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# Assessing habitat diversity and potential areas of similarity across protected areas globally

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ABSTRACT

Biophysical characterization analyses of protected areas (PA) that provide information on their ecological values and potential areas with similar characteristics are needed to make informed PA network planning and management decisions. This study combines and further develops methodologies that use remote sensing and modelling to identify habitat functional types in PAs and map similar areas at the ecoregion level. The study also develops new terrestrial habitat diversity and irreplaceability indices at habitat and PA scale that allow the comparison and ranking of PAs in terms of biophysical gradients and singular environmental conditions. Six PAs were selected to highlight and discuss the results of the proposed methodology. Both individual and composite indices should be considered when trying to compare PAs to understand the overall complexity and ecological values of each PA. Results can inform planning and management of individual and protected area networks as well as identify new areas for conservation. The information provided by the model about similar habitats outside protected areas can also help assess their representativeness and support studies to strengthen ecological connectivity. Besides systematic comparisons, detailed assessments of protected areas can also be performed using medium and high-resolution input variables. This is especially relevant for protected areas in developing countries where undertaking fieldwork is very difficult and the budget devoted to conservation is limited.

## 1. Introduction

Human life on Earth is threatened by two global interlinked environmental crises: the climate change and the biodiversity crisis (De Vos et al., 2015; IPBES, 2019; IPCC, 2021; Keesing and Ostfeld, 2021; Rosenberg et al., 2019). Anthropogenic activities have severe environmental consequences, including increased frequency of flooding, soil erosion and biodiversity loss (Estrada et al., 2017; Hannah, 2008; Thomas and Gillingham, 2015). Globally, there has been an average decline of 68% in monitored vertebrate species populations between 1970 and 2016 (Almond et al., 2020). There are no cost-effective, man-made substitutes for natural ecosystems, which, besides housing populations of different species, also provide several ecosystem services, upon which society relies (Albert et al., 2021; Cardinale et al., 2012). Protected areas contain valuable ecosystems, such as grasslands, peatlands and forests, whose conservation can preserve and enhance their role as carbon pools, their protection capacity against floods or the replenishment of groundwater reserves (Griscom et al., 2017; Marques et al., 2019). The conservation of protected areas is consequently a good option to protect biodiversity, fight climate change and preserve the health and economies of human societies (Lehikoinen et al., 2019; Thomas and Gillingham, 2015).

Modelling and remote sensing methods whose outputs can be translated into information that decision-makers can use at a scale that is relevant for PA network planning and management are increasingly needed (Lucas et al., 2015; Wiens et al., 2009). In this regard, tools that generate environmental stratifications of protected areas to provide information on ecological values, as well as on potential areas with similar

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characteristics are needed at a regional and global scale (Martínez-López et al., 2021; Signorello et al., 2018).

Previous studies concerning the characterizations of PAs (Martínez-López et al., 2021) have recommended that these analyses should extend beyond specific habitat or ecosystem mapping and assessment methods so that a variety of habitats and ecosystem types can be identified. Ideally, the resulting habitat and ecosystem types identified and mapped within PAs should be comparable with existing global typologies and efforts to better deal with uncertainty, contribute to filling the gaps in current knowledge and more easily translate the results into information that can be used by policy and decision-makers. Moreover, models should be flexible methodologies capable of using large scale and time series derived input datasets, representative of longer periods, for regional and global assessments. At the same time, they should be capable of dealing with higher resolution input variables that could provide a more detailed assessment of specific PAs, thus facilitating regular monitoring of these areas.

In this regard, assessing habitat diversity through free and open-source modelling and remote sensing tools can be useful to support management plans for individual PAs (e.g., each of the identified habitat types should be managed differently) or system-level plans for PA networks (e.g. by evaluating the representativeness of PAs in relation to the full range of existing ecosystems within a given ecoregion; (Corbane et al., 2015; Nagendra et al., 2013). This is especially the case in developing countries where undertaking fieldwork is very difficult and the budget devoted to conservation is limited (Buchanan et al., 2018; Turner et al., 2015). On the other hand, measuring habitat similarity and irreplaceability can be also useful to identify new potential protected areas in order to increase connectivity within similar habitat types or between irreplaceable habitats.

Several studies have focused on species diversity to measure irreplaceability and rank PAs (Ejrnæs et al., 2018; Hoffmann et al., 2018). However, biophysical characterizations can complement those species-based studies and have also been used to perform gap analysis and representation in PAs (Forero-Medina and Joppa, 2010; Sayre et al., 2020). As part of the Digital Observatory for Protected Areas (DOPA; (Dubois et al., 2013a) proposed a methodology to assess the irreplaceability of PAs based on biophysical variables by mapping similar areas at the ecoregion level. Subsequently, the methodology developed by Martínez-López et al. (2016) breaks down PAs into distinct areas with homogeneous ecological characteristics to identify habitat functional types (eHabitat+ model). However, none of these methods originally assessed both habitat diversity and irreplaceability of PAs, which is crucial to perform integrated assessments and prioritisation analyses. In this study, we have combined and further developed these methodologies to create single and composite indicators for each PA that reflect both the PA's biophysical diversity and the irreplaceability of their habitats.

The main goal of the model and indices proposed in this study is to allow the comparison and ranking of PAs in terms of biophysical gradients and singular environmental conditions at a national, regional or global scale. This kind of information is especially useful when PAs are located in the same region (or ecoregion) since it can support an improved design of regional PA networks.

## 2. Methods

The software described here supports a fully automated analysis and builds upon different modelling tools developed over time for the DOPA (Dubois et al., 2016), which are described in the following subsections and partly already published as individual modules (Dubois et al., 2013a; Martínez-López et al., 2016). This study combines these methodologies into a single workflow and further develops new standalone and composite terrestrial habitat diversity and irreplaceability indices at habitat (within each PA), as well as at PA level. Six PAs located in different continents were selected, covering a range of biomes, ecoregions and habitats, to show and discuss the results of the proposed methodology. In addition to the five PAs that were already used in our original study (Martínez-López et al., 2016), we added Udzungwa Mountains National Park in Tanzania, to which we had applied the eHabitat+ model in a separate analysis (Brink et al., 2016). Fig. 1 shows the combination of existing and newly developed methodologies and indices carried out in this study, which will be described in detail in the following subsections.

Apart from the newly implemented modules and indices, over time, the eHabitat+ model has been further developed, some minor bugs have been solved and new parameters have been added. In this study, we used the latest version (v1.3) of the model (Martinez-Lopez, 2021). Appendix D describes the default and optional model parameters used in this study. A flowchart to demonstrate the calculation processes of the various indices and their relationship, described in Sections 2.1 and 2.2, can be seen in Fig. 2.

### 2.1. Characterization of PAs in terms of the diversity and irreplaceability of their habitats

The eHabitat+ model (Martínez-López et al., 2016) was developed to systematically stratify PAs globally into different habitat functional types (HFTs) based on remote sensing data and modelling. The methodology uses a combination of several multivariate statistical analyses based on different global predictors that account for the climate, topography, vegetation and water content within each PA.

In this study we use the same set of nine input variables as in Martínez-López et al. (2016), some of them representing long-term averages, such as the mean annual precipitation; the percentage of grassland and woody vegetation cover, the Normalised Difference Water Index (NDWI; an indicator of vegetation and soil water content), the maximum and minimum Normalised Difference Vegetation Index (NDVImin and NDVImax; indicating maximum and minimum vegetation activity), slope, mean annual biotemperature (temperature excluding below zero values) and aridity. A more detailed description of the variables, including data sources, can be found in Martínez-López et al. (2016). While the use of global datasets for the systematic assessment of PAs does not always reflect the specific environmental conditions within single PAs, it allows a proper comparison among them and between HFTs from different PAs. The use of medium or long-term derived datasets also helps capture representative trends.

First, using the eHabitat+ model, we produced maps of the different HFTs found in a PA, together with a graphical description of their ecological features and the relative differences among them. These outputs help to understand the main biophysical gradients within each PA and compare habitat diversity between different PAs.

Second, to identify and characterise potential similar areas, we mapped and quantified the similarity between the habitats found in each PA and the surrounding areas based on a set of ecological indicators within the corresponding terrestrial ecoregion. The methodology behind this step was originally proposed by Dubois et al. (2013a, 2013b) to map and quantify the similarity between a single PA and the surrounding areas, but here we used an updated method, now implemented in the eHabitat+ model (Martinez-Lopez, 2021), which uses as reference areas each of the different HFTs found in a PA, obtained through the automatic segmentation method (Martínez-López et al., 2016) and includes the computation of new landscape pattern analysis and metrics. Previous applications of the original methodology using PAs as reference areas (Dubois et al., 2013b), which are usually composed of different habitats, led to an overrepresentation of similar areas mostly based on the PAs' largest habitat type(s).

Apart from assessing the relative similarity values of all pixels contained in the corresponding terrestrial ecoregion for each HFT, the model now identifies all contiguous areas showing similarity values equal or higher than the mean (or optionally the median) similarity within the reference HFT (see Section 2.2.2). Thus, output raster maps

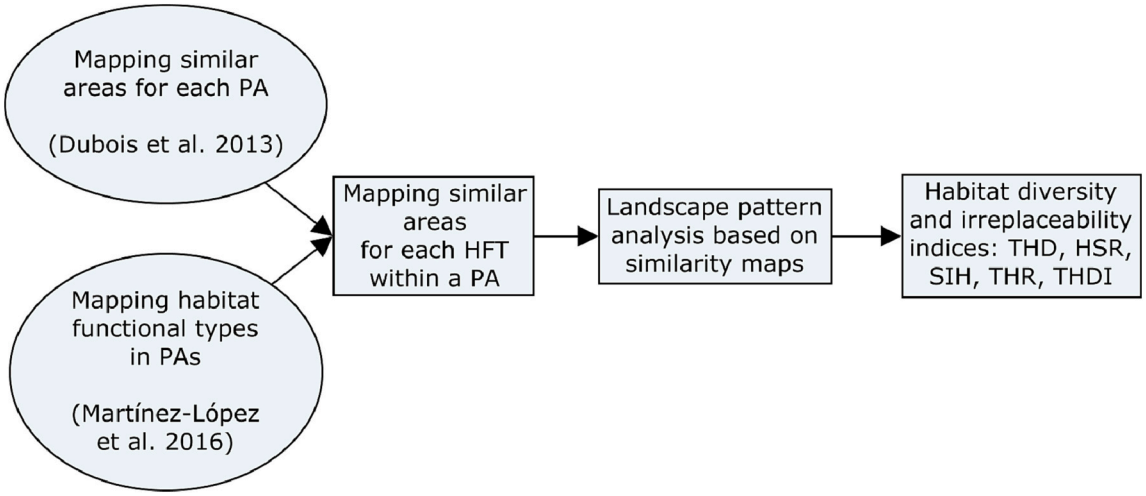


**Fig. 1.** Overview of existing (ellipses) and newly developed (rectangles) methodologies and indices combined in this study. Legend: PA (protected area); HFT (habitat functional type); HSR (habitat similarity ratio); SIH (Shannon's diversity index based on the number of habitats and their relative abundance); THD (terrestrial habitat diversity index); THR (terrestrial habitat replaceability index); THDI (terrestrial habitat diversity and irreplaceability index). See Subsections 2.1 and 2.2 for more information about the indices.

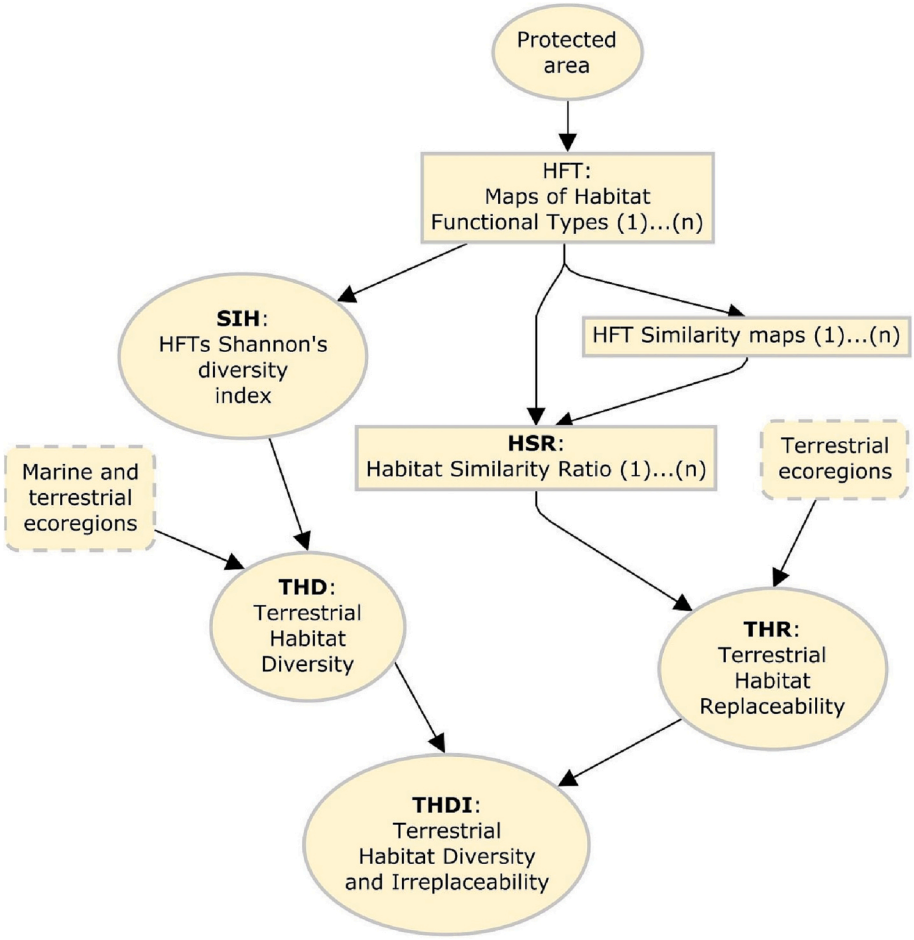


**Fig. 2.** Conceptual diagram showing the calculation of the maps and indices at protected area (ellipses) and habitat scale (rectangles with solid line pattern). The total number of Habitat Functional Types identified in a protected area is represented by the sub-index 'n'. Acronyms highlighted in bold refer to indices. Number of marine and terrestrial ecoregions used in the calculation of the indices are represented within dashed line rectangles.

are both quantitative, corresponding to the similarity values (ranging from 0 to 1 representing lower and higher similarity), and qualitative, corresponding to the presence of all landscape patches complying with the abovementioned criteria. The list with the set of landscape metrics computed based on the resulting similarity maps can be found in appendix A.

### 2.2. Composite indices of terrestrial habitat diversity and irreplaceability in PAs

#### 2.2.1. Terrestrial habitat diversity

We defined and calculated a terrestrial habitat diversity index (THD), using the following variables: (a) the number of terrestrial and marine ecoregions present or adjacent to the PA; (b) Shannon's diversity index based on the percentage of the area occupied by each HFT in the PA. The number of ecoregions in a PA is obtained by intersecting the global ecoregions layer (Olson et al., 2001) with the PA boundary using the WDPA layer (UNEP-WCMC, 2021). Marine ecoregions (Spalding et al., 2007) are also included in this metric together with the number of terrestrial ones since their presence indicates adjacency to coast, which accounts for the presence of coastal habitats.

We first calculated the percentage of the area occupied by each HFT in a PA (PercAreaHFT) and then computed the Shannon's diversity index based on the number of habitats and their relative abundance (SIH) as follows:

$$SIH = -1 \times \sum_{1}^{n} ( PercAreaHFTi \times ln\,(PercAreaHFTi)\ )$$

Where $i$ stands for a given HFT out of the total number of HFTs present in the PA ($n$) and ln stands for the natural logarithm. The higher the number of habitats and the more similar their relative abundances, the higher the SIH.

Finally, we computed the THD as follows:

$$THD = Nr.of\ \ terrestrial\ and\ marine\ ecoregions \times SIH$$

The larger the value of the THD, the more diverse a PA is in terms of different ecoregions and equally represented habitats present. For the case when there is only one type of HFT in a given PA, then the SIH value would be zero and the model would automatically assign it a value of one so that the THD would correspond to the number of terrestrial and marine ecoregions.

#### 2.2.2. Terrestrial habitat replaceability

We defined and computed a Habitat Similarity Ratio (HSR) for each HFT as the ratio between (a) the total number of pixels contained in all similar landscape patches (representing contiguous pixels with similarity values equal or higher than the mean - or optionally the median - similarity within the reference HFT) with an area equal to or larger than the HFT (otherwise only the largest one) and (b) the number of pixels of the reference HFT. The larger the HSR, the more potential similar areas to the HFT were found. An HSR value below 1 indicates that all the similar landscape patches found are smaller than the HFT of reference. It is important to note that the total amount of similar areas (all similar pixels regardless of their spatial pattern and patch size) to an HFT is often much larger than the number of similar areas meeting the criteria used by the HSR (only contiguous pixels, i.e. landscape patches, normalised by the area of the reference HFT). Hence, using this more restrictive metric allows us to provide more realistic replaceability assessments.

We then defined a terrestrial habitat replaceability index (THR) as the median HSR value of all HFTs found in a PA divided by the number of terrestrial ecoregions that are present in the PA. The higher the THR, the more potentially replaceable would tend to be the HFTs present in a PA. By using the median value of the HSR values, we tried to represent the most frequent situation of the HFTs in the PA. Dividing by the number of terrestrial ecoregions present in a PA is used as a way to normalise the THR value, given that PAs that are contained in several ecoregions might tend to show more similar areas (see appendix I).

#### 2.2.3. Terrestrial habitat diversity and irreplaceability

As a combined metric of habitat diversity and irreplaceability, we defined and calculated a terrestrial habitat diversity and irreplaceability index (THDI) as follows:

$$THDI = \frac{THD}{THR}$$

The larger the value of the THDI, the more diverse and/or irreplaceable a PA is. In this case, increasing THDI values do not necessarily imply both higher THD and lower THR scores, since one of them might be comparatively much higher or lower, representing a trade-off.

## 3. Results

### 3.1. Diversity and irreplaceability of habitats within protected areas

Overall, a maximum of six HFTs per PA was found and HSR values were very low for most HFTs, in contrast to some of them, present in Canaima and Virunga National Parks, which showed very high values. A more detailed description of the results for each PA studied can be found in appendix H, including the HFT maps, together with the maps containing the similar landscape patches (appendix B and G) and the HSR values for all HFTs (appendix E). A more detailed description of the PAs analysed can be found in previous studies (Brink et al., 2016; Martínez-López et al., 2016).

In Canaima National Park (Venezuela) six HFTs were found, two of them showing very contrasting patterns and one other HFT notably presenting the highest seasonality and slope values. HFTs in this PA show contrasting HSR values, ranging from 0.07 to 13.85. Some HFTs show abundant and partially overlapping landscape patches with similar areas that can be found mostly inside and around the PA, indicating a potential ecological corridor with other PAs, but also in distant areas of Venezuela, Brazil and French Guiana, very often also overlapping with different PAs. Other HFTs show fewer similar areas, most of them in or around the PA.

In Kakadu National Park (Australia) six HFTs were found. Some HFTs present similar characteristics, being mostly differentiated by NDVI (min and max), NDWI and vegetation cover. All HFTs in this PA have low values on HSR (ranging from 0.01 to 0.59), indicating that these HFTs are all highly irreplaceable. Most similar landscape patches are located around the HFTs, often pointing to the presence of ecotone areas between them. Some similar areas located directly outside the current PA boundary suggest that an expansion of the PA could provide more complete protection for these HFTs.

In the Okavango Delta (Botswana) six HFTs were found. Two of them are similar in most variables, showing a clear predominance of grassland vegetation in contrast to the other HFTs. On the contrary, other HFTs are characterised either by more abundant woody vegetation cover or by lower vegetation cover and higher slope values. A general North-South gradient of increasing aridity can be observed across the PA. All HFTs in this PA have very low values of HSR, ranging from 0.01 to 0.11, indicating that these HFTs are all extremely irreplaceable. Similar areas to the HFTs are therefore very scarce and are located around the border of the PA, often indicating the presence of ecotone areas among HFTs.

In Sierra Nevada Protected Area (Spain) five HFTs were found. Some HFTs show similar patterns in most variables, while others are similar in terms of vegetation type but show very contrasting values for climatic and topographic variables. Two of the HFTs represent high mountain areas, presenting similar climatic patterns but showing very different characteristics in terms of vegetation. All HFTs in this PA have low values of HSR, ranging from 0.04 to 1, indicating that most of these HFTs are highly irreplaceable. Several landscape patches containing similar areas to the different HFTs can be found in their proximity, as well as along other mountainous areas across the Mediterranean region. Since this PA is mostly a high mountain, it contains several bioclimatic zones which are also present in other northernmost latitudes within the Iberian Peninsula. These areas can be identified in the similarity maps.

In the Udzungwa Mountains National Park (Tanzania) five HFTs were found showing a clear gradient of increasing woody vegetation cover from HFT 1 to HFT 5, accompanied by a decreasing gradient of

grassland vegetation cover. In general, there is also an increasing gradient of NDWI values from HFT 1 to HFT 5. All HFTs are quite different from each other, with HFT 3 showing average values in several variables in comparison to other HFTs. All HFTs in this PA have low values of HSR, ranging from 0.06 to 0.77, indicating that these HFTs are all highly irreplaceable. Very few similar landscape patches can be found around some HFTs, sometimes indicating the presence of ecotone areas between them. On the contrary, other HFTs show dispersed similar areas, some of them very distant from the PA.

In Virunga National Park (Democratic Republic of the Congo) five HFTs were found. Two of the HFTs show very contrasting patterns, especially in terms of aridity and vegetation cover, whereas others show more similarities. Seasonality (difference between the minimum and maximum NDVI) is also one of the variables that clearly distinguishes some HFTs from others in this PA. HFTs in this PA have very contrasting values of HSR, ranging from 0.14 to 62.04. Some similar areas are around the HFTs, often pointing to the presence of ecotone areas between them, while others are several kilometres away, sometimes in the proximity of lakes or overlapping with existing PAs, such as the Bokkora Wildlife Reserve, the Pian Upe Game Reserve or the Nyungwe Forest National Park. Some similar areas located directly outside the current PA boundary suggest that an expansion of the PA could provide more complete protection for these HFTs.

### 3.2. Comparison of composite habitats diversity and irreplaceability indices between protected areas

In this section, we compare the selected PAs based on the scores of the composite indices at PA scale and explain the differences among them, moving from the lowest to the highest THDI value (Fig. 3 and appendix F). Kakadu shows a large SIH value but a low number of ecoregions, leading to a rather low THD value. Besides, it also has a rather high THR value, leading to the lowest THDI of this set of PAs. Sierra Nevada also has a high SIH value but a slightly higher number of ecoregions than Kakadu, leading to a higher THD. Since the THR in Sierra Nevada is only slightly higher than in Kakadu, this PA finally scores a higher THDI. Udzungwa has the same number of ecoregions as Sierra Nevada but a lower SIH, leading to a lower THD. However, the THR in Udzungwa is much lower than in Sierra Nevada, leading to a higher THDI. Canaima shows a higher number of ecoregions and a higher SIH value than Udzungwa, leading to a much higher THD value. Although the THR value is also higher than in Udzungwa, the final THDI score is slightly higher in Canaima. Virunga has the same number of ecoregions as Canaima and a higher SIH value, which leads to a higher THD value. Moreover, the THR is lower in Virunga than in Canaima, both resulting in a higher THDI value. Okavango has a lower number of ecoregions than Virunga and a similar SIH value, which leads to a lower THD value. However, Okavango has a much lower THR value, which finally results in the highest THDI of this set of PAs.

The THDI undoubtedly represents a trade-off between the THD and the THR, being very much influenced by the number of ecoregions, the extent of potential similar areas and the habitat diversity (see appendix C with the relative percentage of area occupied by each HFT in the different PAs, which is used to compute the SIH). Although most HSR values across PAs tend to be very low (see appendix E), with only a few HFTs showing very large values, the THR index manages to minimise the

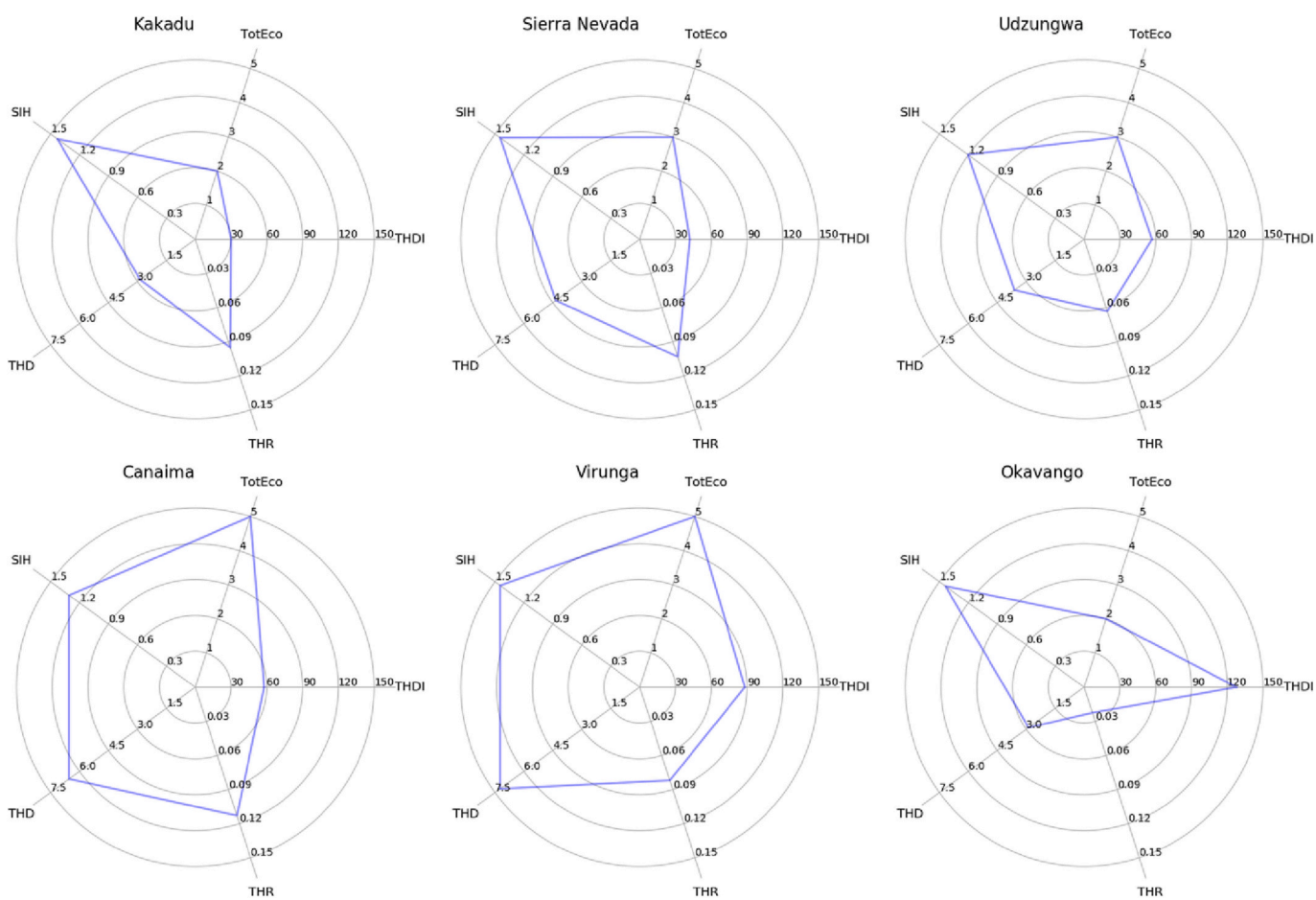


**Fig. 3.** Results for the different indices by protected area. Legend: TotEco (Total number of terrestrial and marine ecoregions); SIH (Shannon's diversity index based on the number of habitats and their relative abundance); THD (Terrestrial habitat diversity index); THR (Terrestrial habitat replaceability index); THDI (Terrestrial habitat diversity and irreplaceability index). Protected areas are ordered from left to right and from top to bottom in increasing order of THDI value.

effect of extreme values producing a gradient of scores across PAs. In general, higher THD values tend to yield higher THDI values, except for Okavango, while lower THR values tend to yield higher THDI values.

## 4. Discussion

The new methodology and indices proposed in this study allow the comparison and ranking of PAs in terms of biophysical gradients and singular environmental conditions at a local, regional or global scale. Several new and complementary indices are provided by our model at different scales - habitat type versus protected area, as well as diversity versus irreplaceability - which should be taken into account when trying to compare different PAs to better understand the overall score of the final THDI value for each PA, in order to make more informed decisions. This is especially relevant at the regional and global scale given that there is limited systematic data on habitat diversity and irreplaceability in protected areas, which is needed for effective conservation management to support the design and evaluation of large-scale conservation plans based on prioritisation studies, one of the targets of the new Global Biodiversity Framework (Cazorla et al., 2021; CBD, 2022; Keith et al., 2022). Additionally, by providing information about existing and potential habitats in and outside protected areas, our model can help to assess whether protected areas are representative of their surrounding ecoregions.

One of the strengths of the methodology is to allow the comparison between PAs at large scales, rather than the precise delimitation and characterization of HFTs in single PAs, the latter being especially dependent on the scale at which the analysis is done. However, more detailed standalone assessments of a single or a set of PAs (e.g., PAs located in a specific ecoregion) could also be performed using higher-resolution input data, which could vary depending on the main ecological drivers in the ecoregion(s) where the PA is located. Besides, environmental impact assessments could be performed using temporal data corresponding to before and after the implementation of a specific human intervention in a PA.

If used in conjunction with forecasted bioclimatic data, the eHabitat+ model can partially help identify new areas for conservation by considering current and climate change scenarios. Our model does not only use climatic variables but changes in those inputs would certainly influence results. Therefore, the similarity maps that are produced can be used, under current and future predicted conditions, to redesign the current boundaries and network of PAs, identify new potential areas to be protected and strengthen ecological connectivity among PAs. Also, the indices computed for individual HFTs within a PA could support management interventions at the habitat level. In this regard, results of our model could be used to integrate remote sensing with in-situ observations to produce essential biodiversity variables (Pereira et al., 2013).

Regarding the THD, it could be argued that the total number of ecoregions plays a major role in comparison with the SIH. This is indeed the case because we wanted to weigh the fact that PAs containing a higher number of ecoregions tend to provide a significantly higher representation of relevant bioclimatic conditions over larger scales. However, an alternative could be to compute the Shannon's diversity index based on the number of ecoregions and their relative abundance, and combine it with the SIH (e.g., by calculating the THD as the sum or the mean value). In this case, the inclusion of marine ecoregions to indirectly account for the presence of coastal ecosystems should be done differently. Therefore, the THD index could be eventually redefined after being tested in a larger set of PAs.

Regarding the THR, there is a risk of overlooking a single or few very irreplaceable (maybe even endemic to the PA) HFTs if all other HFTs in the PA are quite common and therefore have high HSR values. It is also interesting to note that larger HFTs will tend to show lower HSR scores, given that in general, it is more difficult to find such large contiguous similar areas. To address this concern, the THR uses the median value of the single HSR values, which is much more representative of the PA than using the mean values. In this regard, we recommend always looking at the indices at HFT and PA scales (single HSR values versus the THR) to include information from different scales in our assessments. The same can be said regarding the THDI, for which increasing values do not necessarily imply both higher and lower THD and THR scores, respectively, but rather represent a trade-off between both indices. Therefore, diversity and irreplaceability indices should be taken into account individually as well. Moreover, instead of using the proposed THDI, the THD or the THR could be used in isolation or be differently weighted for computing the final THDI, depending on the ultimate objective of the analysis.

Regarding the specific results in the set of PAs analysed in this study, it is not surprising that the Okavango Delta yields the highest THDI values among them given that this is the world's largest inland delta comprising a unique composition of terrestrial and freshwater habitats (Ramberg et al., 2006). However, the values of the proposed set of indices are easier to interpret and compare among PAs located in the same ecoregion(s), where results are more comparable and potential similar areas could be studied also in relation to other PAs, especially for the design of potential corridors among them.

Often, similar landscape patches are inside other PAs (see the case of Virunga for example), which could be systematically quantified and integrated into new indices to assess to what extent similar areas are already protected. This could, for instance, be taken into account in the calculation of a future version of the THR that would eventually distinguish between the amount of unprotected and protected similar areas available. Also, pressure levels on PAs could be taken into account in these or new indices, such as pressures coming from roads, agriculture or population (Dubois et al., 2013b; Dubois et al., 2015, 2016).

New input variables should also be added for large-scale assessments, as suggested by (Martínez-López et al., 2021), such as mean solar radiation, fire frequency, cloud cover frequency, water seasonality, or soil-related variables. This could improve the assessment and eventually make it more comparable to other assessment methodologies at different scales (Jung et al., 2020; Keith et al., 2020; Lucas et al., 2015; Sayre, 2014; Sayre et al., 2020; Tuanmu and Jetz, 2015).

## 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.

## Data availability

Data will be made available on request.

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## Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2023.102090.

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