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ISPRS International Journal of Geo-Information

Accepted/In press: 28/05/2021

Peer reviewed version

Remote sensing methods for the biophysical characterization of protected areas globally: challenges and opportunities

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Abstract

Protected areas (PAs) are a key strategy to reverse global biodiversity declines, but they are under increasing pressures from anthropogenic activities and concomitant effects. Thus, the heterogeneous landscapes within PAs, containing a number of different habitats and ecosystem types, are in various degrees of disturbance. Characterizing habitats and ecosystems within the global protected area network requires large-scale monitoring over long time scales. This study reviews methods for the biophysical characterization of terrestrial PAs at global scale by means of remote sensing (RS) and provides further recommendations. To this end, we first discuss the importance of taking into account structural and functional attributes, as well as of integrating a broad spectrum of variables, to account for the different ecosystem and habitat types within PAs, considering examples at local and regional sale. We then discuss potential variables, challenges and limitations of existing global environmental stratifications, as well as biophysical characterization of PAs, finally offering some recommendations. Computational and interoperability issues are also discussed, as well as the potential of cloud-based platforms linked to earth observations to support large scale characterization of PAs. Using RS to characterize PAs globally is a crucial approach to help ensure sustainable development, but requires further work before such studies are able to inform large-scale conservation actions. This study proposes 14 recommendations in order to improve existing initiatives to biophysically characterize PAs at global scale.

Keywords: Protected areas; remote sensing; biophysical characterization.

1. Introduction

Protected areas (PAs) are one of the main conservation strategies to counter the current biodiversity crisis [1]. However, PAs are under ongoing social, economic and environmental threats and so the conservation of biodiversity within PAs and the restoration of PAs constitute one of the main current socio-political challenges [2]. The long-term conservation benefits of PAs depend on timely management actions based on relevant data and models that can predict the response of ecosystems to various stress factors [3,4].

Anthropogenic activities and the changes in land use they generate have an impact on how efficient PAs are in protecting biodiversity globally [5,6]. Moreover, climate change impacts severely affect PAs, including increased frequency of flooding, soil erosion and plant water stress [7]. It is increasingly recognized that even large, historically stable ecosystems (such as the Amazon) are threatened and could undergo regime shifts to alternative ecosystems within 50 years [8].

The 2030 Agenda for Sustainable Development[1] recognizes that social and economic development depends on the sustainable management of our planet's natural resources. The new EU Biodiversity Strategy for 2030 has further set ambitious goals and objectives regarding PAs, i.e. (i) to legally protect 30% of the EU's land's area and 30% of the EU's sea's area, (ii) to strictly protect at least a third of the EU's PAs and (iii) to effectively manage and monitor all PAs [9]. The forthcoming new global strategy of the UN Convention on Biological Diversity (CBD) is also likely to set targets that are more ambitious than those set for 2020. Addressing these challenges requires large-scale integrated studies that characterize PAs as well as knowledge sharing platforms where scientists, managers and policy makers can work together to address the challenges mentioned above [10,11].

Recently, there has been an increase in the attention paid not only to the conservation of biodiversity within PAs but also to the preservation of important habitat and ecosystem functions and services [12–15]. Indeed, natural ecosystems provide us, among others, with drinking water, timber, food, pollination and carbon storage as well as cultural and spiritual services. This was examined in detail in the Millennium Ecosystem Assessment [16] and was further reflected in Aichi Target 11[2] adopted by CBD parties in 2010. Moreover, habitat and ecosystem characterizations can provide important complementary insights to the more commonly used species-based approaches to conservation [17–19].

Remote sensing is considered a valuable source of information for the management of natural resources and landscapes [20–22], as well as for the development of indicators for monitoring progress towards international environmental targets such as the Sustainable Development Goals (SDGs) [23,24]. Available time series allow, among others, the monitoring of vegetation condition, landscape and habitat changes, land degradation, the assessment of ecosystem services, the identification of disturbed areas, and the monitoring of the spread of invasive species [25–28]. They thus help to understand ecosystem response and resilience to multiple

[1] https://www.un.org/sustainabledevelopment/sustainable-development-goals/
[2] https://www.cbd.int/aichi-targets/target/11

stressors [29]. In this regard, remote sensing has revolutionized our ability to monitor PAs over the past decade [20,30–33].

Several broad types of application can be supported by RS data and models in relation to PAs. A first type would be the near / real time monitoring of biodiversity, pressures and threats, environmental anomalies (such as weather and vegetation) and events such as fires, floods and storms - all highly relevant to inform day-to-day PA management, enforcement and risk management, etc. [34–36]. A second type of application would be the mapping and assessment of specific habitats and ecosystems - relevant for e.g. management plans, monitoring strategies or condition assessment. This latter type of studies paves the way for a third type of application that extends specific habitat or ecosystem mapping and assessment methods and integrates this information to systematically characterize PAs based on their ecological complexity - relevant for e.g. zoning plans, assessment of representativeness, prioritization of PAs or the identification of new areas requiring protection [37–40]. This paper focuses on these biophysical characterization applications.

While there have been a few attempts to characterize landscapes from an ecological perspective from local to regional scale [41–45], global characterization of PAs is urgently needed for the identification of gaps in current protection efforts, the systematic design of complementary PAs, raising awareness about the ecological values of PAs, as well as to support international policy initiatives aimed at preserving biodiversity and ensuring a high provision of ecosystem services [46]. Moreover, global biophysical characterization of PAs can also facilitate and complement biodiversity based protection initiatives and characterizations [47–49]. As an example of previous global efforts, the ‘terrestrial ecoregions of the world’ [6,50] represent a set of large ecologically meaningful regions at global scale, containing distinct assemblages of natural communities and species, but do not provide additional information on ecosystems contained within those ecoregions and have rather been used to prioritize the conservation importance of larger regions [51] .

This study seeks to provide recommendations for the biophysical characterization of terrestrial PAs at global scale by means of RS. To this end, in section 2 we discuss the importance of taking into account structural and functional attributes, as well as of integrating a broad spectrum of variables, to account for the different ecosystem and habitat types within PAs, reviewing examples at local and regional sale. In section 3, we discuss potential candidate input variables at global scale for the characterization of PAs, as well as challenges and limitations of existing global environmental stratifications and biophysical characterization of PAs, and offer recommendations. Computational and interoperability issues are also discussed, as well as the potential of cloud-based platforms linked to earth observations to support large scale characterization of PAs. Finally, section 4 provides a summary list of recommendations. Although focusing on terrestrial areas, we also mention a few examples of RS data used to characterize Marine Protected Areas (MPAs).

2. Relevant ecological units and descriptors

In order to comprehend the ecological complexity in PAs, biophysical characterizations of PAs should take into account the different ecosystem and habitat types that are present within them and, as much as possible, distinguish their ecological attributes, including structural and functional ones. To this end, a wide range of environmental descriptors should be included in the analysis, including drivers that ultimately shape ecosystems (Figure 1).

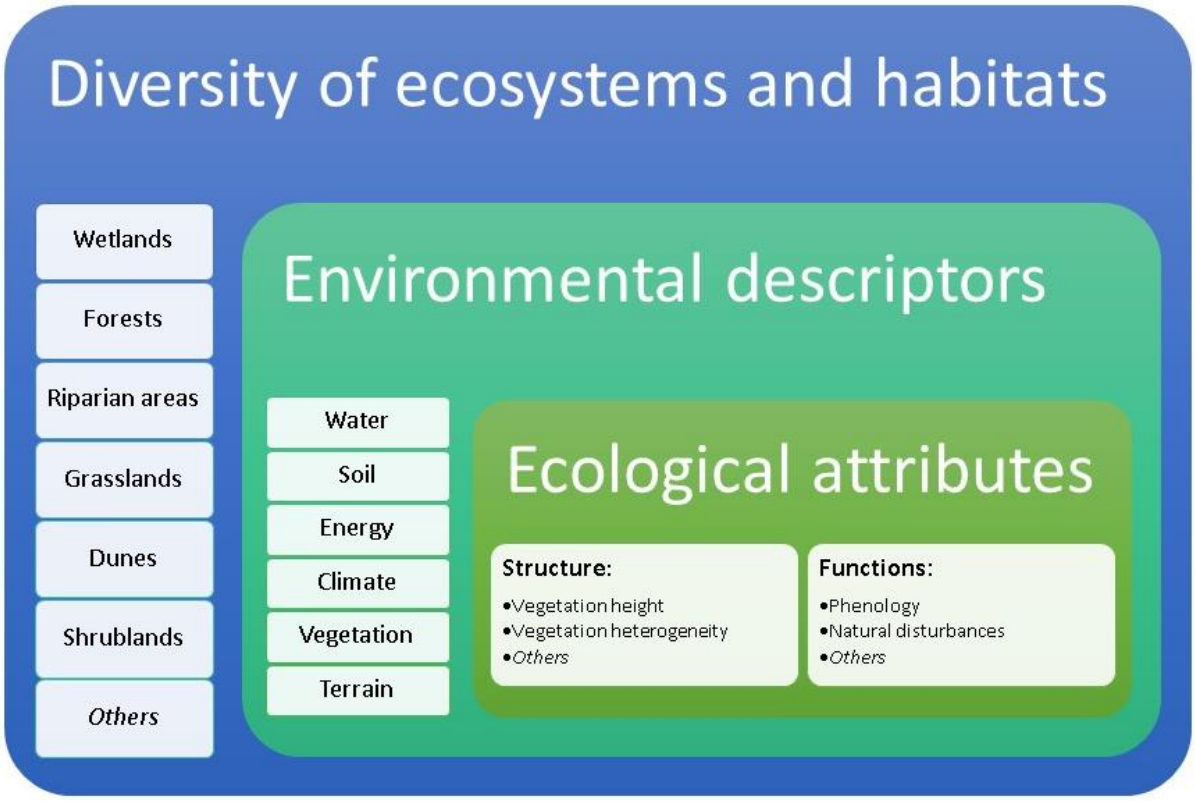

Figure 1. Overview of the different elements that need to be included and analyzed in biophysical characterization of PAs.

The assessment of structural attributes, such as vegetation height or heterogeneity by means of RS, helps distinguish characteristic ecosystems and habitats within PAs - such as forests, wetlands, grasslands, shrublands, dunes and riparian habitats, among others. Furthermore, RS variables related to functional attributes, such as vegetation phenology or energy fluxes, have proven to complement and improve habitat and ecosystem classifications based only on structural features by capturing the occurrence of natural disturbances, vegetation productivity, etc. [52–54]. Several studies have reviewed the use of RS for assessing habitat and ecosystem structure, function and condition in PAs at local and regional scale [24,55–62].

With regard to structural attributes, wetlands, riparian forests and dune habitats for example have been mapped by means of texture and object-based RS data analysis and machine learning algorithms in order to characterize and monitor changes in PAs [63–73]. Grasslands have been accurately mapped using time-series of RS data [74]. Forest and shrubland structure has been mapped by means of very high-resolution imagery [75–77]. Tree species richness across the tropics has been mapped by means of full-waveform lidar data [78]. Vegetation structure has been mapped at local and regional level in PAs by means of manned and unmanned aerial vehicles carrying airborne LiDAR and multi- and hyperspectral sensors

[79–81]. Chetan and Dornik [82] quantified changes in vegetation greenness and structure within Natura 2000 sites over 20 years. Vegetation heterogeneity and pattern has been characterized by means of image texture measures (i.e., Grey Level Co-occurrence Matrix) derived from RS data [83–89].

In relation to functional attributes, several studies have quantified vegetation productivity over time by means of remote sensing derived indices and have found correlation with biodiversity patterns [90–93]. Moreover, the effect of disturbances, such as post-fire forest vegetation regrowth has been studied by means of different RS vegetation indices [94,95]. For a recent review of methods, sensors and ecosystems structural and functional attributes assessed by means of RS in PAs see [33].

Furthermore, given the inherent ecological complexity that can be found within PAs, their systematic characterization needs to extend specific habitat or ecosystem mapping and assessment methods, so that all habitat and ecosystem components that are present within them are taken into account [96,97]. By stratifying the natural landscape into homogeneous regions defining ecological units, the complexity of PAs can be converted into something that is more manageable and understandable [98]. For example, if a protected landscape contains both a lake and mountains, separating both elements cartographically would help inform and support adaptive management. In this regard, methods to characterize PAs should rely on a comprehensive list of environmental quantitative descriptors based on RS data, which could be categorized into different topics: a) vegetation, including structure, phenology and disturbances; b) climate; c) water budget; d) energy exchanges; e) terrain and f) soil, among others (Table 2).

As previously mentioned, vegetation related variables, such as the amount of woody and herbaceous biomass or different vegetation indices, can help us distinguish between broad ecosystem types (such as forests, grasslands or wetlands) by capturing their structure, phenology and productivity [99]. Climatic descriptors, such as precipitation and temperature, are also important variables to be included in biophysical assessments to represent seasonality, extremes and limiting climatic factors [100–103]. Topographic gradients drive many patterns and processes in hydrology and ecology and are key to understanding the variation of habitats and biodiversity [104,105]. Water related variables are also a good proxy for plant water stress and presence of aquatic ecosystems, and can therefore supplement the information on climate and vegetation by distinguishing differing responses to available water [106–108]. Variables that describe the energy exchanges between the land surface and the atmosphere, as well as the partition of energy into ground and vegetation are also essential for ecological assessment and modelling [109].

Soil data are often ignored when characterizing PAs but more than 25% of the Earth's species live only in the soil [110]. Besides, soils form the foundation for many vegetation types and provide key supporting ecosystem services that are crucial for the maintenance of other types of services [111]. Given that soil biodiversity cannot be directly monitored by RS, soil descriptors that can be directly or indirectly monitored by RS and modelling can act as proxies [112,113]. In this regard, soil organic carbon appears as one of the main drivers of soil microbial biodiversity at the global scale [114–116], particularly in extreme environments with low net primary productivity, such as polar [117] and dryland regions [118]. Soil texture is also

a relevant descriptor since previous research has demonstrated that soil biota abundance and biodiversity, particularly soil microorganisms, increase with decreasing soil particle size [119].

3. Global characterization of protected areas

3.1. Global input variables and data sources.

In the previous section we have reviewed the importance of taking into account structural and functional attributes, as well as of integrating a broad spectrum of variables, to account for the different ecosystem and habitat types within PAs. In this subsection we give a list of potential candidate input variables, mapped at global scale, for global characterizations of PAs and discuss some limitations and recommendations.

Data sources presenting time series and regular updates at global scale should be favored over single records in time to allow for the assessment of change over time and identify reference conditions. Often, when correlated variables are used, principal component analysis can be applied in order to compress them and use the resulting uncorrelated axes as input for the models to avoid redundant predictors [120].

Given that global RS data usually shows greater inaccuracies than local or regional datasets, the use of ensembles of different input data or models corresponding to the same variable might be of advantage, providing more accurate outputs, as well as better conveying uncertainty [121–125]. Besides, many biophysical variables mapped at local or regional scale are not available at global scale, which might limit the relevance of global analyses for local scale management. Therefore, global characterization of PAs should be primarily aimed at informing larger scale conservation and management actions and plans, unless no better information is available at local or regional scale.

Table 1 lists a set of recommended variables that can be used at global scale for the biophysical characterization of terrestrial PAs. The list is not exhaustive but provides a wide range of relevant variables, including potential data sources. A more comprehensive list of potential variables can be found at the Global Climate Observing System Programme[3] or the Copernicus Global Land Service[4]. A table with additional information including URLs of data sources can be found as supplementary material. For MPAs, previous studies have highlighted candidate variables measurable by RS relevant to characterize marine habitats [126–130]. They include, among others, bathymetry, concentration of chlorophyll-a, sea surface temperature or sea surface salinity. A comprehensive list of these marine variables - together with access to the RS measurements of these variables - can be also found at the Copernicus Marine Service[5] and the Living Wales Geoportal[6].

Table 1. Relevant biophysical input variables that can be used for the characterization of terrestrial protected areas at global scale. Acronyms used: NASA National Snow and Ice Data

[3] https://public.wmo.int/en/programmes/global-climate-observing-system/essential-climate-variables
[4] http://land.copernicus.vgt.vito.be/PDF/portal/Application.html#Home
[5] https://resources.marine.copernicus.eu/?option=com_csw&task=results
[6] https://wales.livingearth.online/data/environmental-variables/marine/

Center (NSIDC); U.S. Geological Survey (USGS); European Space Agency (ESA); Global Land Analysis and Discovery (GLAD); Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales (HydroSHEDS); General Bathymetric Chart of the Oceans (GEBCO).

Topic	**Variable**	**Based on RS**	**Temporal extent and resolution**	**Spatial resolution**	**Producer**
Climate	WorldClim bioclimatic variables (a set of temperature and rainfall variables specifically developed for ecological modeling)	No	Monthly average climate datasets from the period 1970 to 2000 and future climate data.	1 km	WorldClim version 2.1: [101]
Climate	Mean annual precipitation				
Climate	Potential Evapotranspiration	Yes	Multi-daily datasets from 2001 to present.	500 m	USGS
Climate	Cloud cover	Yes	Monthly average from a 15 years period (2000-2014)	1 km	EarthEnv [131]

Vegetation	Fire frequency	Yes	Monthly data from 2001 to present.	250 m	ESA Copernicus [132–134]
Vegetation	Percentage of woody vegetation cover	Yes	Yearly datasets from 2000 to 2020.	250 m	USGS
Vegetation	Percentage of grassland cover				
Vegetation	Mean of the maximum and minimum Normalized Difference Vegetation Index	Yes	Multi-daily datasets from 2000 to present.	250 m	USGS

Vegetation	Leaf Area Index	Yes	Multi-daily datasets from 2014 to present.	300 m	ESA Copernicus
Vegetation	Vegetation height	Yes	2019	30 m	GLAD [135]
Soil	Surface Soil Moisture	Yes	Daily datasets from 1978 to present.	27.75 km	ESA Copernicus
Soil	Soil organic carbon	No	Reference period: 1905-2016.	250 m	SoilGrids

Soil	Soil texture				
Soil	Soil acidity				
Terrain	Slope, elevation and aspect	Partially	2020	500 m	GEBCO
Terrain	Modified Topographic Index (can be derived from flow accumulation)	Partially	2008	500 m	HydroSHEDS [136]

Water	Mean Normalized Difference Water Index (can be derived from surface reflectance composites).	Yes	Daily datasets from 2000 to present.	500 m	USGS
Water	Water seasonality	Yes	Reference period: 1999-2018.	30 m	GLAD [108]
Water	Snow water equivalent (amount of water contained within the snowpack).	Yes	Daily datasets from 2002 to 2011.	25 km	NSIDC
Water	Snow cover fraction or frequency	Yes	Daily datasets from 2000 to present.	500 m	NSIDC

Energy	Surface albedo				
Energy	Land Surface Temperature (LST; a mixture of vegetation and soil temperature)	Yes	Multi-daily datasets from 2000 to present.	5.6 km	USGS
Energy	Mean solar radiation	No	Monthly average climate datasets from the period 1970 to 2000.	1 km	WorldClim version 2.1: [101]

3.2. Global environmental stratifications.

There are several biophysical characterizations available at global scale partially or totally based on RS data and modelling. Metzger et al. [139] used a broad set of bioclimatic variables to stratify the world in 18 environmental zones in order to support global ecosystem research and monitoring. Ivits et al. [53] mapped Global Ecosystem Functional Types using vegetation phenology and productivity variables by means of principal components and cluster analysis. Sayre [140] developed a map of Global Ecological Land Units using bioclimate, landforms, lithology and land cover variables. Tuanmu and Jetz [141] developed 14 remote sensing-based metrics to characterize habitat heterogeneity at 1 km resolution at global scale based on textural information extracted from the Enhanced Vegetation Index (EVI; [142]), and found out that bird species richness was strongly associated with habitat heterogeneity. Jung et al. [17] developed a global map of terrestrial habitat types following the IUCN habitat classification scheme[7] based on land cover, climate and land use data. Sayre et al. [51] developed a global classification of World Climate Regions and World Ecosystems based on environmental descriptors, such as landforms, moisture, temperature, vegetation type and land use. Finally,

[7] https://www.iucnredlist.org/resources/habitat-classification-scheme

[143] developed a Global Ecosystem Typology, including indicative distribution maps, based on a large set of different environmental descriptors, existing global occurrence maps of specific ecosystem types, and previous global environmental characterizations. They used a hierarchical classification system that first characterizes ecosystems by their ecological functions and then distinguishes ecosystems with contrasting species assemblages.

These global stratification initiatives are not limited to PAs and are indeed useful to prioritize the conservation importance of larger regions. However, RS and modelling efforts specifically aimed to systematically characterize PAs could provide more relevant information needed to inform several policy initiatives, as well as to support management applications in PAs at regional or global scale, such as the assessment of ecological representativeness, the prioritization of PAs, connectivity assessments, the mapping of new areas requiring protection, etc.

3.3. Global characterization of protected areas.

In relation to global characterizations within PAs by means of RS and modelling, [144] developed the EODHaM system for characterizing habitats in PAs and surrounds using earth observation data and expert knowledge. They used a semi-automated statistical procedure based on data related to terrain, vegetation, water balance and land use. As part of the Digital Observatory for Protected Areas (DOPA; [145]), [120] systematically stratified PAs globally into different habitat functional types based on remote sensing data and modelling and allowed for the quantification of the similarity between a reference area (representing a habitat functional type) and the surroundings based on a set of ecological indicators [146–148]. The method also graphically compares the ecological features of each habitat functional type found in a PA to help identify their main characteristics and understand the main biophysical gradients that occur at PA level (Figure 2). The methodology uses a combination of several multivariate statistical analyses based on different global predictors that accounted for climate, topography, vegetation and water exchanges. One of the advantages of this methodology is that the analysis is fully automated and it can be performed at different spatial resolutions, which is especially important when dealing with smaller PAs. Furthermore, the similarity maps that are produced can also be used to identify new potential areas to be protected to strengthen ecological connectivity. When used in conjunction with forecasted bioclimatic data, the approach can further help identify new areas for conservation considering current and climate change scenarios [147].

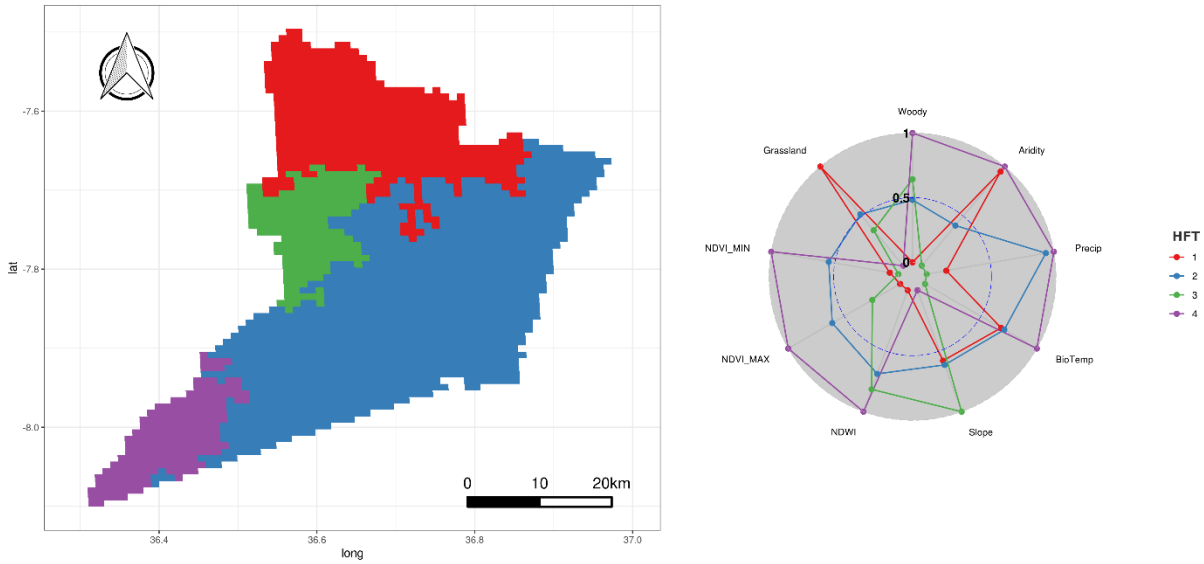

Figure 2. Example map of the habitat functional types (HFTs) identified in the Udzungwa Mountains National Park (Tanzania) and normalized mean values of the biophysical variables used in the eHabitat+ model (EPSG:4326). NDVI stands for the Normalized Difference Vegetation Index and NDWI stands for the Normalized Difference Water Index. A detailed description of the study variables and the methodology followed can be found in [120].

When prioritizing and ranking PAs, most studies have focused on species diversity to measure uniqueness [149,150]. However, biophysical characterizations have been also used, along with biotic variables, to perform gap and representation analyses in PAs [51,151]. Dubois et al. [147] proposed a methodology to assess the uniqueness of PAs based on biophysical variables which, however, lacked means to decompose each analyzed area into areas with similar ecological features. The methodology proposed by [120] partially solves the issue by identifying habitat functional types and mapping similar areas at ecoregion scale. This approach could be used to further create a composite indicator for each PA that reflects the biophysical richness of PAs and the uniqueness of their habitats. Coastal PAs should be especially taken into account when developing this kind of indices, given their inherent complexity as ecotones and the higher pressures they are exposed to because of human developments that are often concentrated along coasts [152–156].

Perhaps the main limitation of global biophysical assessments using RS is the lack of ground truthing and comparison maps in order to evaluate results [157]. In this regard, resulting habitat and ecosystem types based on RS methods could be classified according to existing global typologies in order to serve and support different initiatives of habitat and ecosystem monitoring globally. For example, a hierarchical classification framework could be applied to the ecological features resulting from the methodology developed by [120] in which some key variables guide the first broad set of typologies and other variables help distinguishing more specific subclasses, according to existing typologies. Recent global environmental stratification initiatives previously mentioned already provide potential comparison maps, such as the IUCN Global Ecosystem Typology [158] and the set of World Climate Regions and World Ecosystems [51]. The approach proposed would allow for taking into account similar regional features into consideration as well as to go deeper into a specific global ecosystem type (e.g. Tropical moist forests, Mangroves).

In relation to the marine realm, current efforts to globally characterize PAs by means of RS have focused on the use of bathymetry. As such, DOPA uses a model of global bathymetry that is partially based on RS data to compute a Marine Habitat Diversity index for MPAs [145]. The facts that (a) most RS methods can only derive information from the upper layer of the ocean (with the exception of altimeters for coarse scale bathymetry), (b) that the spatial resolution of available RS data may be too coarse to characterize MPAs, and (c) that RS-based management of MPAs requires large financial and human resources, constitute major impediments to the use of RS data to characterize MPAs [130]. These may explain why global characterization of MPAs using RS is limited. However, initiatives to characterize PAs using a broader set of RS measured variables are more numerous at regional [130,159,160] and local scales [161,162]. Beyond the characterization of MPAs, RS data have been used to assess the connectivity of MPA networks [154,163] and to delineate bioregions that can be further used as a basis to inform the design of MPA networks [164–167].

3.4. Computing infrastructures.

Computational capacity is another important limitation when characterizing PAs at global scale. Most models and processing workflows developed so far are limited by the fact that there is no direct integration with external data sources and models, most of them being standalone desktop or server applications. In this regard, large computational advances have occurred in recent years based on cloud-based infrastructures that support remote sensing data acquisition and processing [168]. Several tools have been already developed at global scale to serve different purposes, such as the Global Surface Water Explorer[8] (GSWE; [169]), the Map of Life[9], the Global Forest Watch[10], the Remote sensing application for land cover classification and monitoring[11], EarthMap[12], the Living Atlas of the World[13], etc. Bastin et al. [170] used the GSWE to assess the level of protection of inland open surface waters and their trends within PAs globally.

Among others, Google Earth Engine (GEE; [171]), ArcGIS online[14] and the European Copernicus Data and Information Access Services[15] (DIAS) offer data and services for cloud-based processing and remote sensing on large scales. Typical environmental applications include detecting deforestation, classifying land cover, estimating forest biomass and carbon, or mapping the world's roadless areas [172]. The advantage of using those services lies in the easy data access (including time series), the possibility to create graphical user interfaces and their remarkable computation speed, as processing is outsourced to cloud servers. Moreover, OpenEO[16] allows interoperability with big earth observation cloud back-ends for several programming languages.

[8] https://global-surface-water.appspot.com/map
[9] https://www.mol.org/
[10] https://www.globalforestwatch.org/map
[11] https://remap-app.org/remap
[12] http://earthmap.org/
[13] https://livingatlas.arcgis.com/en/home/
[14] https://www.esri.com/en-us/arcgis/products/arcgis-online/overview
[15] https://www.copernicus.eu/en/access-data/dias
[16] https://openeo.org/

4. Concluding remarks and recommendations

While the methods for mapping and assessing habitats and ecosystems are equally useful within and outside PAs, integrated assessment methods that systematically characterize and measure the diversity of habitats and ecosystems within a region are especially relevant when applied within PAs at global scale. The global characterization of PAs can provide multiple benefits and applications: (a) support short, medium and long-term management actions, especially at regional and global scale, that can ensure the maintenance of biodiversity and maximize the provision of ecosystem services [173,174]; (b) evaluate the effects of climate change in PAs [175]; and (c) inform policy initiatives, such as the European Biodiversity Strategy or the post 2020 Global Biodiversity Framework, on how to develop monitoring tools and indicators to promote sustainable management of PAs [176]; etc. These kinds of analyses do not only need to be done at a global scale, but also, if possible, repeatedly (i.e. annually) to document the changes that occur [177]. In this regard, the use of variables representing longer-term periods is also useful for capturing the presence of potential habitats and ecosystems, which can be then used as reference for monitoring and condition assessment purposes. Furthermore, although locally derived variables are better descriptors of the ecosystems, global data sources are needed in order to systematically compare PAs across the globe and inform larger scale conservation actions.

In the last decade, cloud-based infrastructures have greatly improved the access to time series of relevant earth observation variables, which are crucial to the proper monitoring and assessment of ecosystems [178], bringing new opportunities for the global characterization of PAs. However, it is also necessary to translate the results from global characterization of PAs into information that can be used in the real world, for example by sharing all data and models generated using online interoperable tools [179–182]. As an example of this, DOPA provides access to various global datasets and indicators that can inform decision-making and PA management [148], such as climate and topographic statistics, information about pressures, occurrence of extreme events, land cover, land degradation and fragmentation, ecosystem services, and species. Moreover, the Protected Planet website allows exploring the World Database on Protected Areas (WDPA), maintained by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC). The CBD mandated WDPA is the key reference dataset for any global protected area analysis, and includes both spatial (mapped boundary or point location) and non-spatial (e.g. name, type, size, age, status) information for over 230,000 protected areas worldwide [183]. Despite accelerated efforts to improve the global PA data, the quality of the WDPA data still varies greatly between countries and regions, and this should be acknowledged in any analysis using the WDPA. Only limited information related to the systematic global biophysical characterization of PAs can be found online yet, such as the Terrestrial Habitat Diversity index in DOPA [145].

Systematic information related to the uniqueness or the importance of PAs based on biophysical variables could, among other things, further support the ranking and prioritization of PAs based on the diversity of their habitats and ecosystems. Biophysical studies also allow us to study the role of habitats and ecosystems in maintaining biodiversity in a context of climate change since species populations can adapt to changes by moving to new areas that meet their ecological requirements [146]. Several applications of habitat models have shown a high correlation between biodiversity and the diversity of habitat types and can help

identifying potential new areas that should be protected in order to maintain species protection into the future [120,184,185].

Table 2 gives an overview of applications of different environmental descriptors, including methods and data, which are relevant for the biophysical characterization of PAs, highlighting the importance of taking into account structural and functional attributes, as well as of integrating a broad spectrum of environmental descriptors, in global biophysical characterization of PAs.

Table 2. Summary table with example applications of different environmental descriptors, including data and methods, that are relevant for the biophysical characterization of PAs. Acronyms used: Object-Based Image Analysis (OBIA); Normalized Difference Vegetation Index (NDVI); Normalized Difference Water Index (NDWI); Machine Learning (ML); Principal Components Analysis (PCA); Light Detection And Ranging (LiDAR); Digital Elevation Model (DEM); Normalised Difference Blue-red Ratio (NDBR); Wide Dynamic Range Vegetation Index (WDRVI); Soil Adjusted Vegetation Index (SAVI); Green–Red Vegetation Index (GRVI); Plant Senescence Reflectance Index (PSRI); Water Band Index (WBI).

Application	**Environmental descriptors**	**RS and ancillary data**	**Methods**
Wetlands and dune habitats mapping [63–70,73,178]	• Vegetation greenness • Vegetation and soil water content • Water seasonality • Topography • Soil	RS-based vegetation (NDVI, WDRVI, SAVI) and water (NDWI) indices; LiDAR or radar derived DEMs; Soil depth layer interpolated from ground collected data points; Modelled spatial and temporal distribution of water.	OBIA; ML; PCA; texture analysis; Cluster analysis.
Riparian, forest, grassland and shrubland habitat mapping [71,72,75–77,81]	• Vegetation greenness • Vegetation height • Topography	RS-based vegetation indices (NDVI, EVI; GRVI); LiDAR derived vegetation height; radar derived DEM.	OBIA; texture analysis; PCA; ML; Cluster analysis.
Assessment of habitat quality, diversity and extent [59,60,83,85,88]	• Vegetation greenness • Vegetation height • Primary productivity • Vegetation seasonality • Canopy shadow fraction (CSF)	RS-based vegetation indices (NDVI, EVI); LiDAR derived vegetation height; Slope derived from a DEM; RS-based water index (NDWI); CSF from RS-based NDBR;	Cluster and landscape pattern analysis; texture analysis; PCA.

	• Vegetation and soil water content • Topography	Vegetation seasonality and productivity products derived from the analysis of temporal dynamics of seasonal changes in NDVI;	
Environmental stratifications [17,51,57,139–141]	• Vegetation greenness • Bioclimatic variables • Altitude • Geomorphology and landforms • Land cover • Lithology	RS-based vegetation indices (EVI); Long term average climate data, such as temperature, precipitation and aridity, interpolated from meteorological stations; geomorphological, landforms and altitude data from a LiDAR or radar derived DEM; global lithology map integrating existing surficial lithology maps; land cover classes interpreted from satellite data.	Cluster analysis; PCA; texture analysis.
Mapping of ecosystem and habitat functional types [52,53,120,144,186]	• Vegetation greenness • Vegetation and soil water content • Vegetation phenology and productivity • Vegetation structure • Land Surface Temperature (LST) • Albedo • Soil moisture (SM) • Bioclimatic variables • Topography	RS-based vegetation (NDVI, PSRI) and water (WBI , NDWI) indices; Vegetation phenology and productivity products derived from the analysis of temporal dynamics of seasonal changes in NDVI; LST derived from satellite thermal infrared bands, such as MODIS; RS-derived albedo; RS-based soil moisture products, such as	PCA; Cluster and landscape pattern analysis; ML; OBIA.

		the ESA CCI Soil Moisture; Slope derived from a DEM; RS-based percentage of woody and grassland vegetation cover; Long term average climate data, such as temperature, precipitation and aridity, interpolated from meteorological stations.	

Finally, we give a summary of the recommendations proposed to improve global biophysical characterization of PAs in relation to different aspects:

Environmental attributes and descriptors:

- Structural and functional attributes of ecosystems and habitats within PAs should be addressed.
- A broad set of variables representative of key biophysical quantitative descriptors should be used to produce integrated assessments, potentially including vegetation, energy, climate, water, terrain and soil.

Data sources and processing:

- Global data sources presenting time-series and regular updates should be preferred.
- Dimensionality reduction techniques are often used to deal with correlated input variables.
- The use of ensembles of different input data or models corresponding to the same variable is recommended to provide more accurate outputs and deal with uncertainty.

Methods:

- The use of interoperable RS cloud-based infrastructures is recommended for large scale processing.
- Analyses should be regularly repeated to document changes.
- The analysis should extend beyond specific habitat or ecosystem mapping and assessment methods, so that a variety of habitats and ecosystem types can be identified.
- Resulting habitat and ecosystem types within PAs should be, as much as possible, comparable with existing global typologies.
- There is a clear need and potential to develop methodologies for assessing the biophysical uniqueness of PAs that could support prioritization analyses.
- Methods should allow the prediction of climate change impacts to ecosystems by using forecasted bioclimatic data.

Application in policy and practice:

- Translate the results into information that can be used by policy and decision makers.

- Ensure transparency and reproducibility by sharing all data and models generated using online interoperable tools.
- Global characterization of PAs should be rather aimed at informing larger scale conservation and management actions and plans, unless no better information is available at local or regional scale.

Acknowledgements

This study and the development and maintenance of the Digital Observatory for Protected Areas were supported mainly by the institutional activities of the Directorate D (Sustainable Resources) at the Joint Research Centre of the European Commission as well as by the Biodiversity and Protected Areas Management (BIOPAMA) EU-ACP programme, an initiative of the African, Caribbean and Pacific (ACP) Group of States financed by the 10th and 11th European Development Funds of the European Union (EU). JML has been supported by a European Commission Expert Contract (CT-EX2020D381533-101). Authors want to thank three anonymous reviewers and the editor for their constructive comments on an earlier version of the manuscript.

Author Contributions: Writing – original draft, Javier Martínez-López; Writing – review & editing, Bastian Bertzky, Simon Willcock, Marine Robuchon, María Almagro, Giacomo Delli and Grégoire Dubois.

Conflicts of Interest: The authors declare no conflict of interest.

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