data Fig. 7). These results highlight that threatened or more evolutionary distinct vertebrate species are well covered by prioritization across all species[34], and their full conservation can be achieved at minimal extra cost.

Discussion

How much area should be managed for conservation, and where, is one of the key questions underpinning global biodiversity convention decisions and conservation planning discussions[5,32]. Our analyses suggest that even ambitious objectives such as 'Half Earth'[25] or '30 by 30'[7] are insufficient, to ensure that no species is threatened with extinction (Fig. 3). However, managing the top-ranked 30% of land areas in terms of their value for biodiversity conservation, as identified here, can maintain or bring over 81.3% of the world's terrestrial species (most vertebrates and a representative sample of plant species) to a non-threatened conservation status, with further increases in area offering minor additional returns (Fig. 3). An extra 20% of the total land area, in addition to the 30% of land area selected for biodiversity, could be dedicated to carbon storage as a contribution to climate regulation[7] and sustainable management of natural resources. This would improve the status of 79% of all species considered to be non-threatened, which is comparable to the high-end ambition of goal A of the CBD Global Biodiversity Framework, to reduce the number of species threatened with extinction by 50% by 2030 and bring that number close to zero by 2050 (ref. [1]). This also underscores the value of accompanying strict protection with spatial planning of land and sea uses to achieve conservation objectives, as stated in Target 2 of the CBD Global Biodiversity Framework. However, our analysis shows that considerable co-benefits can already be achieved by managing an optimally placed 30% of land area, if the conservation of biodiversity, carbon and water are jointly planned for with spatial optimization approaches (Fig. 2).

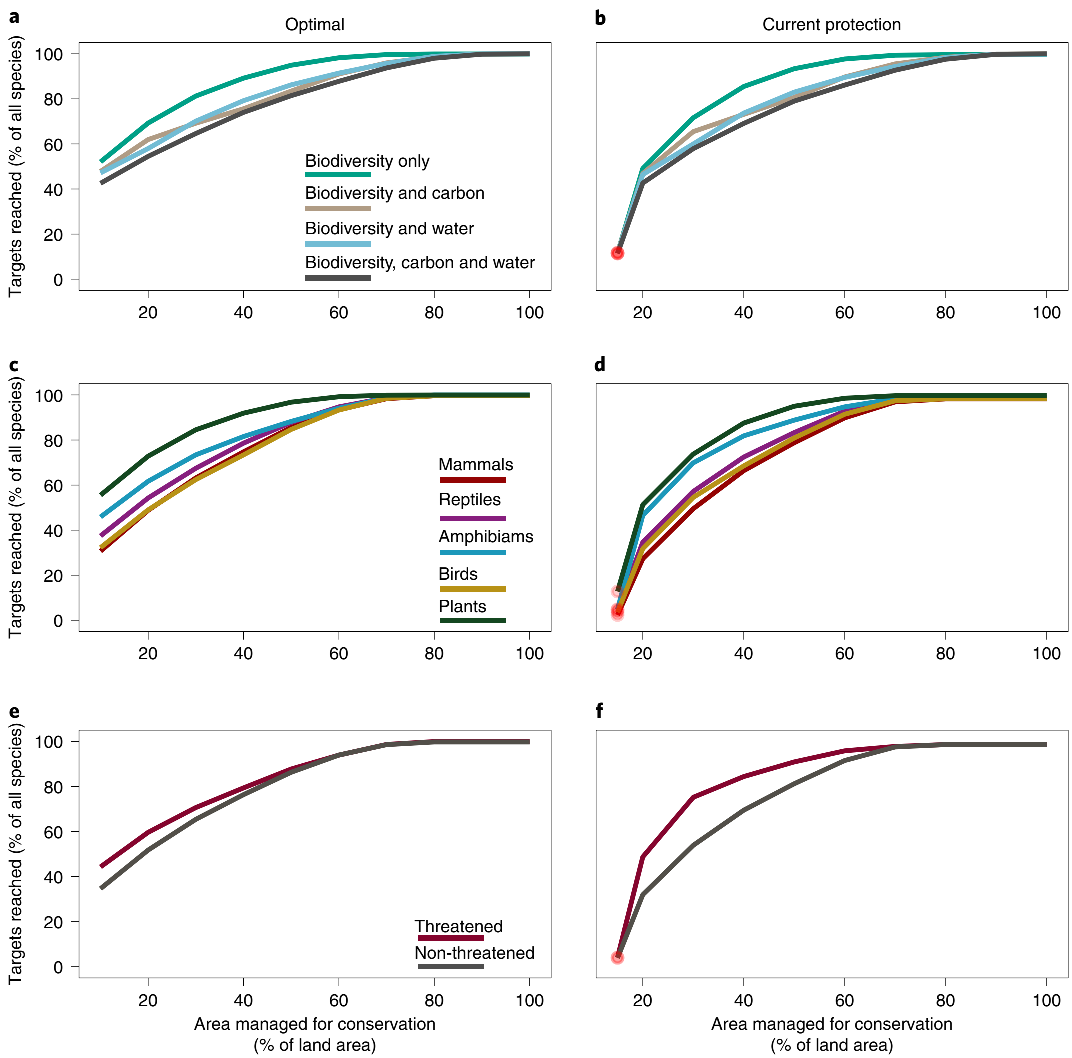

Fig. 3 | Accumulation curves showing how the number of species targets met increases with the amount of land area optimally allocated with and without current protection. a–f, Proportion of species targets reached for an optimal prioritization (**a**,**c**,**e**) and building on current terrestrial protected areas (15% of land area, indicated by a red dot) (**b**,**d**,**f**). Target accumulation curves are shown for analysis variants including other features such as NCP (**a**,**b**); for different taxonomic groups when optimizing biodiversity only to conservation (**c**,**d**); and for species classified as threatened or not (Methods) when optimizing for biodiversity only (**e**,**f**). Accumulation curves of features without biome splits are shown in Extended Data Fig. 5.

Similar to other studies, our analyses are sensitive to the data and methods applied[7,14,16,17]. But, given the expanded taxonomic coverage to plants and reptiles and the explicit accounting of taxonomic uncertainties (Extended Data Fig. 1), we believe our work provides a more robust systematic exploration of uncertainties of global priority areas for conservation than has been achieved so far.

Our work focused on finding priority areas of global conservation importance, thus complementing recent efforts to prioritize transformed areas for habitat restoration, which also found similar co-benefits of restoring habitats for species conservation and carbon sequestration[11]. The ranked priority map is intended to provide broad spatial guidance to decision makers and opportunities for establishing international conservation programmes and funding for biodiversity, carbon and water regulation, but this map is not intended to replace detailed national or sub-national planning. Harnessing these co-benefits will require integrated land-use plans at national to sub-national levels that include both conservation and restoration management actions alongside productive and extractive activities, to maximize environmental and socio-economic benefits. The specific forms of management required will be highly contextual and will depend on local anthropogenic pressures, land tenure, governance, and costs and opportunities for all relevant local stakeholders. Areas of conservation importance that require strict protection and active management (for example, where narrow-ranging and threatened species occur) might be suitable for protected area expansion[35]. Other effective area-based conservation measures[26], such as watershed management initiatives or community-managed forests, might be more suitable in areas where the upper limits of biodiversity, carbon and water value benefits are high but threats to species conservation remain low.

Our analyses impose no constraints on feasibility or equity among countries[36], resulting in over half the territory of some countries falling in the top-ranked 10% land areas of global conservation importance for biodiversity, carbon and water quality regulation, which reflects known patterns of unevenness among countries in species richness, endemicity and NCP provision (Fig. 1). We stress that, when considering implementations of conservation management, beneficial outcomes that maximize both human livelihood benefits and achieving biodiversity targets are necessary if conservation is to be successful. Furthermore, there is a need for fair

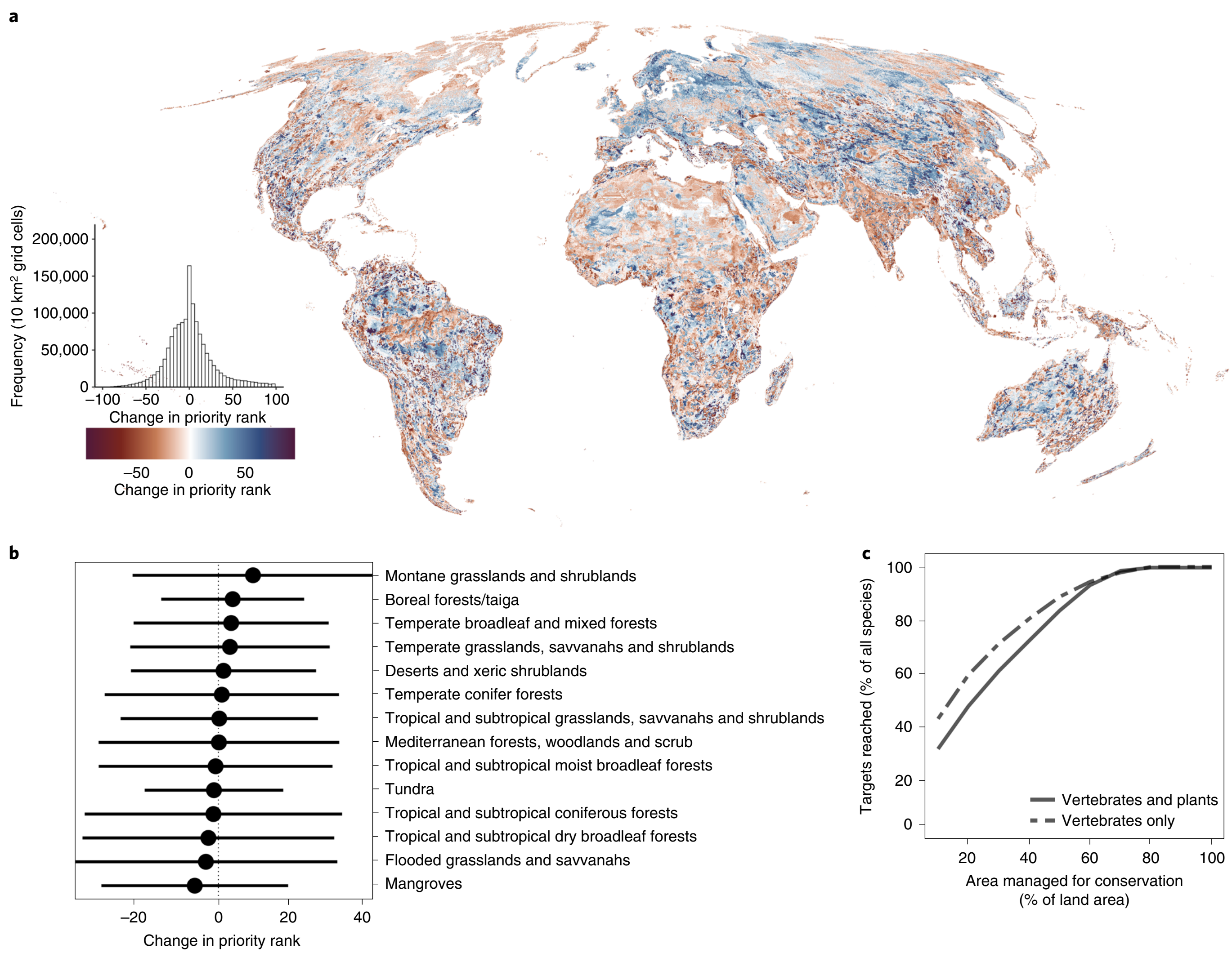

Fig. 4 | Change in global areas of biodiversity-only importance after adding plant species. a, Calculated as the difference in areas of biodiversity importance with plant species either included or excluded. Positive changes (light to dark blue) in rank imply an increase in priority if plant species are considered, while negative changes (light to dark red) show a decrease in priority ranks. The map is at 10 km resolution in a Mollweide projection. **b**, Average change in ranks per biome after plants have been added. **c**, Vertebrate species representation curves of areas necessary to be managed for conservation with (solid) and without (dashed) plants included.

resourcing of such management actions to offset the financial burden on some, predominantly tropical, countries[36,37], while strengthening national institutions and governance. Existing funding mechanisms should further explore opportunities to synergistically benefit both biodiversity and NCP, as has been shown for carbon[29]. Future synergistic prioritization efforts should particularly focus on considering both conservation and restoration[38] and should consider integrated scenarios of the projected future distributions of biodiversity, carbon and water, to support countries in identifying and planning conservation actions at finer scales to maximize the achievement of national and global targets and identify resilient green development pathways.

Our work also reveals research and data gaps in determining the potential value of conserving global terrestrial biodiversity and NCP. We chose carbon and water, but there are others we did not consider[22] such as food provisioning or non-material contributions, including those for Indigenous communities. Similarly, many aspects of species diversity remain under-represented—although we consider a substantial portion of plant species on Earth, and we developed a framework to account for spatial bias in conservation planning resulting from incomplete taxonomic coverage, we acknowledge the need to expand available data on other groups such as freshwater, soil and invertebrate species[39,40]. We also investigated the influence of evolutionary history and threat status on vertebrate but not plant species, for whom hotspots of evolutionary history might differ; addressing this gap requires comprehensive extinction risk assessments and phylogenies of plants at the species level. We also ignored other aspects such as species functional role and rarity[41]. Despite overall similarity between areas of conservation importance for vertebrate and plant species[18,19,42], many hotspots of plant endemism, particularly in temperate biomes (Fig. 4b), can be overlooked if focusing on vertebrate species alone, highlighting the need to account for plant species in spatial analyses of conservation and restoration priorities (Fig. 4c).

Our analyses highlight global land areas whose conservation can maximize synergies across conventions (for example, CBD and the United Nations Framework Convention on Climate Change) and some Sustainable Development Goals, particularly goals 3, 13 and 15. As identified by our global joint optimization, proposed conservation targets (such as 30 by 30 or Half Earth) could be able to conserve most species and NCP globally, if the broad areas with the highest importance from our analysis are managed for conservation.

Particularly, our integrated maps could support international initiatives such as the 2021–2030 Strategic Plan of the CBD and the European Union Biodiversity strategy and could help government and non-government actors in translating these strategies into societal negotiations, actions and policies. Meeting the Sustainable Development Goals requires real, transformative commitments that are yet to be enacted[1]; however, by maximizing synergies in efforts and resources, a pathway towards effective biodiversity conservation can be laid out for the next decade.

Methods

Biodiversity data. We used the best available global species range data (an overview is provided in Supplementary Table 1), including all extant terrestrial vertebrates and a representative proportion (~41%) of all accepted species in the World Checklist of Vascular Plants[43]. Extant mammal (5,685 species) and amphibian (6,660) species range data were obtained from the IUCN Red List database (v.2019-2; ref. [44]), while bird (10,953) range maps were obtained from Birdlife International[45]. Data on the reptile ranges were obtained from the IUCN database when available (6,830 species) and otherwise from the Global Assessment of Reptile Distributions (GARD) database (3,755; ref. [46]). We obtained native plant range maps (193,954 species) from a variety of sources, including the IUCN, Botanic Gardens Conservation International (BGCI) and the Botanical Information and Ecology Network (BIEN). The IUCN and BGCI data contain expert-based range maps and alpha-hulls (Supplementary Information), while the BIEN data consist mainly of herbarium collections, ecological plots and surveys[33,47–54], which we used to construct conservative estimates of species ranges using species distribution models. We used version 4.1 of BIEN, which includes data from RAINBIO[55], TEAM[56], the Royal Botanic Garden and Domain Trust Sydney, Australia, and NeoTropTree[57]. Additional plant plot data from a number of networks and datasets have been included in BIEN, and a full listing of the herbaria data used can be found in the extended acknowledgements and online (http://bien.nceas.ucsb.edu/bien/data-contributors/all/). In cases where multiple data sources were available for the same plant species, we preferentially used expert-based range maps to characterize a species' spatial distribution. A full description of the preparation and processing of the plant data can be found in the Supplementary Information.

All vertebrate range maps were pre-processed following common practice[58] by selecting only those parts of a species' range where (1) it is extant or possibly extinct, (2) it is native or reintroduced and (3) the species is seasonally resident, breeding, non-breeding, or migratory or the seasonal occurrence is uncertain. We acknowledge that these ranges can contain some areas where the species is possibly extinct.

Suitable habitat refinement. Where data on species habitat and elevational preferences were available, we refined each species' range to obtain the area of habitat (AOH) in which the species could persist[59,60]. Data on species habitat preferences and suitable elevational range were obtained from the IUCN Red List database[44], and, for an additional 1,452 reptile species in the GARD database, habitat preferences were compiled from an extensive literature search. For seasonally migrating birds and mammal species, we ensured that separate habitat refinements were conducted for permanent and seasonally occupied areas of their range (that is, the breeding and non-breeding range). Whenever habitat or elevation preferences were not available for a given species, we used the full range, excluding only areas considered to be artificial habitat type classes, such as arable or pasture land, plantations and built-up areas. We note that this could exclude areas suitable for some generalist species. We acknowledge that taxonomic biases can exist in the information on habitat preferences for some species, which can be a limitation to our approach. For the AOH refinement, we used a newly developed global map[61] (Supplementary Information) that follows the IUCN habitat classification system, thereby avoiding crosswalks between habitat preferences and land cover maps[62]. This data product integrates the best available land cover and climate data, while also using newly developed land-use data such as data on global forest management[63]. Finally, for each species range, we calculated the proportional amount (>0–100%) of suitable habitat in each grid cell to include in the prioritization analysis. The development of the habitat type map and all AOH refinement was performed in Google Earth Engine[64].

Global representativeness. There is considerable bias and variability in the completeness of biodiversity records globally, particularly for plant species[33,65,66]. To estimate the amount of geographic bias in the completeness of range data for plants, we first estimated the proportion of species for which we had range data relative to the number of species known to occur in the World Checklist of Vascular Plants[43]. This checklist provides the native regions from the World Geographical Scheme for Recording Plant Distributions (WGSRPD[67]) for each accepted species name. We used geographic delineations for 50 WGSRPD level 2 regions[67], excluding Antarctica and mid-Atlantic islands (Saint Helena and Ascension) for which we had no plant records. For 48 of the 50 WGSRPD regions, we had range data for >10% of all listed native plants (the exception being islands in the southwest and south-central Pacific), relative to the maximum number of species described in a region. This proportion of species varied from 11% in islands of the North Pacific up to 100% in the Russian far east (mean, 60.1%; s.d., 24.5%). For 44 of these 50 regions, we had range data for >40% of described plants in those regions.

Having identified 10% as a minimum common denominator of completeness across most regions, we then used an iterative heuristic algorithm to identify 'representative' sets of plant species. This was done by (1) identifying the number of species that approximate a 10% threshold per WGSRPD level 2 region, (2) calculating random samples that approximated these 10% of species from each WGSRPD level 2 region, and (3) accounting for the fact that some species occur across multiple regions, resampling species at random if necessary. To test whether this approach yielded sets representative of biogeographic patterns of the full dataset, we compared the spatial patterns of scaled vertebrate species richness with the 10% sets of these species for each WGSRPD level 2 region, with random subsets of 10% of all vertebrates and with all vertebrates combined. We performed the test on vertebrates because we had range maps for ~95% of the terrestrial vertebrates described, allowing us to assess whether our subsampling to representative sets can replicate 'true' patterns in species richness obtained with a complete sample of species in a taxonomic group. Compared with a full vertebrate dataset, spatial patterns of scaled species richness were approximately identical across those sets (WGSRPD, Kendall's $\tau = 0.954$; random, Kendall's $\tau = 0.957$), suggesting that this sampling approach can account for incomplete spatial coverage (Extended Data Fig. 8a).

We also checked whether the frequency distribution of range sizes within our subsets matched the range size distribution of the entire set, using mammals as a test group, and found very modest differences between the full set and multiple subsets (Extended Data Fig. 8b). Having confirmed that this procedure re-creates correct biogeographical patterns of conservation priorities and does not alter the range-size distribution (Extended Data Fig. 8), we proceeded to create ten subsets of ~10% of plant species known to occur in each WGSRPD level 2 region and ten non-overlapping subsets of 10% of vertebrate species for all of our analyses. We found little difference among representation curves regardless of whether multiple representative subsets or all mammal species were included in the SCP, although there was greater efficiency in the latter (Extended Data Fig. 9).

Carbon data. We used spatial estimates of the density of above-ground and below-ground biomass carbon and vulnerable soil carbon[9]. Estimates for above-ground carbon were created by selecting the best available carbon maps[68,69] for different types of vegetation classes, identified spatially using the Copernicus land cover map in 2015 (ref. [70]). We used Santoro and Cartus as a baseline for a global carbon biomass map[69], as it is the most recent global above-ground carbon map (2017), its spatial resolution aligns with that of the Copernicus land cover map (100 m) and it is accompanied by an error layer describing the uncertainty of each grid cell's above-ground carbon estimate[69]. In addition, we used more detailed estimates of above-ground biomass for the following land cover classes: African 'open forest' and 'shrubland'[71], global 'herbaceous vegetation' and 'moss and lichen'[72], and 'cropland' and 'bare/sparse vegetation' land cover classes[73]. To map below-ground carbon, we applied corrected root-to-shoot ratios[74] obtained from the Intergovernmental Panel on Climate Change (IPCC) technical guidance documents[75]. A newly developed forest management layer[63] was used to update biomass density by averaging estimates from 2010 (ref. [68]) and 2017 (ref. [69]) in the most dynamic tree-covered classes (for example, short-rotation plantations and agroforestry).

The map of vulnerable soil organic carbon was created following IPCC Guidelines for National Greenhouse Inventories to estimate emissions and removals associated with changes in land use[75]. Vulnerable soil organic carbon was defined as those carbon stocks that could be lost during the next 30 years as a result of land use. We used recently published data on baseline soil organic carbon stocks[76], and vulnerable stocks were estimated separately for mineral and organic soils. Organic soils were defined as those soils with ≥5% probability of being histosols according to the US Department of Agriculture soil order taxonomy[77]. All other soils were considered to be mineral soils. A 30 cm depth was used to estimate vulnerable carbon stocks in mineral soils, while a 200 cm depth was used for organic soils. IPCC change factors (for mineral soils) and emission factors (for organic soils) were used to estimate vulnerable soil organic carbon stocks according to IPCC land cover categories and climate zones. To be consistent with biomass carbon estimations, we created a crosswalk between the Copernicus Global Land Cover map[63] and IPCC land cover classes. The newly developed forest management layer[63] was used to refine vulnerable carbon stock estimates for mineral soils. Managed forests with organic soils were excluded from this assessment given that due to drainage, these areas would often be more suitable for restoration than for conservation action. Finally, all global carbon estimates were reprojected and aggregated (arithmetic mean) to 10 km to match the biodiversity data in scale.

Water data. For capturing water quality regulation, we used estimates of potential clean water provision calculated by WaterWorld[78] and Co$ting Nature[79]. The WaterWorld model uses a long-term climatology (1970–2015), long-term average leaf area index over the same period and the Copernicus land cover map[70] as a baseline to be consistent with other assets in this analysis. For each grid cell, we calculated the volume of water available as the accumulated water balance from upstream based on rainfall, fog and snowmelt sources minus actual evapotranspiration. Clean water was assessed using the Human Footprint on Water Quality (HFWQ) index, which is a measure of the extent to which water runoff is from contaminating human land uses and diluted by passing through natural ecosystems. This index estimates pollution from both point sources (such as urban areas, roads, mining, oil and gas) and non-point sources (such as unprotected cropland and unprotected pasture). The HFWQ index is calculated by aggregating the downstream runoff from polluting and non-polluting land uses and expressing the former runoff as a proportion of the total runoff. WaterWorld has not been validated with discharge at the global scale, but validations for various regions around the world showed good model performance for annual runoff based on the same climatology[80,81]. The index is calculated by assigning an associated pollution (or dilution) intensity (as a proportion of grid cells) to each land-use class (the default values are from ref. [79]). The potential water quality regulation service is calculated for each cell as the inverse of the HFWQ (that is, 100 − HFWQ)—in other words, clean water provided by the grid cell. For the analysis, we ranked each grid cell per level 3 river basin[82] to determine their relative importance in delivering clean water within the basin.

Prioritization analysis. We determined global areas of conservation importance, quantified as maximum value in the present state, to be managed for conserving biodiversity, carbon and water by using an SCP approach[83]. We divided the world into 10-km-resolution (see Supplementary Information for a justification of the scale) 'planning units' (PUs, grid cells on the terrestrial land surface excluding Antarctica), in which 'features' are distributed (all species, plus carbon stocks and water quality regulation), each of which had specific conservation targets allocated to it (see the next section). For each PU, we calculated the amount of suitable habitat for each species whose range intersected that PU. We also calculated the total carbon (tC) and normalized ranks (0–1) of cubic megametres of water (Mm^3). All PUs had a cost c equivalent to the amount of land within them ($0 < c \leq 1$), which we calculated from Copernicus land cover data[70]. We did not use socio-economic conservation cost estimates as they are relevant only when prioritizing specific conservation actions that incur those costs, rather than when identifying areas of conservation importance more broadly. Moreover, available global opportunity and management cost data may inadequately capture the spatial heterogeneity in these costs[84,85], with lower costs seen in areas more suitable for less profitable activities (such as subsistence or small-holder farming[84]) and in areas with lower governance scores, which in turn may reduce the feasibility and effectiveness of conservation interventions[86,87]. We do highlight, however, that conservation planning with the aim of implementing concrete actions needs to consider return on investment and appropriate counterfactuals. As the global budget (B), we set different percentages of the terrestrial land surface area starting at 10% and then increasing by 10% increments until all targets were met.

Target setting. One of the most impactful decisions in SCP frameworks is the definition of feature targets. In the past, many studies set targets for species representation according to rules[35,88,89] or area-based policies (for example, 30% of a species range), which are arbitrary rather than being based on individual species conservation needs. We set targets relative to the minimum amount of species' habitat necessary to qualify the species for the conservation status Least Concern following by IUCN criteria[15,27]. We recognize that this considers only the contemporary range (area of suitable habitat), ignoring other factors of extinction risk (such as population size and trends), but the purpose is to provide ecologically credible area-based conservation targets rather than estimating extinction risk. For all species, these targets were defined as

$$t_s = \min(\max(2{,}200, 0.8\text{AOH}_s), 10^6), \tag{1}$$

where t_s, measured in km^2, is the species range to conserve for a given species s and AOH_s is the total area of suitable habitat for the species. The parameters are guided by the IUCN Red List criteria: Criterion B2 specifies that the area of occupancy should not fall below 2,000 km^2 (plus a 10% buffer) for limiting the 'Least Concern' category; Criterion A specifies that a species population is not to decline by more than 30% in ten years, which parsimoniously equates to 80% of its range[15]; and the upper limit is defined as 1 million km^2 owing to the logistic difficulties of managing extremely large areas for conservation (but see ref. [15]). Whenever AOH_s was smaller than 2,200 km^2, the target t_s was set to the whole AOH. Targets for carbon and water were set to 100% of their terrestrial coverage but were weighted in relation to biodiversity (see below).

Problem formulation. Areas of importance for the conservation of biodiversity, carbon and water were determined by solving a series of global optimization problems. For each feature j included in the analysis, we aimed to minimize the proportional shortfall, noted as y_j (ref. [90] and equations (1) and (2))—that is, the relative difference between the part of the distribution of a feature that is under conservation management and the conservation target t_j of that feature (equation (2)). This minimization was subject to not exceeding a defined total area under conservation management (area budget B_k), set as percentages of the terrestrial land surface of the world ($k = 10, 20, \ldots, 100\%$), with each PU having a cost $c_i \in [0,1]$ (equation (3)). The amount of each feature j in PU i is denoted as r_{ij} (suitable habitat in km^2, total tons of carbon (tC) or normalized Mm^3 of water (0–1)). We defined x_i as a proportional decision variable [0,1] indicating the proportion of the PU that is selected to be managed for conservation (equation (4)).

Furthermore, weights w_j were assigned to each feature j to act as multipliers of the proportional shortfall and regulated the relative emphasis given to meeting conservation targets for species, carbon and water under area constraints. We tested different weights for carbon and water relative to biodiversity and different weights among species based on their global threat status or evolutionary distinctiveness (see below). The problem is formulated as follows:

$$\text{Minimize} \sum_{j=1}^{J} w_j \frac{y_j}{t_j} \tag{2}$$

subject to

$$y_j = \left\{ 0, \text{ when } t_j < \sum_{i=1}^{I} x_i r_{ij};\ t_j - \sum_{i=1}^{I} x_i r_{ij} \text{ otherwise} \right\} \tag{3}$$

$$\sum_{i=1}^{I} x_i c_i \leq B_k \tag{4}$$

$$x_i \in [0, 1] \tag{5}$$

$$x_{iB_k} \geq x_{iB_{k-1}} \tag{6}$$

Additional constraints ensure that the overshooting of t_j is not valued more than reaching the target, thereby focusing the attention of the spatial optimization towards under-represented features (equation (3)); ensure that the sum of PU costs is smaller than or equal to the global budget (equation (4)); and limit the decision variable x_i to a proportional amount (equation (5)). The problem is then solved for each budget B_k incrementally, while ensuring that current decisions build on previous solutions (equation (6)), thus effectively building nested sets of priorities with increasing B_k. We repeated this process for each problem variant (defined by the set of weights in equation (7), next section) and for a representative set of features (defining the species targeted for conservation in equations (1) and (2)).

Analysis variants. To identify current gaps in the conservation of species, carbon and water by protected areas, we constrained the optimization by locking in the proportion of currently protected areas (as a fraction of the land area, Supplementary Information). To explore where conservation management would be best placed to complement the existing network of protected areas, we then jointly optimized globally for biodiversity, carbon and water by minimizing the proportional shortfall[90] in reaching the targets for each given budget B_k ($k = 10, 20, \ldots, 100\%$ of the terrestrial land surface). We also considered a number of optimization variants in which we modified either the targets or the weights assigned to each feature (biodiversity, carbon and/or water).

We tested the effect of different weights for carbon storage and water quality regulation relative to biodiversity in all analysis variants that included carbon and water. To do so, we assigned sequences of weights for carbon and water from 'none' up to 'equal' preference, which is obtained when their shortfall is weighted by

$$w = S + 1 \tag{7}$$

where S is the total number of biodiversity features in the analysis (each with weight 1). The addition of 1 is needed as there are $S + 2$ features in the problem formulation, S species + carbon or water. This weighting ensures that NCPs are treated as equivalent to all species combined and that feature targets are treated 'equally'—for example, a decrease in value of 10% is proportional to an average 10% decrease across all species targets, in the optimization. We varied w from 1 to $S + 1$ with intermediate values of 1 or 1/10, 2/10,…, 9/10 of maximum w. We visualized all variants with increasing budget and by the shortfall in carbon, water and species targets (Fig. 2). Because of the high computational cost of calculating $(2N_w - 1) \times N_B$ prioritizations, where N_w is the number of weights and N_B the number of budgets, for each of the ten representative sets, we assessed differing weights at 50 km rather than 10 km resolution. When compared with a 10 km resolution, both spatial patterns and accumulation curves were highly similar (Supplementary Information and Extended Data Fig. 10), so we do not expect the results to differ between these resolutions. We did not explore differential weightings of species relative to carbon and water (Figs. 1 and 2), since all species received equal preference in the prioritization.

For biodiversity only, we also considered variants accounting for species intraspecific variation, threat status and evolutionary distinctiveness (Supplementary Information). To capture intraspecific variation, we considered each part of a species range occurring in geographically separate biomes as a separate feature with its own target[31]—for example, the tiger (*Panthera tigris*) was split into five separate features, one for each of the five biomes overlapping the tiger range (Supplementary Information). However, we considered this split only for features in which at least 2,200 km² of the AOH (the minimum absolute target area, see 'Target setting' above) was contained within a different biome from the biome with the majority of the species range. Compared with a version without these splits and when optimizing for biodiversity, carbon and water, the overall differences were relatively minor (Extended Data Fig. 5) but potentially locally important. We also collated data on species' current threat status from both the IUCN and BGCI and, for vertebrates, data on their evolutionary distinctiveness using phylogenetic distance to the closest relative (Supplementary Information), and we then calculated weights for each species following ref. [13]. Using vertebrates only and identical species, we created variants where species were unweighted, weighted by threat status or weighted by evolutionary distinctiveness. We then optimized all variants by minimizing the target-weighted shortfalls across all biodiversity features, subject to budget constraints, and compared the identified areas of conservation importance at a 10% land area budget (Extended Data Fig. 7).

Optimization algorithm and ranking. All problem variants were solved using a linear programming approach, which has been shown to outcompete global search algorithms and heuristics in both speed and performance[91,92]. For each problem variant and representative set of species, we obtained ten nested optimal solutions, each resulting from solving to optimality the problem defined in equations (2) to (6) with a specific set of weights (problem variant), representative set of species and area budget. All solutions of the same problem variant and set of species are by design nested as area budgets increased, because we locked the solution at a budget level (for example, 30% of land area) into the problem formulation of the next budget level (for example, 40% of land area). For all non-spatial analyses (for example, target accumulation curves), we report the results across all representative sets. When representing spatial patterns of priorities, to take advantage of the full plant dataset and to analyse only one global rank for each problem variant as opposed to ten, we combined the ten nested sets for any given problem variant (one for each of the ten representative sets) into one single rank. This was calculated as the arithmetic mean $\left(\frac{1}{n}\sum_{i=1}^{n} p_i\right)$ of the ten representative sets and ten budgets ($n = 100$), each with the proportion p of the grid cells that are part of a solution, which are then ranked and binned. Constructing a grand total average across different problem formulations does not formally constitute an optimal solution, because there are 100 different objective functions (one per budget and representative set), and these cannot be jointly optimized and synthesized further than ten optimal nested sets, as we did, without resorting to heuristic solutions. Our heuristic combination of optimal nested sets has the following characteristics: (1) it closely resembles spatial patterns and accumulation curves of individual nest sets, (2) it allows us to make full use of the plant database while accounting for spatial biases in data availability, and (3) it allows for an estimation of the uncertainty in priority ranks due to the choice of alternative representative sets (Extended Data Fig. 1).

All maps, unless otherwise noted, were the result of aggregating the nested sets of priorities for problem formulations with both carbon and water shortfall weighted as $w = S + 1$, where S is the set of biodiversity features in the analysis. This equal weighting was chosen because it yielded the lowest combined shortfall across features and the most similar shortfall across features (Fig. 2 and Extended Data Fig. 4).

We calculated and reported on the number of targets achieved and the mean shortfall from targets by calculating the shortfall first within each representative set, feature and area budget and then as the average across sets. The second step is necessary because some species are present in more than one representative set. We investigated how these performance metrics varied across taxonomic groups, threatened species and problem variants. Furthermore, ranks were extracted using country boundary shapefile data from Natural Earth and the average (arithmetic and area-weighted mean) calculated per country (Supplementary Table 2).

All data preparation and analysis was conducted in R (ref. [93]), mainly relying on the prioritizr package[94] with the Gurobi solver enabled (v.8.11; ref. [61]).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All maps will be made available through https://unbiodiversitylab.org/ and on a data repository (https://doi.org/10.5281/zenodo.5006332). The raw input data can be requested from the respective data providers (namely, IUCN, GARD, Birdlife International and Royal Botanic Gardens, Kew), and the predicted plant range data will be made available as part of the BIEN initiative[47]. The IUCN habitat type map used to construct the AOH is made available in the Supplementary Information. The carbon layers will be published openly in a separate data descriptor manuscript and are available upon request. Any additional raw data not listed can be made available from the authors upon reasonable request.

Code availability

Code to run comparable optimization analyses has been made available at https://github.com/Martin-Jung/NatureMapCode.

Received: 10 December 2020; Accepted: 7 July 2021;
Published online: 23 August 2021

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Acknowledgements

This work was conducted by the Nature Map consortium. We thank R. Corlett and T. Brooks, who provided feedback on an earlier version of the manuscript. We further thank T. Hengl (OpenLandMap) for his advice on the soil organic carbon analysis. This study has benefited from a number of data providers and networks. We explicitly acknowledge all data providers in a separate Extended Acknowledgements owing to their length (Supplementary Information). The Nature Map project acknowledges funding from Norway's International Climate and Forest Initiative (NICFI). The collection of the plant data used in this analysis has benefited from funding in the form of GEF grant no. 5810-SPARC, 'Spatial Planning for Area Conservation in Response to Climate Change'. C.M. acknowledges funding from NSF (National Science Foundation) grant no. DBI-1913673. R. Gallagher was supported by Australian Research Council DECRA Fellowship no. DE170100208. E.A.N. and X.F. were funded by the Bridging Biodiversity and Conservation Science Program of the University of Arizona. N.M.-H. was supported by the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant no. 746334. M.D.M. acknowledges support from the MIUR Rita Levi Montalcini programme. J.-C.S. considers this work a contribution to his VILLUM Investigator project, 'Biodiversity Dynamics in a Changing World', funded by VILLUM FONDEN (grant no. 16549), and his Independent Research Fund Denmark—Natural Sciences project, TREECHANGE (grant no. 6108-00078B). The views expressed in this publication are those of the author(s) and do not necessarily reflect the views or policies of the Food and Agriculture Organization of the United Nations.

Author contributions

M.J. and P.V. designed the study. M.J. led the analysis and interpretation of the data and drafted the manuscript. P.V. conceived the study and contributed to the analysis and drafting of the manuscript. J.O.H., B.L.B. and C.M. contributed to creating the software used in this work. A.A., C.R., S.G.-R., M. Lewis, D.S., A.v.S., M.M., J. Mark, S.P., I.O., C.M., B.J.E., X.F., P.R.R., B.L.B., B.M. and R. Gallagher contributed to the acquisition, analysis and interpretation of the data. B.B.N.S., J.O.H., M.D.M., J. Mark, W.J., D.S.R., J. McGowan, M.O., M.R. and X.d.L. contributed to the interpretation of the data. G.O., U.R., S.M., M. Lewis, R. Gallagher, M. Lesiv and O.T. contributed to the acquisition and interpretation of the data. X.d.L., V.K., L.M., N.B., G.W., S.F., J.D.S., G.S.-T. and M.O. contributed to the conception of the study. V.M.A., S.C.A., J.R.B., L.H., R. Govaerts, P.A.M., J.K.M., N.M.-H., E.A.N., D.S.P., P.R.R., J.-C.S., C.V. and J.J.W. provided data and contributed to the interpretation of the data. All authors contributed to revising the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41559-021-01528-7.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41559-021-01528-7.

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Peer review information *Nature Ecology & Evolution* thanks Richard Schuster and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

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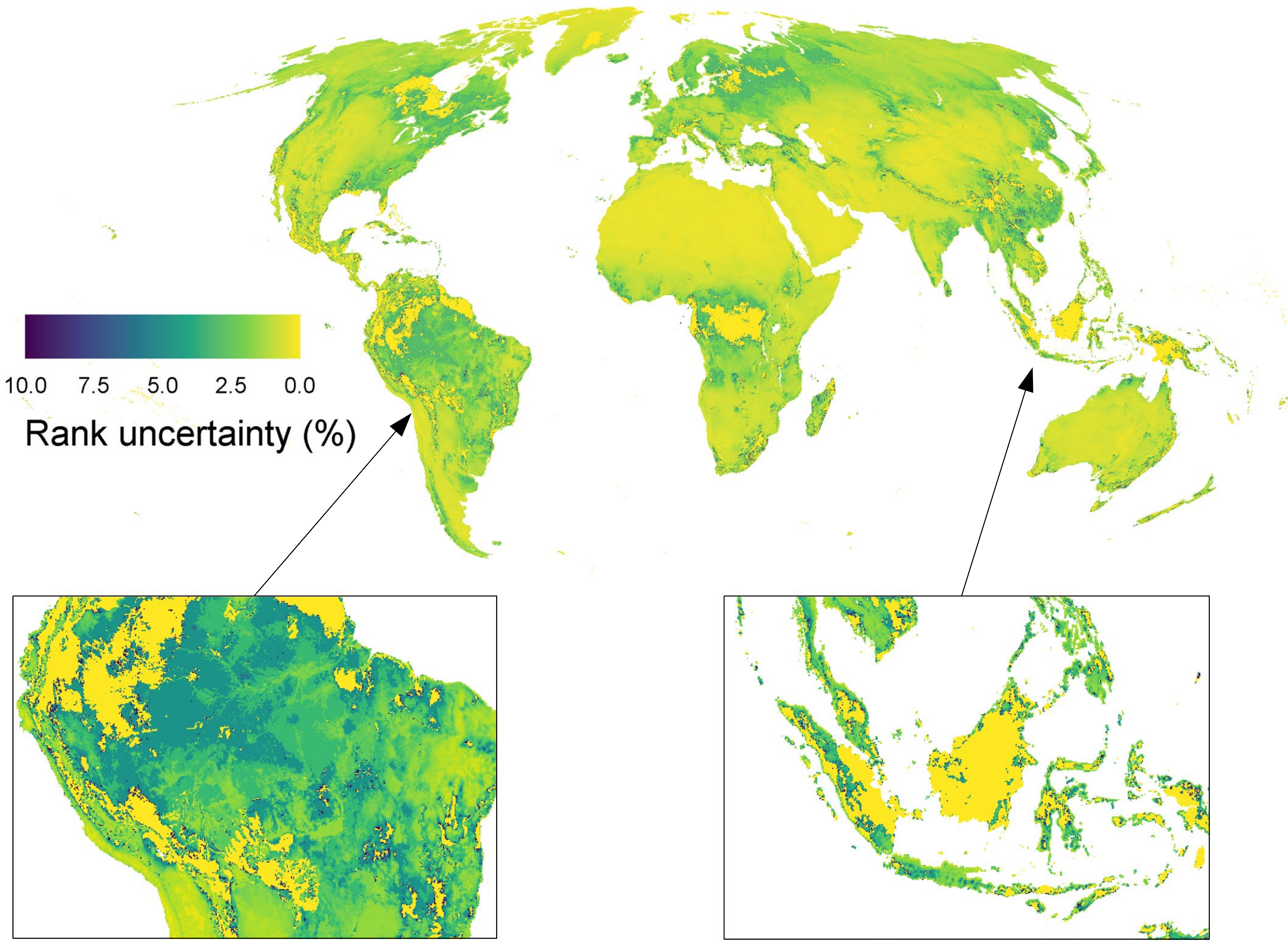
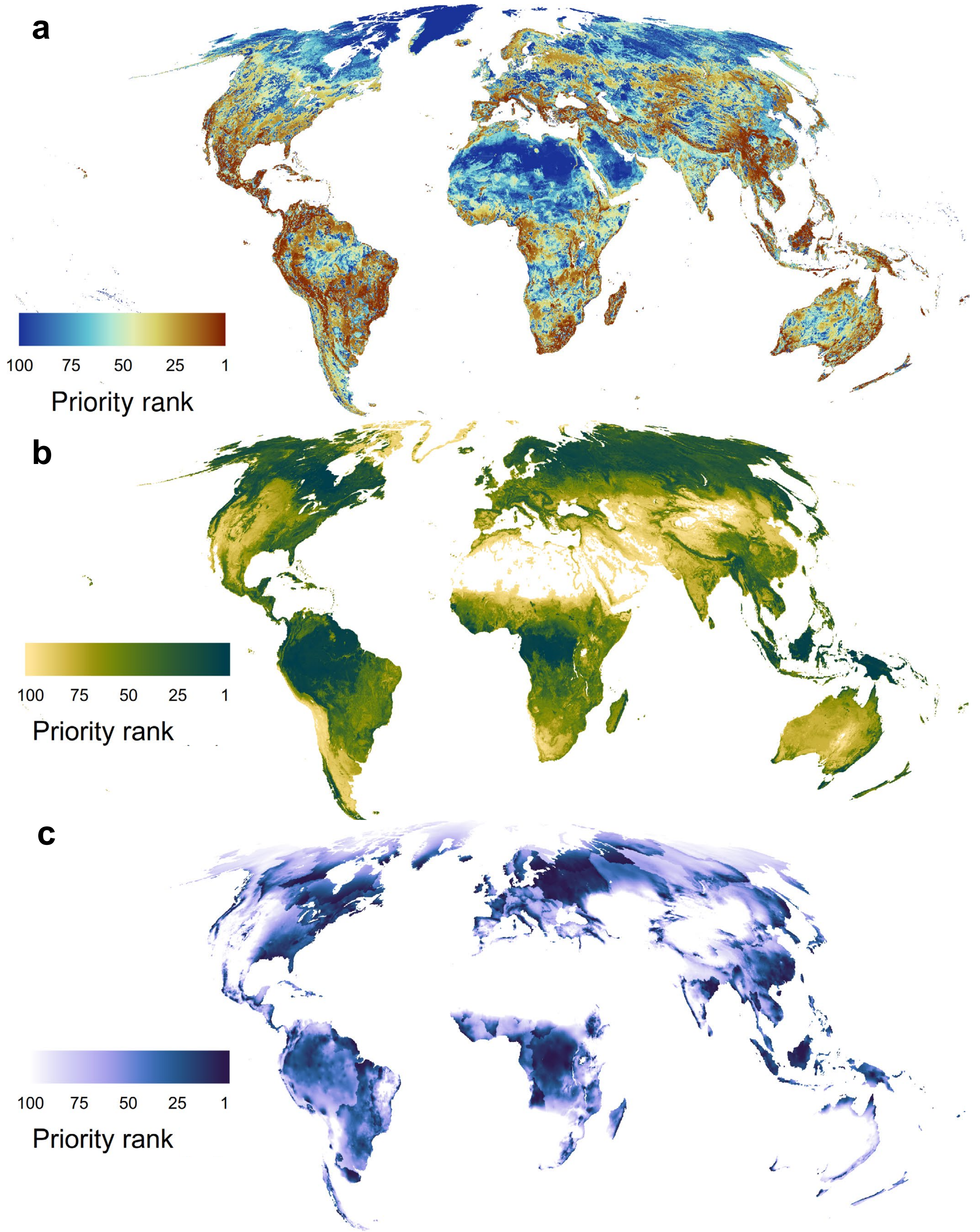
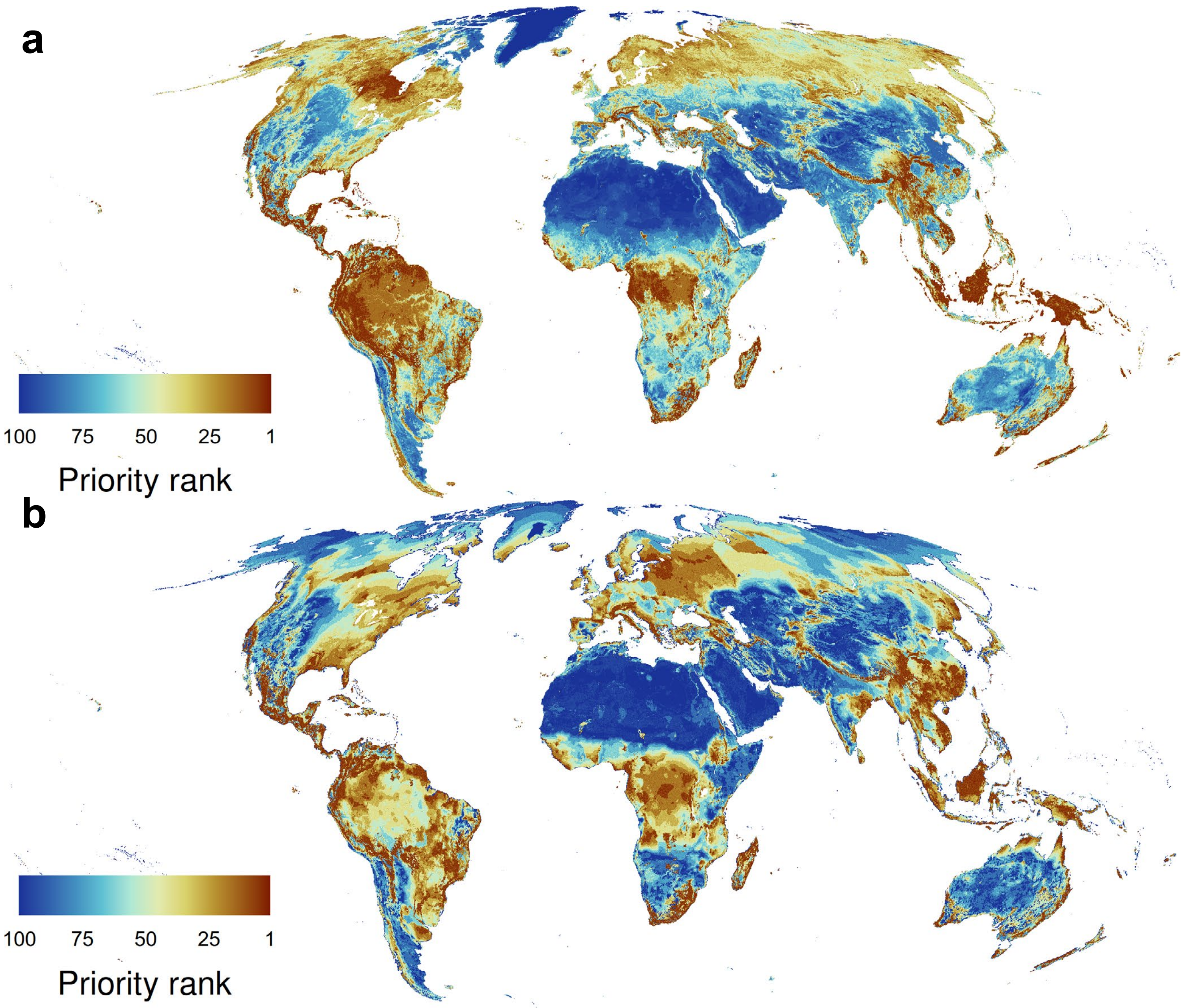


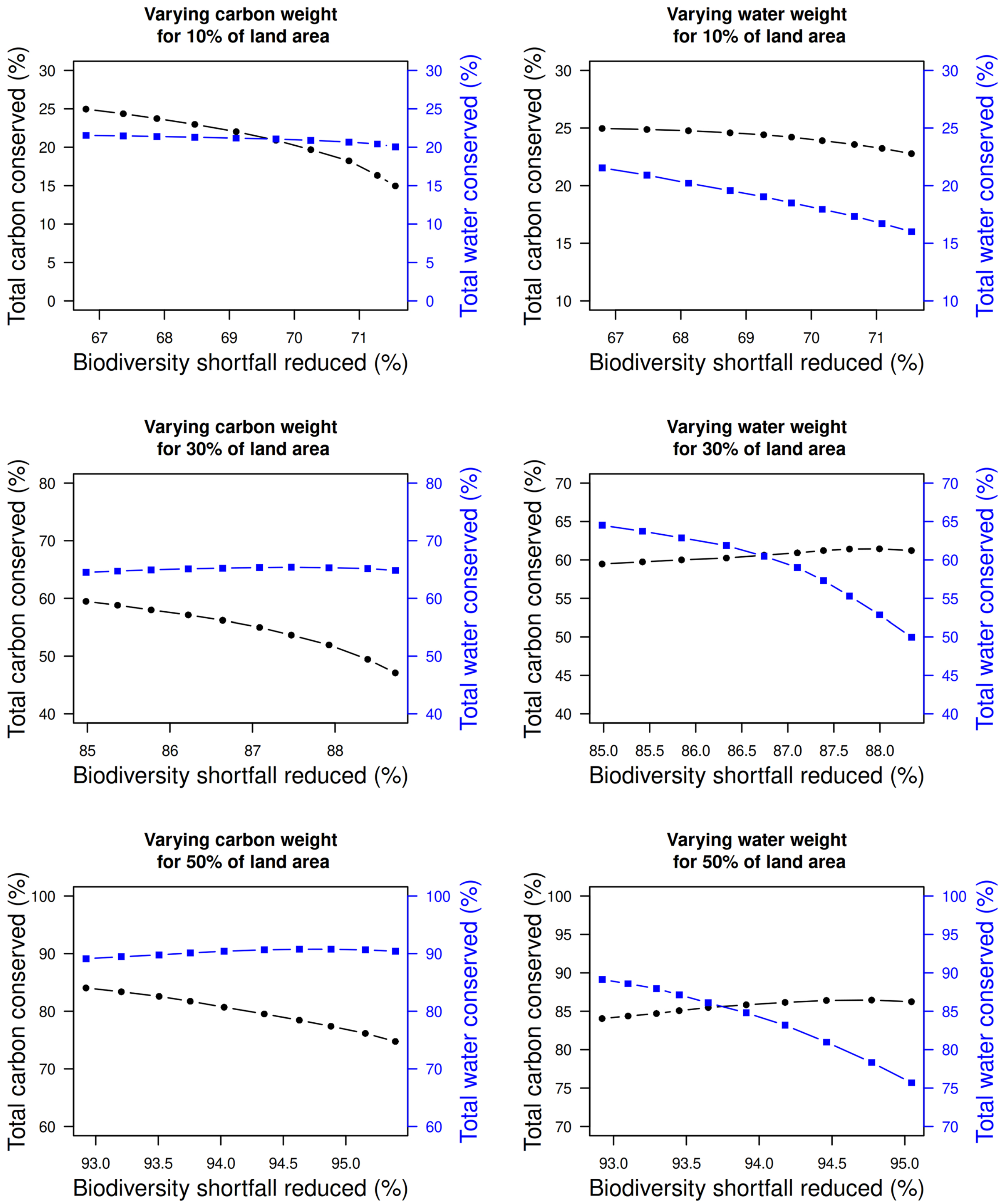
Extended Data Fig. 1 | Uncertainty in ranks of areas of importance for biodiversity, carbon and water. Calculated as coefficient of variation across optimal solutions with different representative sets. Expressed as percentage with lower values indicating higher precision of ranks. Map can be interpreted as overall confidence in the mapped ranks (Fig. 1), given existing biases in species range data. Maps are at 10 km resolution in Mollweide projection.



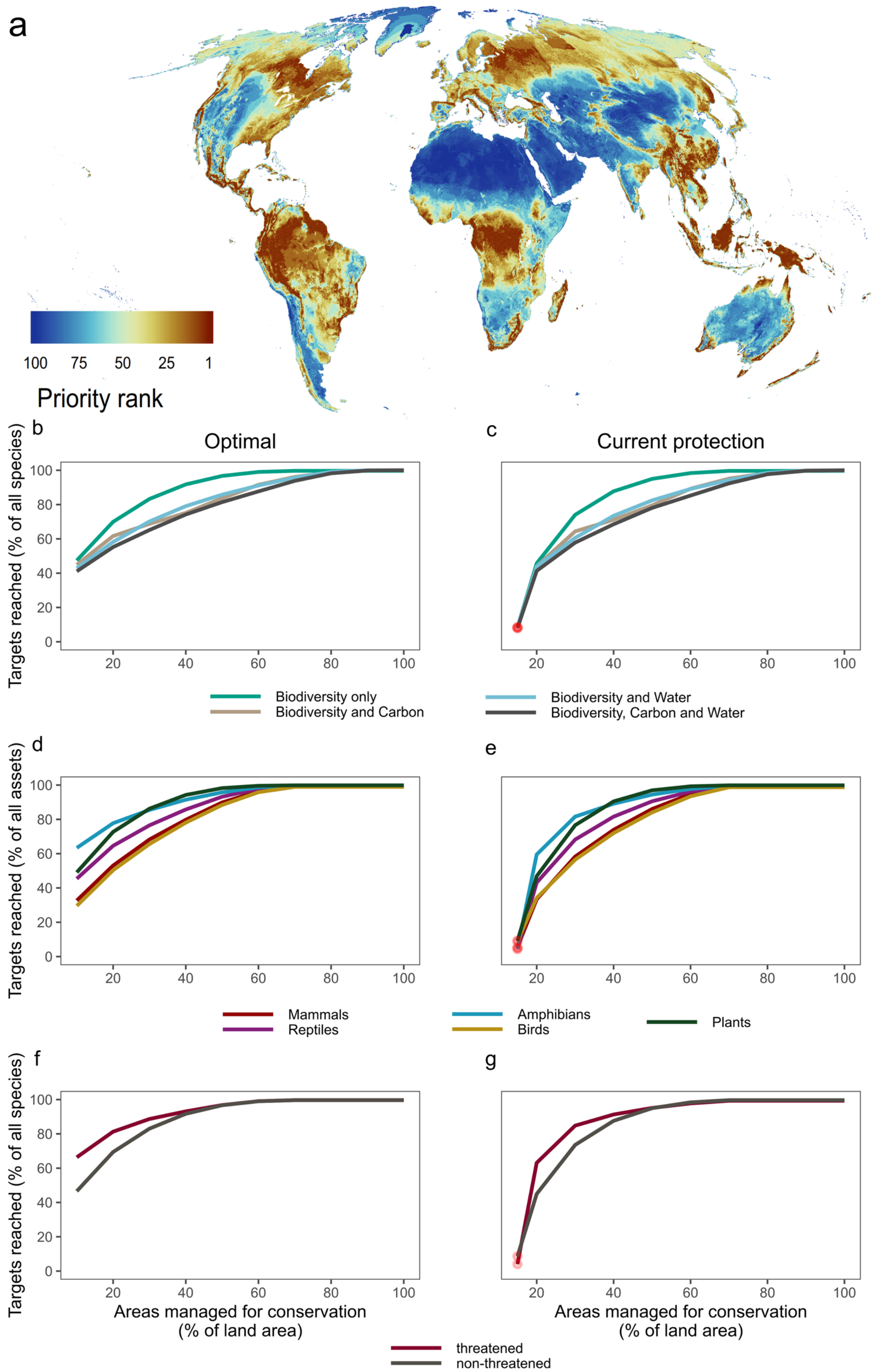
Extended Data Fig. 2 | Global areas of importance for conserving biodiversity, carbon or water only. Ranked hierarchical maps by the most (1–10) and least important areas (90–100) to conserve all of **(a)** biodiversity, **(b)** carbon and **(c)** water globally. Maps are at 10 km resolution in Mollweide projection.



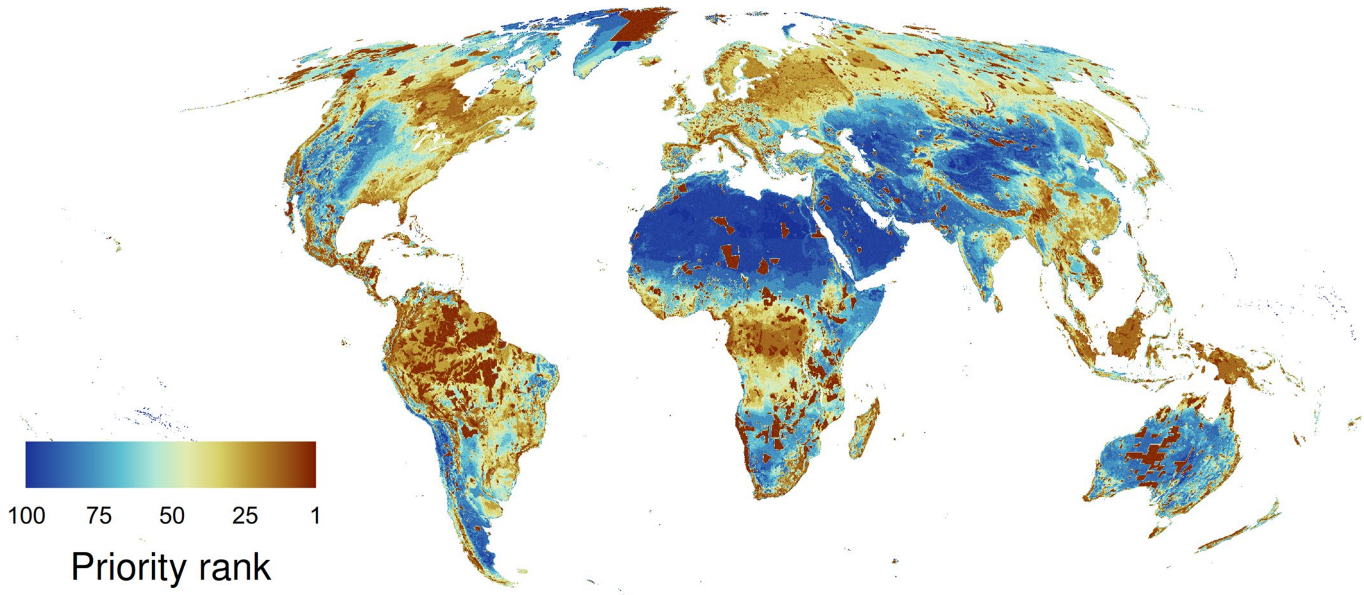
Extended Data Fig. 3 | Global areas of importance for biodiversity and carbon or biodiversity and water. Showing an optimization across 10 representative sets for either (**a**) biodiversity and carbon or (**b**) biodiversity and water. All assets were jointly optimized and ranked hierarchical by the most (1–10) and least important areas (90–100) to conserve globally. Maps are at 10 km resolution in Mollweide projection.



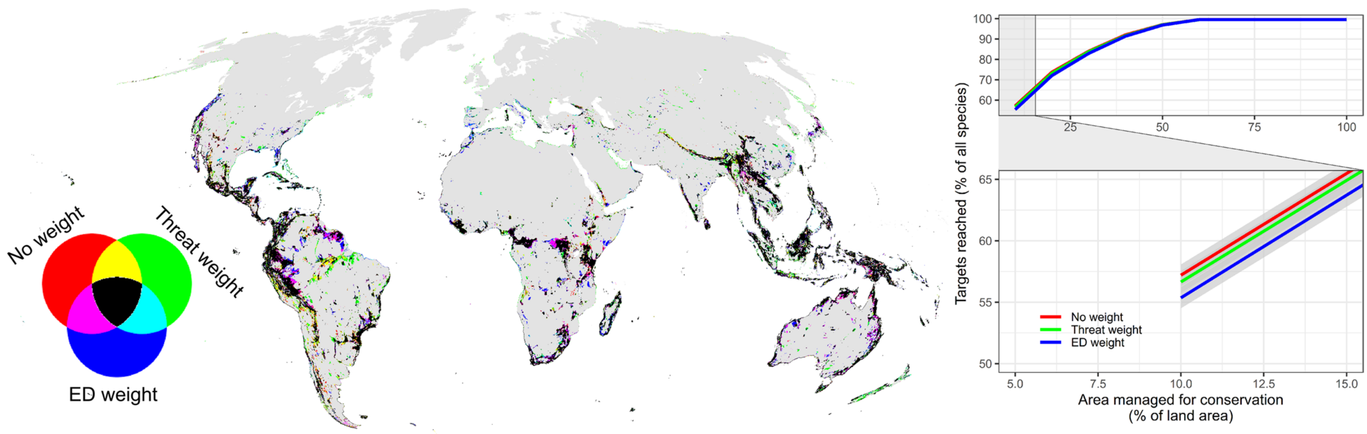
Extended Data Fig. 4 | Varying weights and shortfalls. We tested for various weights (points) given to either carbon or water and how it affected the trade-off with biodiversity conserved across a selection of different budgets (10%, 30%, 50%). We varied carbon or water weights across a range from none, for example equivalent to a single species, to equal, where weights are estimated as the sum of all other feature weights (all species + 1 other NCP) weighting (as shown in Fig. 2) with all assets (biodiversity, carbon and water). The x,y and z-axis show the shortfall as a percentage of their respective targets for either biodiversity, carbon or water.



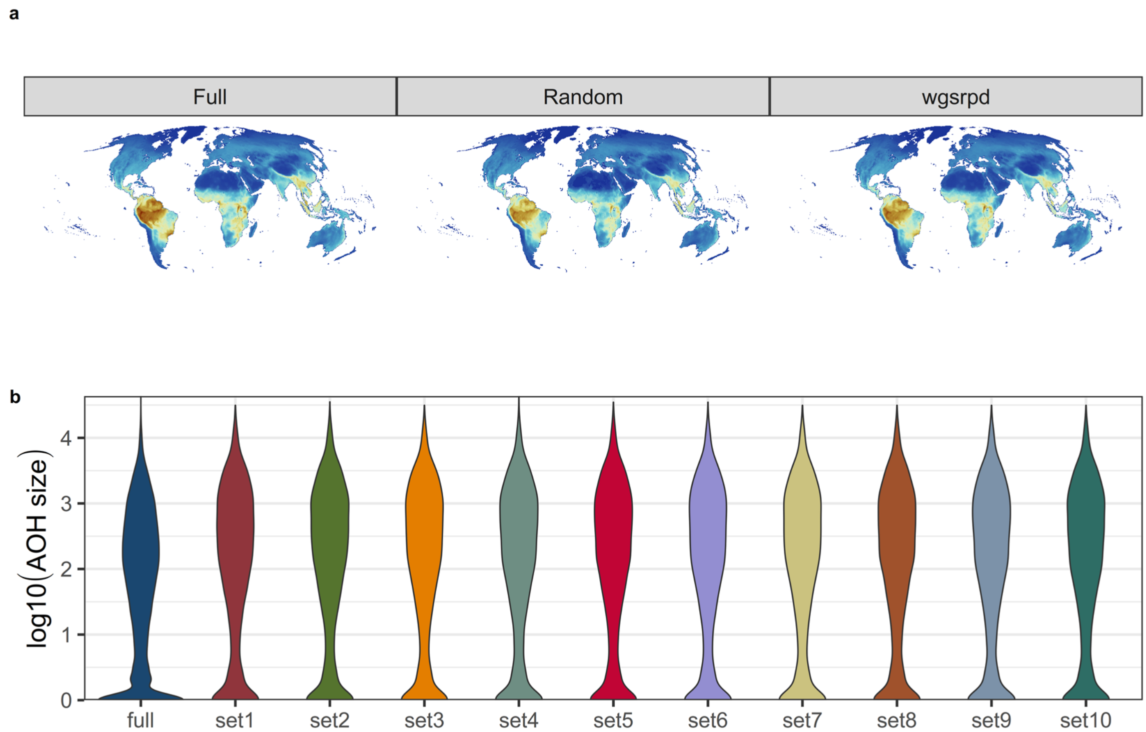
Extended Data Fig. 5 | Global areas of value for conservation and accumulation curves for terrestrial biodiversity, carbon and water without biome splits. (**a**) All assets were jointly optimized with equal weighting and ranked hierarchical by the most (1–10) and least (90–100) important areas to conserve globally. The map is at 10 km resolution in Mollweide projection. (**b–g**) Proportion of species conservation targets reached for an optimal prioritization (b,d,f) and considering current protected areas (c,e,g). (b,c) Target accumulation curves for analysis variants including other assets; (d,e) for different taxonomic groups when optimizing biodiversity only to conservation; (f,g) for species classified as threatened or not (see Methods) when optimizing for biodiversity only.



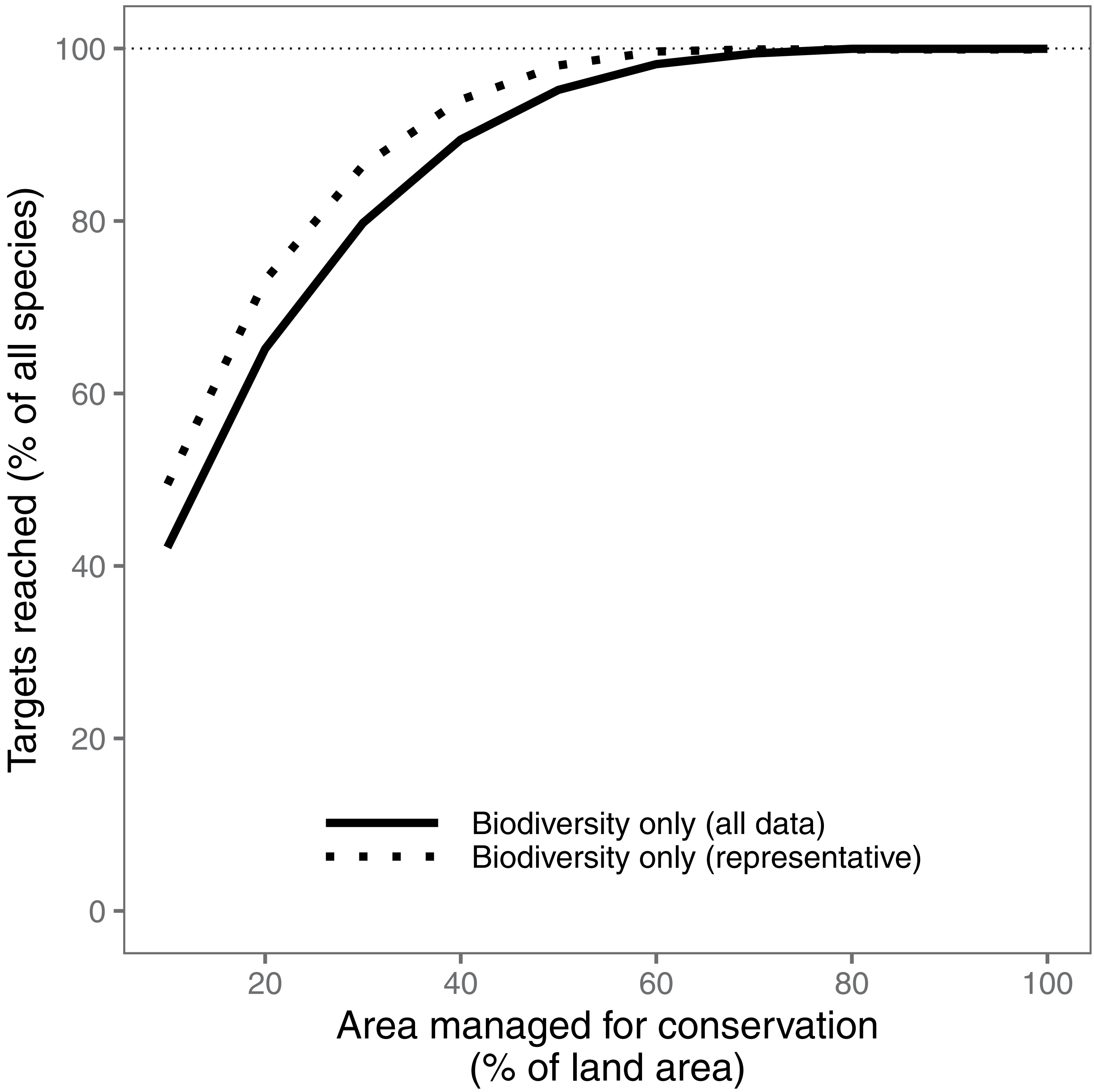
Extended Data Fig. 6 | Global areas of importance for biodiversity, carbon and water considering current protected areas. All assets were jointly optimized and ranked hierarchical by the most (1–10) and least important areas (90–100) to conserve globally. The proportion of grid cells currently managed for conservation (https://www.protectedplanet.net) are considered to be part of the most important areas. Maps are at 10 km resolution in Mollweide projection.



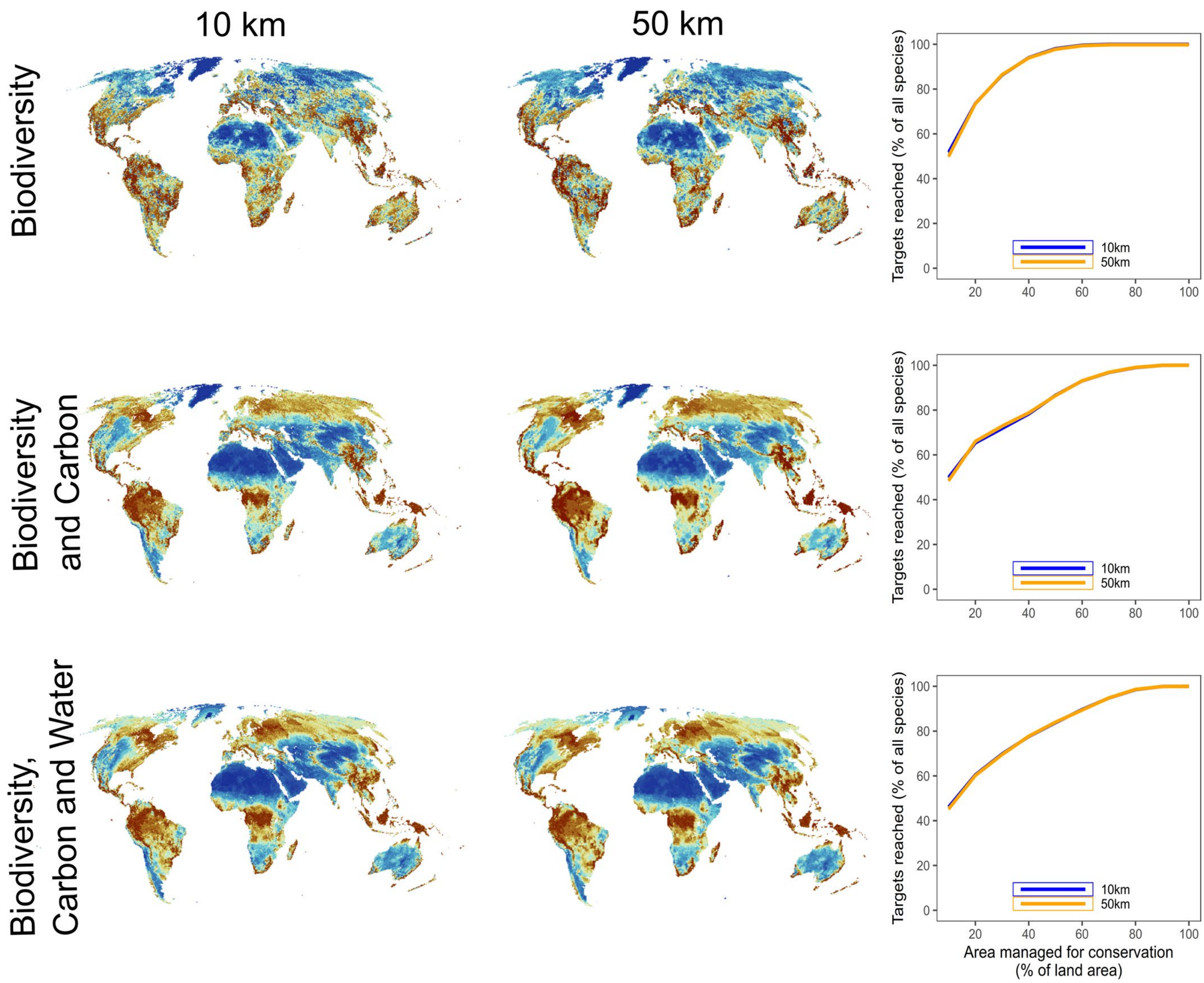
Extended Data Fig. 7 | Difference in the top-ranked 10% solution for varying vertebrate species weights. For each biodiversity feature a weight was assigned equating to either no differential weight (red), current threat category (green) or evolutionary distinctiveness (ED) (blue). Comparison was made only for vertebrate species, where data on both threat category and evolutionary distinctiveness was available. Grid cells coloured in black were selected in all three solutions. Map in Mollweide projection at 10 km resolution. The line plot shows the amount of land area necessary for all species to reach all conservation targets, defined as the amount of land area needed for a species to be considered non-threatened (see Methods). Shown for either no weight (red), species weighted by threat status (green) and weighted by evolutionary distinctiveness (blue). The inset zoom highlights the difference among solutions at a budget of 10% terrestrial land area. The confidence bounds of accumulation curves indicate the uncertainty among representative sets.



Extended Data Fig. 8 | Comparison of representative sets spatially and in range size distributions. Compared to a full dataset, both subsampling at random and per WGSRPD region produces similar patterns in space and species area-size distributions. (**a**) Spatial map in Mollweide projection showing aggregated richness layers of all vertebrate species for the full dataset, a random sample and a representative sample by WGSRPD level 2 regions. Colours indicate low and high species richness (blue to brown). **(b**) Shows the log10-transformed Area of Habitat (AOH) of all species in the full dataset (dark blue) compared to representative subsets of species (other colours).



Extended Data Fig. 9 | Accumulation curves showing how the number of species targets met increases with amount of land optimally allocated to conservation. Estimates shown for representative subsets (dotted line) and for all species included (solid line).



Extended Data Fig. 10 | Comparison of global areas of importance at 10 km and 50 km areas. Comparisons in variants of areas of importance for conserving biodiversity only; biodiversity and carbon; and biodiversity, carbon and water. Colour scale of map as in Fig. 1. Inset graphs show how the number of species conservation targets met increases with amount of land optimally allocated to conservation for both 10 km (blue) and 50 km (orange).

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Last updated by author(s): Jun 29, 2021

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☒	☐	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	N/A.
Data analysis	All analysis was conducted in R or with open-source GIS software (QGIS). In R particularly the most recent version of 'prioritizr' (https://prioritizr.net, ver. 4.1.5) at the time of the analysis was used to run the optimizations. All optimizations were solved with the commercial solver Gurobi (https://www.gurobi.com/, ver. 8.1.1) which can be used at no extra cost for academic purposes. The used analysis code to create the analysis results and main figures has been made available at https://github.com/Martin-Jung/NatureMapCode

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All produced integrated priority maps will be made available through https://unbiodiversitylab.org/ and are available on a data repository upon acceptance (see data availability statement). The raw input data can be requested from the respective data providers, namely IUCN, GARD, Birdlife International, Kew Gardens and predicted plant distribution data will be made available as part of the BIEN initiative. The IUCN habitat type map used to construct the AOH is made available in the

Supporting Information. The carbon layers will be published openly in a separate data descriptor manuscript and are available upon request. Any additional data not listed can be made available from the authors upon reasonable request or will be openly published separately.

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Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study identifies the most important areas for biodiversity as well as NCPs including carbon storage and water provisioning, to be managed for conservation globally.
Research sample	We obtained fine-scale distribution maps for the world's terrestrial vertebrates as well as the largest sample of plant distribution data ever considered in global species-level analysis, ~41% of all accepted species names in this group. As NCPs we use the latest global spatial data on above- and below-ground biomass carbon, and vulnerable soil carbon, as well as the volume of potential clean water by river basin. Data was obtained from IUCN, GARD, BGCI, KEW & BIEN.
Sampling strategy	All species for which suitable range estimates could be obtained were considered in the analysis. To counter spatial bias in the considered plant data, we implemented a subsampling heuristic that obtain representative sets of species native to each WGSRPD region according to checklists in Plants of the World online and IUCN. In total 10 representative sets of species were included in the analysis.
Data collection	Spatial data was collected by IUCN (iucnredlist.org), GARD (http://www.gardinitiative.org/), BGCI (https://www.bgci.org/), Kew Gardens (https://www.kew.org/) & BIEN (https://bien.nceas.ucsb.edu/bien/)
Timing and spatial scale	The reference time period is the year 2015 (for which Copernicus Land cover is currently available). The spatial extent is global and the resolution 10km, respectively 50km. The used geographic projection is World Mollweide projection
Data exclusions	We excluded all species that were extinct and where the species is non-native in a given region. Parts of a species range for which the species is unlikely to occur were removed from their range using species habitat affiliations, thus refining the species range to an Area of Habitat (Brooks et al., 2019).
Reproducibility	Code to reproduce the main results with similar data has been made available as stated in the Code availability section. Raw input data are available for research purposes at no extra costs from the data providers or are published separately.
Randomization	Representative sets of species ranges were constructed by drawing random samples that approximated 10% of plant species from each WGSRPD level 2 region while accounting for the fact that some species occur across multiple regions. To test if this approach yielded sets representative of biogeographic patterns of the full dataset, we compared the spatial patterns of scaled vertebrate species richness to the 10% sets of these species for each WGSRPD level 2 regions, random subsets of 10% of all vertebrates and for all vertebrates combined. Code and sets of species to reproduce the main results will be made available upon acceptance.
Blinding	N/A and data was not blinded in this analysis.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

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☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging