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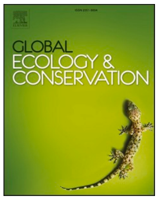

Identifying science-policy consensus regions of high biodiversity value and institutional recognition

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ABSTRACT

Under unsustainable rates of global biodiversity loss, there is urgent need to improve area-based conservation interventions and focus on regions with the highest conservation value. Efficient conservation plans require knowledge of the most important biodiversity areas, but several global prioritization maps show incongruent definition of these areas, slowing down global conservation efforts. We developed a framework to systematically identify and combine areas of high biodiversity value from published spatial prioritization maps. We retrieved 63 articles presenting prioritization maps (out of 5137 screened) and grouped these into three separate clusters based on their underlying methodology and input data, using Multivariate Component Analysis and Hierarchical Clustering on Principal Components. By combining these maps, weighted according to their cluster characteristics, we generated a map of scientific-consensus regions with the highest overlap of independently generated biodiversity priorities. We also created a map of policy-consensus, representing regions with the highest potential to attract the interest of the international conservation organizations. While regions with the highest science-policy biodiversity consensus value are mostly located in the tropics, we found several regions in temperate areas. Alarmingly, less than one third of the top-ranked science-policy consensus regions are currently protected. Thus, there is high potential for targeting area-based conservation interventions in regions that represent consensus priorities for biodiversity conservation and have high potential for policy support. Securing these areas should be a strategic priority for implementing the post-2020 Framework of the Convention on Biological Diversity, as focusing on other areas will lead to trade-offs among multiple biodiversity objectives.

1. Introduction

The number of species at imminent risk of extinction is rapidly growing (Johnson et al., 2017; Pimm et al., 2014), and conservation action is urgently needed in regions that have been identified as having high biodiversity importance. However, there is uncertainty

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around the likelihood of success of conservation investment, and global conservation budget remains insufficient (Bottrill et al., 2008; McCarthy et al., 2012). Some have argued that conservation needs a transformative change that tackles societal production and consumption systems (Díaz et al., 2019). Different approaches have been suggested in recent decades for identifying priority regions for conservation action (Brooks et al., 2006; Smith et al., 2019). Some approaches have focused on regions identified as highly valued under different criteria, such as high vulnerability to threats, as it is the case for Crisis Ecoregions (Hoekstra et al., 2005), or high irreplaceability (Margules and Pressey, 2000), as it is the case for the top-200 ecoregions (Olson and Dinerstein, 2002), or a combination of both, as it is the case in biodiversity hotspots (Myers et al., 2000). Other approaches were built on spatial conservation prioritization methods, which identify priorities for a cost-efficient (or area-efficient) expansion of the protected area network (e.g., Di Minin et al., 2016; Pouzols et al., 2014; Venter et al., 2014; Carwardine et al., 2008; Rodrigues et al., 2004a). However, there appears to be limited consensus around what constitutes an area of global "conservation priority", and the plethora of approaches adopted have led to criticism about duplication of efforts and lack of clarity (Brooks et al., 2006). Having multiple maps of biodiversity priorities can be problematic as it results in the generation of redundant and competing, rather than complementary, priority sets (Mace et al., 2000).

It is likely that different conservation organizations will promote different spatial conservation priorities in order to advance their own specific objectives and goals. Nevertheless, focussing global conservation priorities and strategies on regions where a high conservation value has been attributed by many organizations has obvious benefits. These would be regions identified under several independent approaches, and for multiple elements of biodiversity. If conservation action in such regions was to be promoted by multiple conservation organizations, their policy uptake would be maximized. This could be particularly relevant in the context of the implementation of the post-2020 Global Biodiversity Framework (Convention on Biological Diversity, 2020).

Our goal here is to identify regions of high biodiversity importance and institutional recognition. We call these "science-policy biodiversity consensus regions", and propose that safeguarding them is advantageous (albeit not sufficient) for both biological reasons – these regions have been classified as important under several independent approaches– and policy reasons – the conservation of these areas might gain support from multiple conservation organizations. Our approach is not meant to identify a comprehensive set of areas that would meet a broad biodiversity policy goal, rather we identify regions that represent immediate opportunities in terms of biodiversity conservation potential and policy support. We did not run a spatial prioritization analysis, rather we developed a framework to combine priority regions from published spatial conservation prioritization analyses. We combined these maps using Multiple Correspondence Analysis (MCA), accounting for the methodology with which they were derived, their similarities and differences. Our framework is repeatable and customizable, for example to add new maps or assign different weights to maps with different characteristics.

2. Methods

We collected and systematically reviewed scientific articles presenting maps of global conservation priorities published in peer-reviewed journals since the year 1990. We analysed the different methodologies and approaches for the identification of each conservation priority map, and used MCA as Zizka et al. (2021) coupled with a Hierarchical Clustering on Principal Components (HCPC), instead of a kmeans clustering, to detect and represent underlying common characteristics in the maps. Based on these characteristics, we grouped maps into separate clusters. We then generated a map of "scientific biodiversity consensus regions", by combining each map while accounting for its cluster position (Fig. S1). Instead of simply overlaying maps with each other, this approach allowed us to avoid pseudo-replications in the definition of spatial priorities (see Yang et al., 2020) and to include each elements of biodiversity without favoring those receiving higher research attention such as vertebrates vs invertebrates (Di Marco et al., 2017).

For each article, we also defined a map of "affiliation", representing the potential support from different international conservation organizations, NGOs, and research institutes that were involved in the articles. We excluded those for which the scale of the organization's work is regional, national, or local, in order words, geographically narrower than would be necessary to implement actions guided by their global prioritization. We combined the maps of affiliation to create a map of "policy consensus regions", showing which areas were subject to the interest of several entities implied in conservation. Finally, we combined the map of scientific consensus regions with that of policy consensus regions to identify areas which we called "science-policy biodiversity consensus regions".

2.1. Literature review

The literature review was conducted using *Scopus* to search for all scientific articles published between 01/01/1990 and 30/06/2020 that produced priorities for terrestrial biodiversity conservation with global extent. We run 10 different queries, using various combinations of words to be searched in the title, abstract, or keywords of each article (Table S1 in Supplementary Material). We stopped running additional queries when we verified no new titles were being retained as relevant.

In order to identify articles focused on conservation prioritization, all the results were screened recursively by the lead author, first by title only, then abstract, and finally by full-text. Results were merged to eliminate duplicate titles. Additionally, we screened the reference lists of each of the retained articles in search of other relevant publications that we might not have found from the *Scopus* search. Finally, we used *Google Scholar* to search for recent publications (from 2020 onwards) citing one or more of our selected articles. This latter search allowed us to add relevant studies that were still not included in the *Scopus* database at the time of data processing (as they were too recent).

2.2. Article classification

The articles retained were classified according to 5 main different criteria to characterize their prioritization methodology and scope: (1) the approach used to identify priority regions (threshold-based, if they were using an index such as species richness; or target-based using optimization techniques, e.g., spatial prioritization approach); (2) whether the strategy was reactive (prioritizing regions of high current vulnerability) or proactive (prioritizing regions of low current vulnerability); (3) the biodiversity dimension included in the analyses (taxonomic, phylogenetic or functional); (4) the conservation feature that could be represented by a taxonomic unit of focus (different species groups) or non-taxonomic unit of focus, (ecosystems or habitats); (5) and the consideration of constraints (e.g., cost) during the priority areas identification process (Table S2).

Due to the unbalanced literature focus on some taxonomic groups over others (Clark and May, 2002), the level of our taxonomic categorization was different for vertebrates vs other groups. For articles focussing on terrestrial vertebrates, we used taxonomic classes as our categories ("mammals", "birds", "amphibians", and "reptiles"). All invertebrate animals were aggregated into an "invertebrate" group, and all plants were aggregated into a "plant" group. This strategy was necessary to avoid having taxonomic categories with too few articles to be used in the MCA classification (see below). We added also two "summary" categories, "Conservation Feature: Vertebrates", and "Conservation Feature: Ecoregion/Habitat". These categories would be triggered if any of the sub-categories was triggered (e.g., the category "Conservation Feature: Vertebrates" would apply if one or more type of vertebrates were taken into consideration). We obtained a total of 19 non-mutually exclusive different categories among all criteria analysed.

2.3. Definition of articles clusters

We used MCA to analyse the relationships between articles, based on their characteristics and input data. MCA, also known as homogeneity analysis, is a tool to explore complex data and is usually used to analyse data obtained through surveys (Husson et al., 2017, 2010), and its main aim is to summarize and visualize a data table where the individuals are described by qualitative variables. MCA can be considered as the counterpart of Principal Component Analysis (PCA) for categorical data (Abdi and Williams, 2010) and involves reducing data dimensionality to provide a subspace that best represents the data in the sense of maximizing the variability of the projected points with the aim of summarizing the relationships between the variables (Costa et al., 2013; Groenen and Josse, 2016).

Thus, articles that fall in the same category are plotted close to each other and articles in different categories are plotted as far apart as possible on the new axes. MCA is then applied to multivariate categorical data coded in the form of an indicator matrix (Nenadic and Greenacre, 2005). To run an MCA on our data, we converted each category within each criterion into a binary variable (Abdi and Valentin, 2007). We then created a disjunctive table, or dummy table (Table S3), with individual articles in the rows and separate levels in the columns, each representing a possible zero/one answer to our classification criteria. The element x_{ij} of this table has a value of one if article i carries category level j, and zero if it does not. Each article could match one or more categories for each given classification criteria, e.g., in case it focussed on more than one taxonomic group. When performing an MCA, it is important to select the categories that are used to calculate the distances between individuals and thus contribute to the construction of the MCA dimensions. In the MCA it is better to avoid rare categories, that is, those with very small frequencies, as MCA attributes a lot of importance to these categories (Cornillon et al., 2012), but in our dataset there was no variable with a frequency lower than 5%.

We used HCPC to group articles into clusters, based on the results of the MCA. HCPC is a type of cluster analysis which aims to find patterns or groups of similar objects within a data set based on their similarity with respect to a set of observed variables. The agglomerative clustering is the most common type of hierarchical clustering and, in contrast to partitioning clustering (such as kmeans clustering), it does not require to pre-specify the number of clusters to be produced. The hierarchical clustering was performed through the HCPC function on the results of the MCA outputs, according to the methodology of Husson et al. (Husson et al., 2017, 2010). We used HCPC to arrange articles into a hierarchical tree (dendrogram) according to the MCA dimensions object scores (Husson et al., 2017, 2010). The HCPC function adopts Euclidean distance to characterize the distance between "individuals" (in our case, articles) and the Ward's agglomeration method to build the hierarchical tree. Agglomerative clustering works in a "bottom-up" manner, at each step of the algorithm, starting from single elements cluster (leaf), each object, or group, is joined in bigger cluster (nodes) until all the individuals are part of one single cluster. This results in a minimum set of clusters able to represent all the broad types of prioritization analyses presented in the articles.

To select the combination of variables corresponding to the best clustering, we followed a multi-criteria decision analysis, to derive the simplest possible model that had good classification performance (similar to a minimum adequate model approach, see Appendix A1). We repeated the MCA several times, each time reducing the number of variables by one (the least relevant variable), for each MCA, we performed an HCPC and evaluated the goodness of the clustering using two internal cluster validation indices, the average silhouette coefficient (S) (Rousseeuw, 1987) and the Dunn index (D) (Dunn, 1974). The S coefficient is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation) and it goes from -1 (the observation is probably placed in the wrong cluster) to 1 (the observation is well placed); a value of S around 0 means that the observation lies between two clusters. The D index aims at identifying sets of clusters that are compact and well separate. It represents the ratio between clusters separation (minimum distance between clusters) and compactness (maximum distance between data points of the same cluster), with range of 0 to infinite where larger values mean better clustering performance.

The MCA and HCPC were performed jointly, using the 'FactoMiner' package in R (Lê et al., 2008) and the S and D indices were computed using the 'fpc' package in R (Hennig, 2020).

2.4. Map generation and raster manipulation

We collected the GIS version of spatial conservation prioritization maps available from each retained article that made their data available either online or upon request. In a few cases we preferred to assign more recent maps to older articles that followed similar methodologies, and use more updated representations of biodiversity (see Table S4). All the maps were resampled at a 10 km resolution and re-projected into Mollweide equal-area projection. As a sensitivity test, we also re-run all analyses at a 50 km resolution. As we needed binary maps for our analysis, we binarized all maps that had a continuous value, to define their "priority" areas; in this case we tested the use of multiple binarization thresholds: 10%, 20%, 30%, 40%, or 50%. After the MCA and HCPC analysis, each map was assigned to a cluster. In order to identify the scientific consensus regions, we applied a formula [1] to overlay the different maps and obtain a score for each 10 km cell, taking into consideration the number of maps and their classification within each cluster:

$$Scientific\quad Consensus\quad Score = \sum_{i=0}^{n} x_i \left(1 + \frac{nmaps_i}{clustersize_i}\right) \tag{1}$$

where x_i can have values of 0 or 1 depending on the presence of at least one map from cluster i in the grid cell, $nmaps_i$ is the number of maps belonging to cluster i and represented in the grid cell, and $clustersize_i$ is the total number of maps in cluster i. This formula assigns a higher score to grid cells identified under alternative prioritization strategies (as represented by the different clusters) and, secondarily, a higher score to grid cells identified by several different articles (maps) within the same strategy.

We looked at the institutional affiliation of the different co-authors of each article and also whether a particular approach was employed that could clearly be linked to a conservation organization. In case there was no specific affiliation to a conservation institution in the author list, but the article used a methodology which is explicitly part of an NGO's core mission, we assigned the affiliation to the appropriate conservation institution. For each of institution identified, we produced a binary (policy) map overlaying all the priority maps affiliated with that institution. The policy processes of conservation organizations are almost never solely determined by science, and institutional strategies (even missions) can change quite rapidly. Thus, we make the assumption that more recent publications reflect current priorities better than older ones, and therefore will have more support consequently, we established a discount rate, that we called 'affiliation weight', such that older articles are weighted less than recent ones when it comes to potential institutional endorsement. Each priority maps affiliated with an institution was thus weighted considering the number of years since publication (n) following eq. [2]:

$$Affiliation\quad Weight = 1.1 - (n * 0.05) \tag{2}$$

Under this formulation, an article published in 2010 would have a lower policy consensus score (0.6) compared to an article from 2019 (1.05), while even any article published in year 2000 (the oldest publication date for our retained articles) would contribute to the total score to some extent (0.1). The affiliation weight was used as input in the policy consensus score, such that a grid cell associated to several recent publications from multiple agencies gets a higher score. We summed up all the affiliation scores from individual policy maps and obtained a final global policy consensus map indicating the potential cumulative interest of several conservation institutions.

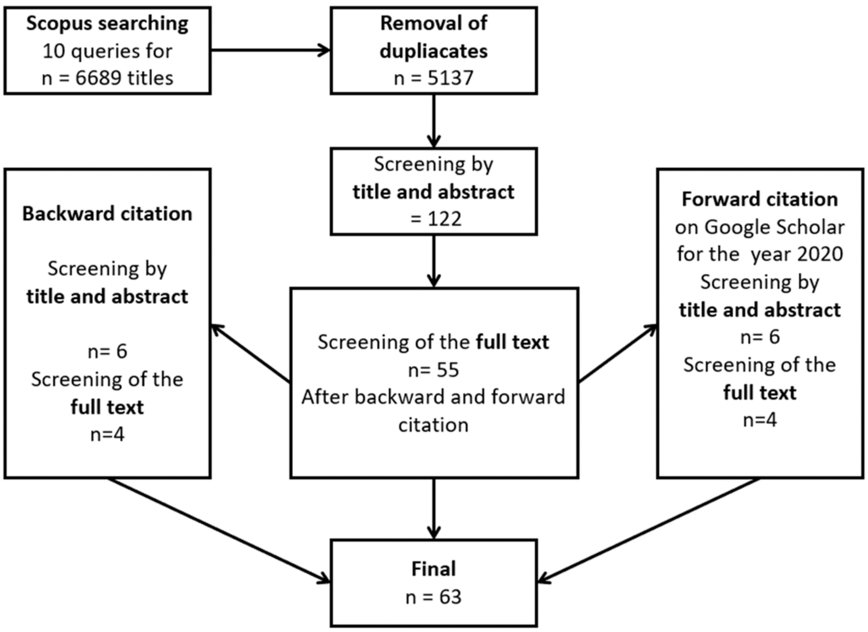

Fig. 1. Results of the literature review process, outlining outcomes of articles at searching and screening stages.

2.5. Science – Policy consensus regions and existing conservation prioritizations

We combined the scientific consensus score and the policy consensus score of each grid cell, creating a bivariate map to illustrate the relationship between the two elements. We then calculated the Pearson's correlation between the two maps and measured what proportion of the scientific and policy consensus maps is covered by protected areas according to the World Database on Protected Areas (UNEP-WCMC and IUCN, 2020), after filtering the WDPA dataset following the methodology suggested by UNEP-WCMC (https://www.protectedplanet.net/c/calculating-protected-area-coverage). Sites with status "Proposed" or "Not Reported", UNESCO Man and Biosphere Reserves were excluded, and only the points with "Reported Area" were included. We also created circular buffer with an area equal to the reported area around protected areas reported as points but lacking polygonal representation.

For each analysis, we considered the highest 10%, 30%, and 50% of scientific consensus regions, policy consensus regions, and their combination, respectively. We used R packages 'raster' (Hijmans et al., 2020) and 'sp' (Pebesma and Bivand, 2005) for GIS operations.

3. Results

3.1. Literature search and articles classification

The literature search returned 6689 results across 10 queries. After the exclusion of duplicates (articles found by more than one query), we had 5137 individual articles to screen (Fig. 1). Based on the title and abstract, we selected 122 articles (2.37%) for a full text examination, from which we retained 55 relevant articles (1.07% of those originally retrieved). We subsequently identified ten further potentially relevant articles which were not retrieved from our original queries but were cited in one or more of the papers we retained as relevant (backward citation); we retained four of these articles. We also identified six recent articles that cited one or more of the articles we retained and were also of potential relevance (forward citation); we retained four of these articles. Our final selection thus consisted of 63 articles (Table S5).

Most of the selected articles (48 out of 63) referred to mammal species (alone or amongst other taxa), followed by birds, amphibians and reptiles. Only few articles focused on invertebrates ($n = 6$ or 9.5%) or plants ($n = 10$ or 15.8%). The most frequent prioritization approach used was spatial conservation prioritization, with 27 articles (42.8%), followed by index-based approaches for 26 (41.3%) articles, and species-richness approaches for 15 (23.8%) articles. The majority of articles ($n = 45$, 71.4%) adopted a proactive conservation strategy, while 30 articles (47.6%) adopted a proactive approach and 12 articles (19%) used both the strategies (Table S6).

3.2. Definition of article clusters

The best MCA model included 11 variables: taxonomic, functional and phylogenetic dimension, mammals, reptiles, invertebrates, plants, ecoregions and habitat as conservation feature, summary class of terrestrial vertebrates and ecoregion/habitat (Table S7) resulting in an HCPC with 3 clusters. We verified that the addition of any of the excluded variables would not improve the overall classification output of the model.

Based on the MCA technique, applied to the categorization of the articles, we obtained a summary of the relationships between the variables that define the different spatial prioritization maps. The first three axes respectively explained 32.1%, 18.1%, and 13.3% of the total inertia (Fig. S2-S4). The first axis was defined by articles that focus on the conservation of ecoregions or habitats, invertebrates and/or plant, such as Mittermeier et al. (2003), Riggio et al. (2020) and Di Marco et al. (2019), thus was named "Ecoregion/Habitat Priority" axis (Fig. S5). The second axis was defined by articles that focus on the conservation of terrestrial vertebrates, such as Visconti et al. (2015) or Butchart et al. (2015) and Mokany et al. (2020), and we named it "Vertebrate Priority"(Fig. S6). The third axis was defined by articles focussing on functional and/or phylogenetic diversity, such as Oliveira et al. (2020), Brum et al. (2017) and Girardello et al. (2019), and we renamed it "Functional/Phylogenetic Priority" (Fig. S7).

The HCPC analysis, performed on the outputs of the MCA, and based on the change in inertia, yielded three clusters (see dendrogram in Figs. 3, 4). The median silhouette value was $S = 0.39$, and none of the articles had a negative silhouette coefficient which indicates good coherence within each cluster (Fig. S8). The Dunn index was $D = 0.35$, which indicates compact and well-separated clusters. Most of the articles (45/63 or 71.4%) belonged to cluster 1, while there were 11 articles (15.9%) in cluster 2, and 7 articles (11.1%) in cluster 3 (see Figs. 2, 3, Fig. S9-S10). The first cluster is mostly characterized by articles that use any vertebrate group as a conservation feature (especially mammals), do not use ecological units, and are not focused on the phylogenetic or functional dimensions of biodiversity. The first cluster included articles that are plotted close to the second axis called "Vertebrate Priority". The categories that best represent cluster 2 focus on the phylogenetic and functional dimensions of biodiversity, and articles included in this cluster are plotted close to the third axis "Functional/Phylogenetic Priority". The third cluster is mainly described by articles that are plotted close to the first axis "Ecoregion/Habitat Priority" and use the ecoregions or habitats as conservation feature to plan the prioritization and do not focus on mammals or any other specific taxon (see Table S8).

3.3. Identification of scientific consensus regions

The map of scientific consensus region was the results of the combination of 54 available maps out of 63 total maps (Table S5). When combining maps together to identify scientific consensus regions across 10 km grid cells, we had similar results across the multiple percentage cut-off we used to binarize continuous maps (10–50%). The maximum number of maps overlapping in a pixel was 43 with a 10% cut-off to binarize continuous maps which increased with higher cut-offs (up to 49 maps under a 50% cut-off). Our

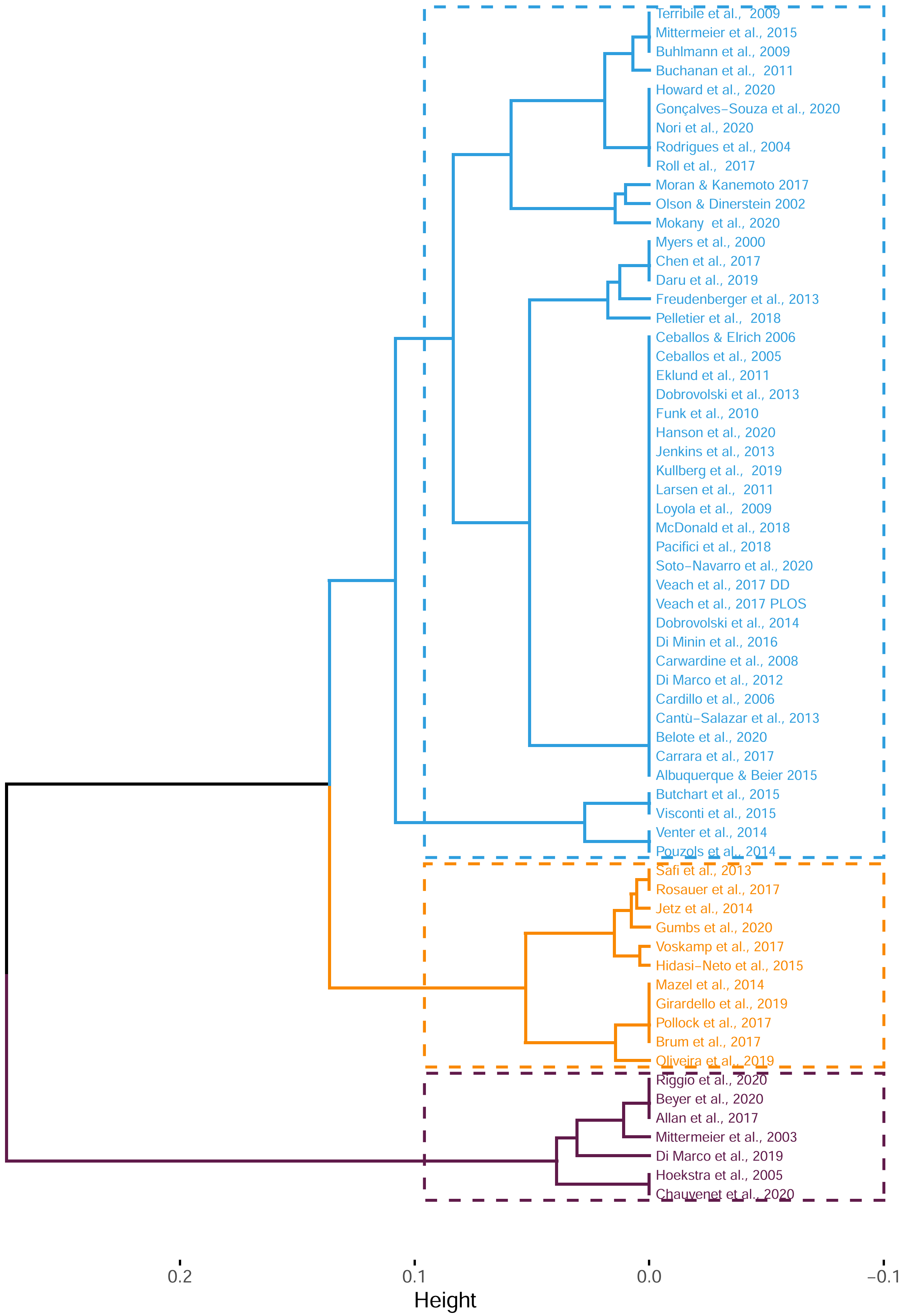

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Fig. 2. Dendrogram of the hierarchical clustering on MCA leading to three clusters. Cluster 1 is depicted in blue, cluster 2 in orange, and cluster 3 in plum. The height of the fusion, provided on the horizontal axis, indicates the (dis)similarity/distance between two objects/clusters and corresponds to the inertia gain. The upper limit of these rectangles indicates the point at which each tree has been cut.

results indicate that regions identified as top-10% ranked science consensus with the highest priority score are mainly (82.8%) located in the tropics, including the Amazon, sub-Saharan Africa and Southeast Asia (Fig. 4, Fig. S11-S12) while top-30% are equally distributed across tropical and temperate regions. The top 30% scientific consensus regions cover most of Central America and the Amazon, cells on the west coast of north America, Florida peninsula, and in Canada around the Hudson Bay. In Africa, most of Congo basin area and Gulf of Guinea cost, east RDC and Tanzania, Southwest and Southeast coast with other sparse cells in Madagascar belongs to the top 30%. Other top priority areas can be found on the coasts of Mediterranean basin, in Southeast and central India, Sri-Lanka, the Himalayan Mountain range plus some cells in Nepal, then China, Vietnam, Indonesia, the Philippines, Papua New Guinea, few sparse cells in Russia, Japan, few cells in the Kamchatka peninsula and then also Central Australia and Australian east coast, few cells in New Zealand and almost whole Tasmania (Fig. 4).

Our results were not highly sensitive to the selection of a threshold to binarize continues maps, as the main conservation priority areas remained largely the same regardless of the threshold adopted (Pearson's r between 0.81 and 0.89; Fig. S13). Hence, we chose to adopt the intermediate threshold of 30% as a reference. Similarly, the resolution at which we did the analysis did not influence the final results, and the consensus score maps at 10 km and 50 km resolution were highly correlated (Pearson's r 0.88 with a 30% cut-off).

Five maps had the highest influence in defining the final cumulative map of consensus biodiversity regions: Jenkins et al. (2013), Dobrovolski (2014), Beyer et al. (2020), Chauvenet et al. (2020), Riggio et al. (2020). Those maps had an average area of 7574, 898 km^2, about 5% of land surface, almost twice the size of the average map (3,985,145 km^2). In the top-quartile of largest maps we found 7 maps of cluster 1, 3 from cluster 2, and 4 from cluster 3. Based on this distribution, individual maps from cluster 3 (namely Mittermeier et al., 2003; Beyer et al., 2020; Chauvenet et al., 2020; Riggio et al., 2020) weighted more than those from other clusters (Fig. S14).

3.4. Identification of policy consensus regions

We identified 15 global conservation institutions (see Table S9), who have contributed to one or more of our selected articles as represented in the authors affiliation and the methodology employed in the articles. From the sum of the different affiliation map we obtained a map of policy consensus region (Fig. 5, Fig. S15-S16). The map created using a weighting based on article publication year had a max value of 14.1, compared to 15 when no weighting was implemented (Fig. S17). The areas characterized by a high interest from conservation NGOs were found in Central America, the Amazon, the south coast of Occidental Africa, the Congo basin, Himalaya Mountain chain, Southeast Asia and the East coast of Australia.

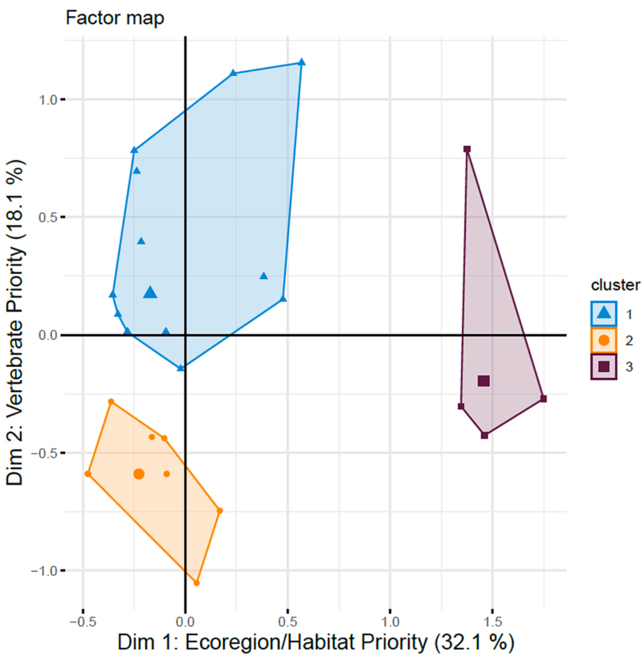

Fig. 3. Plot of the final distribution of the articles on the two most prominent MCA dimensions. Articles are colored and represented by a symbol based on the cluster to which they belong, larger symbols in the middle of the cluster represent their barycentre (the mean points of groups).

3.5. Protected area coverage of the science-policy consensus regions

The ranked scientific consensus score and the policy consensus score maps were highly correlated, with Pearson's r equals to 0.69. The scientific and policy consensus scores for regions of high biodiversity importance were correlated with protection status, with higher rank areas having higher overlap with PAs (Fig. S18-S22). However, even areas with the highest scientific/policy consensus scores were only partly protected: respectively 35.4% and 36% protection for the top-10% ranked areas, and 25.6% and 28.4% protection for the top-30% areas. Combining the map of scientific score with that of policy score, we obtained a map of science-policy biodiversity consensus (Fig. 6; Fig. S23). In this case the protection was higher but still only partial: 46.6% protection for the top-10% ranked areas, and 29.7% protection for the top-30%.

4. Discussion

By performing a comprehensive review of proposed "conservation priorities" and combining them based on the study settings, we were able to represent a comprehensive snapshot of consensus biodiversity regions. Key regions were mainly found in the tropics, but also in temperate regions in North America, Mediterranean basin, and East Asia. In most cases, the same regions were also identified as having high institutional recognition. Most of terrestrial regions include important areas identified by one or more global prioritization schemes, often overlapping and not complementary to each other (Brooks et al., 2006; Venter et al., 2014).

Spatial conservation prioritization exercises account for different conservation features, threats to such features, and the social and economic constrains of conservation action. We reviewed articles presenting spatial conservation prioritization maps which accounted for some or all of the above-mentioned elements, and we used these elements as part of our MCA articles classification approach. Our analysis refines and synthesizes global conservation priorities, making a synthesis of the maps currently available from the literature and allowing periodic update as new maps are produced. Our results underline the importance of using an MCA approach for summarizing information to be implemented in conservation prioritization as in Zizka et al. (2021), where the authors summarize existing methods for conservation prioritization in three different family, or clusters.

We combined prioritization maps focusing on different taxa and not only those which are better studied, such as mammals and birds (Di Marco et al., 2017). We included works focusing also on phylogenetical and functional diversity, which some authors have demonstrated to not necessarily overlap with taxonomic diversity (Brum et al., 2017), even if taxonomic diversity is an effective surrogacy for them in determination of conservation priorities (Rapacciuolo et al., 2019). With our work we also integrate maps using a proactive approach with maps using reactive prioritization approaches, putting together areas that are currently at risk with region that are mostly intact today but might become so in the near future. Indeed, our results recall the unified approach proposed by Brooks et al. (2006), mapping the overlay of approaches proposing reactive and proactive conservation. These are two contrasting strategies, but their reconciliation is fundamental to identify high value biodiversity region (Mokany et al., 2020). Interestingly, however, the

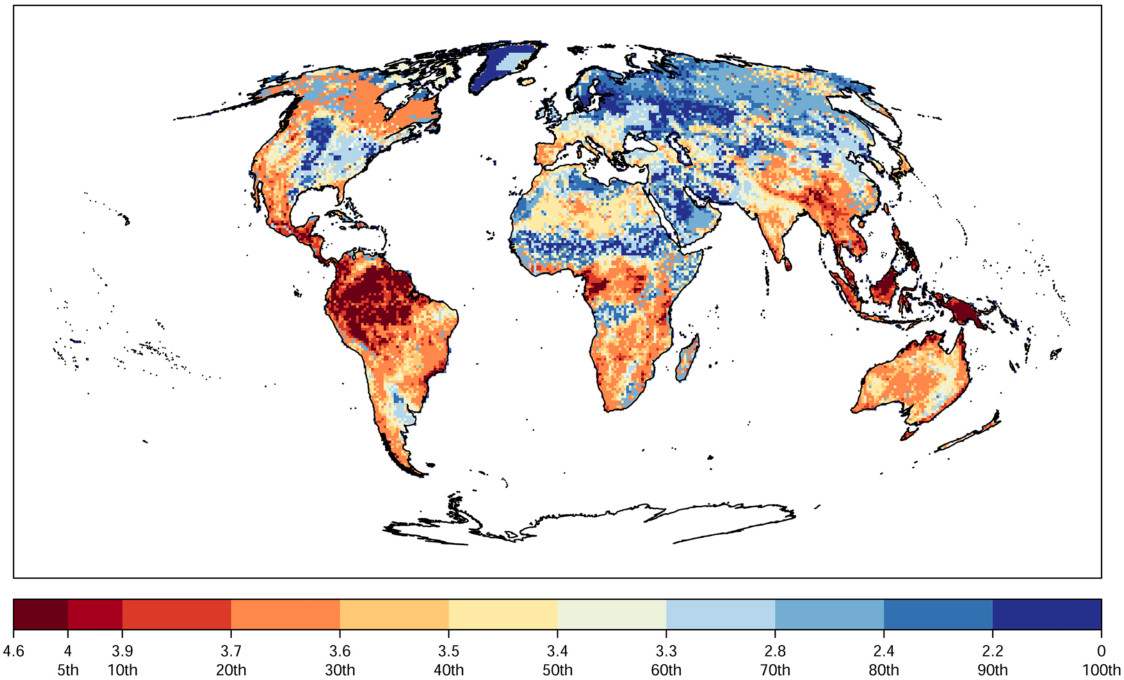

Fig. 4. Scientific consensus score, color-coded based on score decile (and 5th percentile). This map was created using a 30% cut-off to binarize continuous priority maps.

strategy with which the priorities were defined was not a key determinant for the definition of our article's clusters. The variables "reactive strategy" and "proactive strategy" were in fact not retained in the final model.

The variables retained in the final model, from the stepwise process, contributed to the creation of well-defined and not overlapping clusters of articles. This clustering did not give any case of problematic classification, but at the same time highlighted the scarcity of conservation study on invertebrates and plants at large scale (Cardoso et al., 2011). In fact, there were not enough articles focusing on these groups to create another independent cluster based on these variables. Consequently, these articles were clustered together with those focusing on ecoregions and habitats, and separately from articles on vertebrate species.

Our results indicate that the top-30% consensus biodiversity regions are almost equally distributed across tropical and several important temperate regions, for example in South Argentina, North American West coast, Alaska South coast, areas around Hudson Bay in Canada, a small part of Sahara, small coastal or mountainous region in the Mediterranean basin, Northeast Siberia and Australia. Many of these areas would not be identified under most individual global-scale prioritization studies analysed here. This is probably due to fact that we integrated maps focusing on diverse taxa, including plants and invertebrates, and multiple dimensions of biodiversity. Furthermore, we also made sure to assign equal representation to all aspects of biodiversity (including typically neglected ones). Consequently, in concordance with previous works (Hidasi-Neto et al., 2015; Mokany et al., 2020; Pelletier et al., 2018; Safi et al., 2013) our results highlighted some areas not usually included in global conservation priority schemes, sometimes at the expenses of other regions known for their importance for well-known taxa. Articles contributing the most to the definition of the first two axes of the MCA belonged respectively to cluster 3, focusing on habitat and ecoregions, and cluster 1, focusing on taxonomy. These had a major role in the identification of unrecognized regions as priorities. Wilderness areas in north America, Sahara, Russia and Australia were highlighted as priority mainly due to articles belonging to cluster 3 (only in a few cases due to cluster 1). Cluster 1 contributed together with cluster 2 to the identification of priority areas in central America, west and east coast of south America and Africa, cells in Sub Saharan Africa, west coast of India, China, Japan, Sumatra and Java Island and East coast of Australia (Fig. S14).

While the policy consensus score and the scientific consensus score were highly correlated, a small number of grid cells (ca. 2% of the top-30% scientific consensus areas) have a low affiliation score but a high biodiversity consensus score, while there is slightly higher percentage (2.4% of the top-30%) of grid cells with high affiliation score and low scientific consensus score (see Fig. 6). Thus, our results indicate that there are a few regions of high biodiversity importance which currently receive little attention from major international organizations, e.g., in Africa on the coasts facing the Gulf of Guinea, in Indonesia on the coasts facing the Java Sea or in South America in the Andes between Bolivia and Argentina. As a note of caution, we acknowledge that the calculation of our affiliation score is not comprehensive, considering that there are many more NGO working in conservation than those emerging from our analysis of literature (e.g., more than 100 international NGOs are members of IUCN). Nevertheless, our results incorporate the major conservation NGOs, and suggests there is a potential for these conservation organizations to expand their mission in a way that supports the conservation of otherwise neglected areas. On the other hand, there are regions which are potentially supported by policy even if they did not emerge as having high biodiversity importance from global analyses. It is possible that these regions have high local importance even if not a global one, and they did not emerge from global-scale analyses.

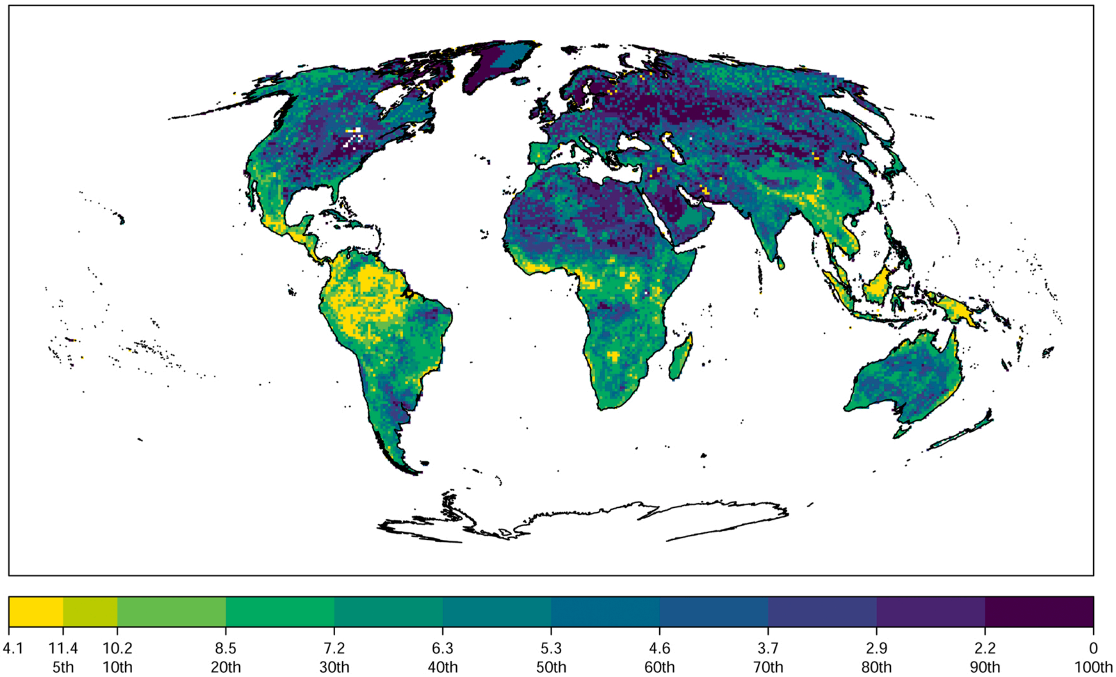

Fig. 5. Policy consensus score, color-coded based on score decile (and 5th percentile).

The primary response of the conservation community to the rapid loss of natural habitat has been to advocate for a system of protected areas, and other area-based conservation interventions, that adequately protects biodiversity (Margules and Pressey, 2000). While this has resulted in positive local-scale impacts (Butchart et al., 2012), the rate of global biodiversity loss has been much faster than the rate at which protected areas have been established (Watson et al., 2016). Overall, international conservation investments have slowed but not stopped the global biodiversity crisis (Tittensor et al., 2014; Díaz et al., 2019). In fact, different studies have demonstrated that the global protected area network is biased toward area that are cheap to protect because of their higher elevations, steeper slopes and distance from human infrastructures and urban areas, with low agricultural value and unlikely to undergo land-cover/use change (Joppa and Pfaff, 2009; Venter et al., 2018). Moreover, the expansion of global protected area coverage (UNEP-WCMC, IUCN and NGS, 2018) has not been ecologically representative (but see Brooks et al., 2004; Chauvenet et al., 2020), nor were new protected areas located in a way that strategically reduced the risk of biodiversity loss (Rodrigues et al., 2004b; Venter et al., 2018). This is reflected in our results as only one third of the regions that we identified as having the top-30% highest score of science-policy biodiversity consensus is protected. This means there is high potential for expanding protected areas over regions which are identified as important under multiple aspects of biodiversity, and according to multiple conservation organizations. Of course not all these areas will require protection, e.g., some areas might not face any imminent threat thereby not representing an immediate conservation priority (Pressey, 1997). Yet, losing those areas to habitat loss would mean that important conservation opportunities are lost, and the next-best option might generate conservation trade-offs between multiple actors.

With this work we did not aim to find a comprehensive set of regions that represent a definitive plan for area-based conservation interventions, but rather we collected all the priority maps available in the literature, defining a science-policy consensus score for regions that retain high importance for biodiversity according to multiple (independent) analyses, and have the potential to receive policy endorsement by multiple conservation organizations. We included in our analysis all available global spatial prioritization maps, regardless of their characteristics (which we then used to classify maps into clusters). Thus, our analysis assigned the same potential importance to each map, even if our approach is sufficiently flexible to allow assigning a different weight to the different

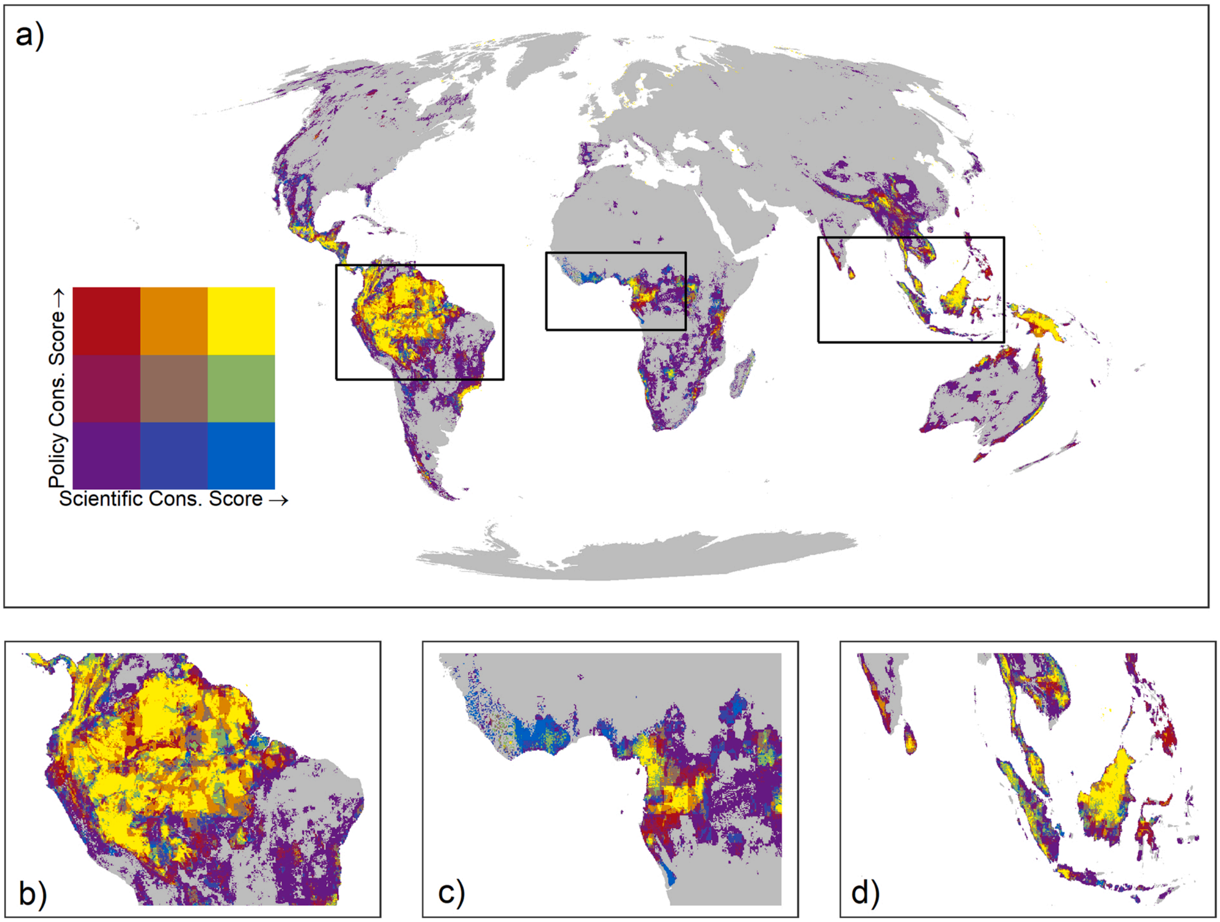

Fig. 6. a) Science- policy consensus regions, based on scientific consensus score (form purple to blue) and policy consensus score (from purple to red). The grid cell with the highest score for both the parameters are in yellow. This map reports only the top-30% highest value areas (for increased readability), while Fig. S23 reports the full results. Insets zoom in panel **b)**, **c)** and **d)** highlight blue and red areas respectively in the Amazon, coast on Gulf of Guinea and Indonesia.

clusters and even to different individual maps. Also, being aware of the constraints of global prioritization maps (Wyborn and Evans, 2021) we only suggest areas that would benefit from conservation attention, without going into details of which actions are needed and how these could be locally implemented. Thus, we propose that the scientific-policy consensus score could be used to identify candidate regions that represent great candidates for biologically and institutionally supported conservation intervention, including (but not limited to) the establishment of protected areas and other effective area-based conservation measures as part of the post-2020 Global Biodiversity Framework.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2021.e01938.

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