Title: Developing a framework to improve global estimates of conservation area coverage

Rachel E. Sykes[1], Diego Juffe-Bignoli[1], Kristian Metcalfe[2], Helen M.K. O'Neill[1], P.J. Stephenson[3], Matthew J. Struebig[1], Piero Visconti[4], Neil D. Burgess[5, 6], Naomi Kingston[5], Zoe G. Davies[1] and Robert J. Smith[1]

[1] Durrell Institute of Conservation and Ecology, School of Anthropology and Conservation, University of Kent, Canterbury, UK

[2] Centre for Ecology and Conservation, College of Life and Environmental Sciences, University of Exeter, Penryn Campus, Penryn, Cornwall, UK

[3] IUCN SSC Species Monitoring Specialist Group, Laboratory for Conservation Biology, Department of Ecology & Evolution, University of Lausanne, Lausanne, Switzerland

[4] Biodiversity, Ecology and Conservation Group, Biodiversity and Natural Resources Management Programme, International Institute for Applied Systems Analysis, Laxenburg, Austria

[5] UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), Cambridge, UK

[6] Centre for Macroecology, Evolution and Climate, GLOBE Institute, University of Copenhagen, Denmark

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Correspondence details: Professor Bob Smith, Durrell Institute of Conservation and Ecology, School of Anthropology and Conservation, Marlowe Building, University of Kent, Canterbury, Kent CT2 7NR; UK. Tel: +44 1227 823667. E-mail: R.J.Smith@kent.ac.uk.

Developing a framework to improve global estimates of conservation area coverage

Abstract

Gaps in existing global conservation area datasets hamper efforts to measure progress towards international coverage and biodiversity representation targets. Here we present a framework to produce more accurate global conservation area metrics, based on selecting a representative set of nations for future collection of the best available data on protected area (PA) and other effective area-based conservation measures (OECM). First, we identified 10 factors that are drivers of conservation area establishment and drivers of biodiversity patterns, and then produced maps sub-dividing each factor into a number of categories to produce 89 features. Second, we used a global search algorithm to select the smallest number of nations needed to contain at least 10% of each feature, identifying a total of 25 countries and finding that some countries could be swapped with others without impacting the efficiency of the results. Third, we repeated the prioritisation approach with the same targets to identify a series of 100 km^2 grid squares within these countries to avoid over-representing the larger nations. Collecting and analysing data for this sample could produce quicker, more accurate estimates of conservation area coverage and representativeness, and this approach could potentially improve other global conservation metrics.

Introduction

Conservation areas are an essential component of global efforts to prevent biodiversity loss (Watson et al. 2014). To this end, the 196 signatories to the Convention on Biological Diversity committed through Aichi Target 11 to conserve 17% of the global terrestrial area within protected areas (PAs) and land under other effective area-based conservation measures (OECMs) by 2020 (CBD 2010). Progress towards Aichi Target 11 and other international commitments, such as the environment-related Sustainable Development Goals, is assessed using data from the World Database of Protected Areas (WDPA). This database is compiled and maintained by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), based on conservation area data approved by each national government or following an expert review and validation process (Lewis et al. 2019; Bingham et al. 2019; UNEP-WCMC and IUCN 2021). This makes the WDPA an extremely important source of information and this needs long-term, sustained resourcing to maintain its accuracy (Juffe-Bignoli et al. 2016). However, there are data limitations (Visconti et al. 2013), as some countries lack the capacity to provide up-to-date and accurate information, so it can take time for newer PAs to be included (UNEP-WCMC 2019). More generally, non-state PAs and OECMs are under-represented in the database (Stolton et al. 2014; Bingham et al. 2017; Garnett et al. 2018; Corrigan et al. 2018; Donald et al. 2019), partly because governments have only recently started collecting data on conservation areas not owned or managed by the state, and partly because some owners of non-state conservation areas lack the capacity or are wary of providing information to the government about their land (Fitzsimons & Wescott 2007; Clements et al. 2018).

These limitations make it difficult to measure progress towards international area-based conservation targets accurately. It also makes it difficult to measure how well the global network represents biodiversity, especially as recent work suggests that non-state PAs can play a vital role in representing species and ecosystems that are missing from state PAs (Gallo et al. 2009; Archibald et al. 2020). Both these issues then hamper the process of setting new targets, which is particularly important given that the international conservation community is pushing for more ambitious goals for conservation area extent and representativeness post-2020 (Dudley et al. 2018; Maron et al. 2018; Visconti et al. 2019; CBD 2021). One way to address this is to invest in improving the quality of global conservation area datasets and there is an ongoing process for increasing the accuracy for state PAs and collecting information on non-state PAs and OECMs (UNEP-WCMC 2019). Such work is vital but a long-term process (Juffe-Bignoli et al. 2016), so complementary approaches are needed.

One potential solution is to adopt an analogous methodology to that of the Sampled Red List Index, an approach that produces a metric to better understand species status and trends by accounting for taxonomic biases in the groups that have been fully assessed in the IUCN Red List (Baillie et al. 2008; Henriques et al. 2020). Developing the Sampled Red List Index involved selecting a taxonomically representative set of species, conducting Red List assessments for those species that had not been assessed, and combining results for all of the selected species to produce a single measure (Lewis & Senior 2011; Brummitt et al. 2015). The equivalent for developing an estimate of global conservation area coverage would involve selecting a representative set of nations and then collecting the best available PA and OECM data to produce more accurate global indices. This would have similar benefits in terms of time and resources because data collection efforts would focus on a subset of countries. Just as importantly, producing this estimate based on a sample of data would not involve reporting results per country, so the analysis could use the latest and most accurate conservation area datasets without contradicting official data reported by governments. Here we present the first step in producing such a sampled approach for future estimates of global conservation area coverage and representativeness, developing a framework to identify a representative set of countries, and a set of sampling sites within them.

Identifying a representative sample of countries, so that conservation area data from this subset can be used to estimate the extent to which the existing global PA and OECM network meets area and biodiversity targets, involves considering two sets of factors: drivers of conservation area establishment and drivers of biodiversity patterns. Establishment of conservation areas is likely influenced by a range of economic, political and social factors. For example, it is well known that conservation area coverage is higher on land that is of lower value for commercial agriculture or resource extraction (Pressey & Tully 1994; Loucks et al. 2008; Joppa & Pfaff 2009). Drivers of biodiversity patterns include latitude and elevation, as species and ecosystems show strong variation across these and other gradients (Gaston & Spicer 2013). Selecting a set of countries that best mirror these patterns is mathematically defined by the minimum set problem, a problem formulation commonly used to identify priority areas for conservation, so our framework is based on algorithms typically designed to solve these problems. This involves: (a) selecting and mapping the features that influence conservation area extent and/or biodiversity pattern features, such as elevation zones and landcover types; (b) setting targets for how much of each feature should be included in the sample, and then; (c) using complementarity-based algorithms to choose sets of countries that best meet these targets (Kukkala & Moilanen 2013).

Using this approach also involves choosing a cost metric, so that the prioritisation process minimises the cost while also meeting the targets (Naidoo et al. 2006). In our case this metric needs to reflect the time and effort involved in collecting the conservation area information, as this is what we want to minimise. PA and OECM data are generally collected and collated at the national level (Bingham et al. 2019), so each new country added to our sample would add an extra cost in terms of effort required to obtain their datasets. Thus, we define our cost metric as the number of countries in which our sample areas are found. Such a metric is a simplification, as the effort required will vary between countries based on their capacity and the number of conservation agencies that are responsible for national or regional data collection. We partially account for this in our study by dividing larger countries into their highest administrative units below the level of national government, such as states or provinces, which better matches the devolved nature of conservation management and data collection in these countries.

Collecting data at the national level has one obvious disadvantage though, as these large sampling units are likely to contain some land that is not needed to meet the targets, producing a less balanced sample because larger countries will be over-represented (Nhancale & Smith 2011). However, overcoming this simply involves repeating the spatial prioritisation using smaller sample units within the subset of selected countries. So, here we describe a sampling approach using this two-stage process to identify a representative set of countries and grid squares, designed to inform future efforts to collect, collate and supplement existing national PA and OECM datasets and produce more accurate measures of global patterns in conservation area coverage.

Methods

Our approach consisted of four steps, beginning with: (i) choosing socio-economic and biogeographic factors that represent drivers of conservation area extent and global biodiversity patterns, and (ii) defining and mapping the features that make up the categories within each factor. This was followed by a two-stage analysis: (iii) Stage 1 to identify the minimum set of countries needed to meet targets for each feature, and; Stage 2 to identify sets of 100 km^2 grid squares that meet these targets within this subset of countries (Figure 1).

Figure 1

Choosing factors affecting biodiversity patterns and area-based conservation efforts

We conducted a literature review to identify factors that likely determine total conservation area network extent and patterns of global biodiversity. We then ran a workshop with 12 conservation area network experts to discuss these and other possible factors (Supplementary Materials Table S1) before generating a final list of the most important. We then identified ten available global datasets that mapped these important factors: biomes, elevation, government effectiveness, islands and continents, landcover, latitude, income, population density of humans, realms and subregions. Three of these factors were selected to represent only drivers of conservation area network extent, five to represent both drivers of conservation area network extent and global biodiversity patterns and two to represent only global biodiversity patterns (Table 1, Figure 2).

Table 1

Figure 2

Defining and mapping the features

To produce a representative sample, we needed to divide each factor into a number of categories (referred to as 'features' hereafter), either by using the existing classification system for categorical data or choosing appropriate thresholds for continuous data. We used three datasets for the factors that only represent drivers of conservation area network extent. For government effectiveness features we used the World Bank's Worldwide Governance Indicators dataset, grouping countries into four categories based on government effectiveness scores of 0 - 24.9, 25 - 49.9, 50 - 74.9 and 75 - 100 (World Bank 2019a). For income features we used the World Bank low, lower-middle, upper-middle and high income country categories, which are based on per capita gross national income (World Bank 2019b). For human population density features we used UN data (UNPD 2013) classified into five categories using a logarithmic scale (0 - 0.9, 1 - 9.9, 10 - 99.9, 100 - 999.9 and > 1000 people per km^2) to ensure that the data adequately represented areas with very low and very high population densities.

We used five datasets for the factors that represent drivers of conservation area network extent and global patterns of biodiversity. For biome features we used WWF's global ecoregion GIS layer, where each of the 16 biomes is a broad ecosystem type (Olson et al. 2001). For elevation features, we used the Shuttle Radar Topography Mission's 1 km elevation data and divided these into five elevation categories of 0 – 299 m, 300 – 799 m, 800 – 1399 m, 1400 – 1999 m, ≥ 2000 m, based on existing studies of biodiversity and elevation gradients (Bruijnzeel & Veneklaas 1998; Linkie et al. 2010). For landcover features, we used the European Space Agency's GlobCover landcover map which divides the terrestrial realm into 12 broad landcover types (ESA GlobCover Project 2009). For the latitude features we created a latitudinal zone layer by dividing the globe into seven bands. Each band has a width of 20°, apart from at the poles where we used bands of 40° to avoid over-representing differences in these relatively small regions. For the subregion features we used the United Nations subregions classification to group countries into 22 categories (UNSD 2019).

We used two datasets for the two factors that only represent global biodiversity patterns. For the realm features we used WWF's global ecoregion dataset, where each of the eight realms is a large biogeographic unit (Olson et al. 2001). For the island and continent features, we used the Global Administrative Areas dataset (GADM 2018) and grouped them into five categories of < 1,000 km^2, ≥ 1,000 - 10,000 km^2, ≥ 10,000 - 100,000 km^2, ≥100,000 - 1,000,000 km^2 and "Continent" (>= 1,000,000 km^2). As part of this, we removed islands with an area < 1 km^2 because these are less likely to contain important terrestrial biodiversity (Whittaker & Fernandez-Palacios 2007). In addition, we classified islands as belonging to the continent feature if they were both <10 km^2 and within 100 km of a continent or Greenland, as these are likely to have similar species composition to their associated continents (Whittaker & Fernandez-Palacios 2007).

Producing the prioritisation systems

We adopted a systematic conservation planning approach to identify a representative sample of the terrestrial realm based on meeting targets for each of the 89 features from the ten factors. This involved two stages. Stage 1 identified the set of countries and territories. Stage 2 then identified 100 km^2 grid squares within these countries (Table 2), thus refining the sample from Stage 1 to avoid over-representing larger nations. In both stages we used the Marxan spatial prioritisation software (Ball et al. 2009), which uses a simulated annealing approach to determine near-optimal portfolios of planning units that meet targets, whilst minimising planning unit and boundary costs. Each Marxan analysis involves running the software multiple times and producing a near-optimal portfolio each time. Marxan then produces two key outputs: the "best" output, which is the portfolio from the run with the lowest cost, and the "selection frequency" output, which counts the number of times each planning unit appears in each of the portfolios. Planning units with high selection scores are always needed to meet the targets; lower scoring planning units can be swapped with similar planning units without affecting target attainment (Ball et al. 2009).

Table 2

To conduct the spatial analysis we created planning systems for both Stage 1 and Stage 2 using the CLUZ plugin (Smith 2019) for QGIS 3 (QGIS 2019), based on the Mollweide map projection. This involved dividing the planning region into a series of planning units, giving each planning unit a cost for including it in a portfolio, and calculating the amount of each feature in each planning unit. For Stage 1, planning units were derived from the Database of Global Administrative Areas (GADM 2018) and consisted of countries for nations with an area < 1,000,000 km^2 or the highest sub-national administrative level polygons for larger countries (e.g. states, provinces, etc that are classified as L1 in the database and referred to as 'sub-national planning units' hereafter). We took this approach because larger nations tend to have sub-national conservation agencies and legislation, so we wanted to minimise the number of these sub-national administrative units selected to avoid having to collect data from a large number of sub-national expert groups. We followed established practice for reporting terrestrial coverage statistics by excluding Antarctica from our analyses (Butchart et al. 2015). We then converted each layer into a 1000 x 1000 m resolution raster and calculated the area of each feature (i.e., each category type of each of the ten factors) in each planning unit using CLUZ.

In the Stage 1 analysis, we needed to select a set of countries that represented all the features, while also minimising the number of countries selected. To do this we set the combined planning unit cost of each country as 1, so that selecting more countries was more costly. To account for the larger nations being split into several planning units, based on the sub-national administrative units, we set the planning unit costs as the inverse of the number of sub-national units in the country. For example, each of South Africa's nine provinces had a planning unit cost of 0.111. In addition, we needed to ensure that Marxan met targets by selecting the sub-national planning units from the same countries whenever possible. To do this we manipulated the Marxan boundary cost file so it appeared that every sub-national planning unit in the same country shared a boundary. This meant that if Marxan selected one sub-national planning unit in a particular country then it would be less costly to select subsequent sub-national planning units from the same country. To make sure this cost would be the same per country, we set the boundary length equal to the inverse of the number of different sub-national boundary pairs in each country so, for instance, the nine provinces in South Africa produced 45 combinations of sub-national pairs and so the boundary length was 0.0222. This manipulation of the boundary cost data has been used in previous studies to ensure that certain planning units are more likely to be selected together, even when they are not physically adjacent (Possingham et al. 2005; Hermoso et al. 2011; Makino et al. 2013).

The Stage 2 planning system was based on a global set of 10 km x 10 km grid squares, which was created in QGIS 3 using the Create Grid tool. We then used the Union tool to combine this global grid layer with the national and sub-national planning units used in Stage 1 to produce the final planning unit layer. The amount of each feature present in each of these smaller planning units was calculated using CLUZ. For this finer-scale analysis we used the planning unit area as the cost metric and did not account for boundary cost. This was because in Stage 2 we were simply seeking to identify the smallest area of land needed to meet the targets, as the logistical cost of collecting PA coverage data is not affected by whether the Stage 2 planning units neighbour each other.

Spatial analysis

To ensure that the planning units selected in Stage 1 and 2 were representative of the terrestrial realm, we applied the same percentage target for every feature. We carried out a sensitivity analysis to select this target, based on identifying a good compromise between sampling a sufficient proportion of the planet to produce a robust estimate of conservation area coverage, whilst minimising the number of national and sub-national planning units. Based on this sensitivity analysis we chose a target value of 10%, as the number of planning units required to meet higher targets increased more than two-fold (Supplementary Material Table S2).

We then ran the Stage 1 analysis using Marxan, which consisted of 1,000 runs of 10,000,000 iterations and used a Boundary Length Modifier value of 1.5. These parameters were selected to produce results that minimised the number of countries and planning units selected. Of the resulting 1,000 portfolios, 284 had equally low costs, i.e., contained exactly the same number of countries and planning units. To produce our final list of sample countries we therefore needed to develop our own scoring system to choose between these low-cost portfolios. We did this by first selecting portfolios with the most even spread of countries selected across the continents to further improve the representativeness of the sample. We then identified the portfolios containing planning units that were selected most often in the 1,000 runs, based on calculating their mean selection frequency score. This provided us with our final set of national and sub-national planning units that were then used in the Stage 2 analysis. Thus, our first step in Stage 2 was to update the planning system to specify in CLUZ that all of the 100 km^2 planning units found outside the national and sub-national regions selected in Stage 1 should be excluded from subsequent Marxan analyses. The Stage 2 Marxan analysis also consisted of 1,000 runs of 10,000,000 iterations (with a Boundary Length Modifier value of 0 because we were not interested in selecting adjacent planning units).

Comparative analyses

To assess whether the samples reflect global patterns, and whether the sample of grid squares is an improvement on the sample of national and sub-national planning units in terms of representativeness, we undertook two analyses. The first analysis compared the percentage of the terrestrial realm covered by PAs with the percentage of each of the 1,000 Marxan outputs produced in the Stage 1 and Stage 2 analyses. We also compared them with a 1,000 randomly selected sets of national and sub-national planning units (analogous to the Stage 1 Marxan analysis) and 1,000 randomly selected sets of the 100 km^2 planning units (analogous to the Stage 2 Marxan analysis but based on all the planning units across the global terrestrial realm, rather than those only found within the areas selected in the Stage 1 Marxan analysis). To do this, we developed a Python script (Van Rossum & Drake 2009) that added randomly selected planning units until the set met or exceeded the combined area of the best respective Stage 1 or Stage 2 Marxan output. The PA data came from the publicly available WDPA dataset downloaded in May 2021 (UNEP-WCMC and IUCN 2021). It should be noted that this dataset does not include most PAs in China and India. We followed the standard protocol (UNEP-WCMC & IUCN 2016) by excluding PAs that are 'Proposed' or 'Not Reported' and UNESCO-MAB Biosphere Reserves. We also only used point data if the PA extent was recorded, converting it into a polygon of the required size by producing a buffer with the required radius around the point (UNEP-WCMC & IUCN 2016). We combined the PAs for each country and then used QGIS to calculate the total area of each grid square using the Clip and Dissolve functions, before using these data to calculate the area per Stage 1 administrative unit.

For the second analysis, we developed a Python script to calculate how many of the targets were met by each of the 1,000 Stage 1 and Stage 2 Marxan outputs and the 1,000 Stage 1 and Stage 2 randomly selected sets of planning units.

Results

Stage 1 analysis

The best portfolio identified using Marxan consists of nine whole countries and territories, and 33 of the sub-national planning units within another 16 countries (Figure 3a). These 25 countries and territories are: Argentina, Australia, Brazil, China, Democratic Republic of the Congo, Dominican Republic, France, French Polynesia, Greenland, Indonesia, India, Italy, Kazakhstan, Kiribati, Mexico, Mali, Papua New Guinea, Russia, Saudi Arabia, Sudan, South Georgia and the South Sandwich

Islands, South Africa, Sweden, Tanzania and the United States of America. Only 17 of these 42 planning units were selected in every one of the 1,000 portfolios identified by Marxan (Figure 3b), meaning that each of the other 25 planning units could be swapped for planning units containing similar amounts of the different features to produce similarly efficient portfolios.

Figure 3

Stage 2 analysis

The best portfolio identified by Marxan contained 4,581 of the 137,287 planning units, covering 10.86% of the terrestrial area (Figure 4a). The area of each of the 42 Stage 1 planning units also selected in Stage 2 ranged between 27.8% for French Polynesia and 100% for three US states, with a median of 92.5% (Figure 3a); only 7 had less than half their area selected in Stage 2. The percentage of Stage 1 planning units selected in Stage 2 mirrors the selection frequency results, with low selection frequency scores for planning units where Marxan only needed to select a smaller proportion of the national and sub-national planning units (Figure 4b).

Figure 4

Sampling comparison

The area of the terrestrial realm, excluding Antarctica, in our analysis is 135,008,972 km^2. The mean selected area of the 1,000 Stage 1 Marxan outputs was 16.82% (S.E. < 0.031) of the terrestrial realm and the mean selected area of the 1,000 Stage 2 Marxan outputs was 10.88%. (S.E. < 0.001). The publicly available WDPA data showed that 15.25% of the terrestrial realm is under protection, compared to 15.34% (S.E. = 0.069) for the 1000 Stage 1 Marxan outputs, and a mean of 15.92% (S.E. = 0.008) for the 1000 Stage 2 Marxan outputs. This compares to a mean area under protection for the Stage 1 random sets of planning units of 15.26% (S.E. = 0.080) and for the Stage 2 random sets of planning units of 15.22% (S.E. = 0.018).

The global area of the different features varied between < 0.001% for the Micronesia subregion and 94% for continents. All of the Stage 1 and Stage 2 Marxan outputs met all the 89 feature coverage targets, whereas the random sets for Stage 1 failed to meet a mean of 20.9 targets (S.E. = 0.152) and the random sets for Stage 2 failed to meet 15.9 targets (S.E. = 0.109). The mean percentage target met for the different factors for Stage 1 ranged between 12.94% of the elevation features and

22.18% of the subregion features and for Stage 2 ranged between 10% of the elevation features and 14.08 % of the subregion features (Table 2, Supplementary Material Table S3)

Discussion

Well-defined, measurable conservation targets, and accurate on-the-ground data to compare against them, are vital for driving forward progress towards our goal of a sustainable and ecologically healthy future for the planet (Mace et al. 2018). However, obtaining such data for the entire globe is a slow process (Juffe-Bignoli et al. 2016), a problem compounded by a lack of monitoring capacity in some high biodiversity countries (Stephenson et al. 2017). An alternative is to derive estimates from a sample of features, an approach pioneered by the Sampled Red List Index and similar projects (Butchart et al. 2007; Baillie et al. 2008). In this study we propose a framework for producing more accurate estimates of progress towards global conservation area targets by identifying a sample of countries and grid squares that are representative of the factors that determine total conservation area network extent and patterns of global biodiversity.

Choosing the factors and features

When choosing factors to include in our study, we sought to represent those that influence conservation area establishment across the world and broad patterns of biogeographic diversity. There is an established literature on the factors that determine global biodiversity patterns, so we can be confident that our final sample is representative at this global scale (Gaston & Spicer 2013). The literature on conservation area establishment factors is less well established, although we know that demographic, economic and governance factors are important (Mascia et al. 2014; Kroner et al. 2019), so differing social and socio-economic conditions will result in conservation area networks with differing extents (Bohn & Deacon 2000). More specifically, a number of previous studies have shown the importance of human population density and proxies of agricultural opportunity cost, such as elevation and landcover (Loucks et al. 2008; Joppa & Pfaff 2009) and the link between government effectiveness and wealth in determining conservation outcomes (Waldron et al. 2017).

Some factors that our expert group identified as potentially important could not be included because they have not been mapped at the global scale (Supplementary Material Table S1). Political and public support for conservation in each country, for example, may have an effect on conservation area establishment but global datasets were not available. This could be resolved in future through polling data and citizen science initiatives (McKinley et al. 2017). Collecting data on national land tenure systems might also be important, as this is likely to have a large impact on the extent of privately- and communally-managed PAs and OECMs in each country (Bingham et al. 2017). However, we did broadly account for this, as well as other potential factors, by using the geographic subregions dataset, ensuring representation of countries with shared legal, cultural and historical backgrounds. Another issue is that while some of our datasets are a snapshot of the current situation, conservation area coverage reflects both past and current circumstances, although governments often add or remove conservation areas in response to immediate conditions (Mascia & Pailler 2011; Radeloff et al. 2013).

Defining the planning units and selecting the sample

The second key aim of our study was to ensure that the sampling approach was also a feasible basis for future data collection and study. Such data collection is resource intensive (Juffe-Bignoli et al. 2016), so we needed to balance between selecting a sample that was large enough to be sufficiently representative, but not so large as to make collecting data for every area in the sample unrealistic. We based Stage 1 of our framework on identifying countries and large within-country sub-regions to be included in our sample. This is because the nation state is the functional unit in conservation area data collection and reporting (Dallimer & Strange 2015) but large countries often have sub-national conservation agencies. Thus, by minimising the number of countries in our sample we also minimised the number of agencies and organisations involved in data collection. For the largest countries we also assumed that their conservation authorities would have a devolved structure, with national and sub-national agencies, hence our use of sub-national boundaries as planning units. Research is needed to test these assumptions and better assess this trade-off between sample size and sampling effort.

The best portfolio identified in Stage 1 comprised nine whole countries and 33 administrative units in a further 16 countries. The selection frequency scores, which are based on how many times each planning unit was selected in each of the runs, showed that only 17 of these planning units were chosen every time (Figure 3b). The other planning units are potentially interchangeable, which is important because if obtaining data from a particular country was impossible for logistical or political reasons, these units could be excluded and the analysis run again to find suitable replacements (Ball et al. 2009). The selection frequency results for the Stage 2 analysis also showed potentially interchangeable planning units, mostly within the largest sub-national planning units selected in Stage 1 containing additional land not needed to meet the targets (Figure 3). This Stage 2 result also shows the efficiency benefits of using a complementarity-based algorithm to select areas (Ball et al. 2009), as Marxan was able to meet the 10% targets for each feature in close to 10% of the planning region, even though features belonging to different factors have different spatial distributions and extents. This involved selecting more than 10% for some features that are found in lots of planning units and so are over-represented through meeting targets for other features (Table 2, Supplementary Material Table S3). However, this is not expected to impact estimates of conservation area coverage based on the Stage 2 sample because the over-represented features include those with both high and low opportunity costs.

Comparing the analysis outputs in terms of their percentage in PAs is less straightforward for two reasons. First, the publicly available WDPA information used in this analysis does not include every PA provided by each country, as China and India have chosen to restrict some of their data (Bingham et al. 2019). This explains why the global PA coverage of the terrestrial realm calculated from our analysis of 15.25% is less than the 15.67% calculated by UNEP-WCMC based on all the data (UNEP-WCMC 2021). Second, our sampled approach was developed in part because of known limitations with the WDPA, so while comparing levels of protection based on the WDPA provides helpful insights, the results should not be seen as definitive. One clear trend from our results is that the Stage 1 and Stage 2 random sets of planning units had near identical levels of PA coverage as the global figure. However, none of these random outputs met all of the feature targets, so would be less suitable for assessing the extent to which a sample of conservation areas represented biodiversity adequately. The Stage 1 and Stage 2 Marxan outputs met all the targets, indicating that they could be used to measure conservation area representativeness, but the mean PA coverage for the Stage 2 Marxan outputs is 0.65% more than the global figure. More research is needed to understand this disparity, but in the short-term it would probably be prudent to modify conservation area estimates from this sampled approach based on the difference between the global and sample WDPA PA coverage.

Policy implications and wider relevance

Ongoing monitoring of progress towards conservation targets is essential but the required data are often lacking (Brooks et al. 2015). Resolving this will need more resources and capacity building (Stephenson et al. 2017), especially at the level of the nation state where most action is carried out and thus where guidance is most needed (Smith et al. 2009). At the same time, we need timely global estimates of progress to inform international policy. Our proposed solution is to identify a representative sample of countries and collect better data just from these, taking advantage of the availability of accurate information that has not yet been officially approved. Importantly, such a study would not need to report the estimated conservation area coverage for each country, avoiding problems associated with reporting unofficial national datasets.

In this study, we have shown that it is possible to identify such a representative sample of areas across the globe within a small enough number of countries to make data collection realistic. More research is needed on the trade-off between the percentage of the terrestrial realm included in the sample and the number of countries and sub-national administrative units required to provide the data. Nonetheless, we have demonstrated proof of concept and identified a sample of reasonable size that is also a realistic basis for data collection. Our sampling approach is also likely to be suitable for marine conservation areas, as the existing literature suggests that their distributions are similarly impacted by comparable social and socio-economic factors (Devillers et al. 2020).

The next step is to collect data on conservation areas within the sample we have identified, working with local experts and non-government sources. This should then be used to develop improved global conservation area metrics, measuring coverage, connectivity levels (Saura et al. 2018) and how well these conservation area networks represent biodiversity (Butchart et al. 2015). This will be particularly important for OECMs, as national- and regional-scale data suggest they enhance PA network connectivity and cover different biodiversity elements (Dudley et al. 2018). More broadly, we hope that this sampling approach could be used to produce global estimates of a range of other conservation metrics, related to costs and effectiveness (Coad et al. 2015; Iacona et al. 2018) and social impacts, governance and equity (Dawson et al. 2018; Gill et al. 2019; Naidoo et al. 2019). In doing so, our sampling approach could help monitor progress towards meeting a number of international conservation targets and policies.

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Table 1. Factors that drive global biodiversity patterns and conservation area extent used in our analysis.

Factor	**Drivers of conservation area extent**	**Drivers of global biodiversity patterns**
Biomes	Conservation area extent is higher in biomes with less land suitable for agriculture, such as deserts, and rock and ice (Hoekstra et al. 2005).	Biodiversity differs greatly between biomes, with ecosystem types sharing similar species compositions (Gaston & Spicer 2013).
Elevation	Conservation area extent tends to increase at higher elevations (Joppa & Pfaff 2009).	Species composition varies across elevation gradients (Gaston & Spicer 2013).
Government effectiveness	Stable countries with higher bureaucratic quality have greater capacity to expand conservation area networks (Laurance 2004).	
Income (per capita)	Wealthier countries have more resources to fund the expansion of conservation area networks (Waldron et al. 2013).	
Islands and continents		Islands are often geographically and biologically distinct, with unique and highly threatened biodiversity (Gaston & Spicer 2013).
Landcover	Conservation area extent differs between landcover types (Joppa & Pfaff 2009).	Species composition varies between vegetation types and land-uses (Gaston & Spicer 2013).
Latitude	Conservation area extent is higher at latitudes with less land suitable for agriculture, such as closer to the poles (Hoekstra et al. 2005).	Species composition shows strong latitudinal gradients (Gaston & Spicer 2013).
Population density	Conservation area extent is lower in regions with high human population density (Joppa & Pfaff 2009).	
Realms		Biodiversity shows strong biogeographic patterns at the continental scale (Gaston & Spicer 2013).
Subregions	Sub-sections of continents have relatively similar histories, economies and legislative frameworks (Siegfried et al. 1998).	Biodiversity shows strong biogeographic patterns at the sub-continental scale (Gaston & Spicer 2013).

Table 2. Details of the factors used in the analysis that are likely to determine total conservation area network extent and patterns of global biodiversity, the extent of the feature with the smallest and largest area for each factor in the terrestrial realm, and the per factor mean percentage coverage of each feature identified in the Stage 1 and Stage 2 best portfolios.

Factor	**Number of features**	**Global area of feature with smallest extent (%)**	**Global area of feature with largest extent (%)**	**Stage 1 mean of % of each feature in the selected sample**	**Stage 2 mean of % of each feature in the selected sample**
Biomes	16	0.24	20.67	15.23	10.99
Elevation	5	5.38	41.24	12.94	10.00
Government effectiveness	4	17.34	35.99	15.28	10.95
Income	4	10.66	44.91	15.45	11.51
Islands and continents	5	0.36	94.23	14.95	10.71
Landcover	12	0.01	19.41	17.26	11.65
Latitude	7	0.16	23.74	17.79	13.35
Population density	5	0.79	39.82	13.76	10.73
Realms	9	<0.01	38.95	21.79	13.34
Subregions	22	<0.01	15.95	22.18	14.08

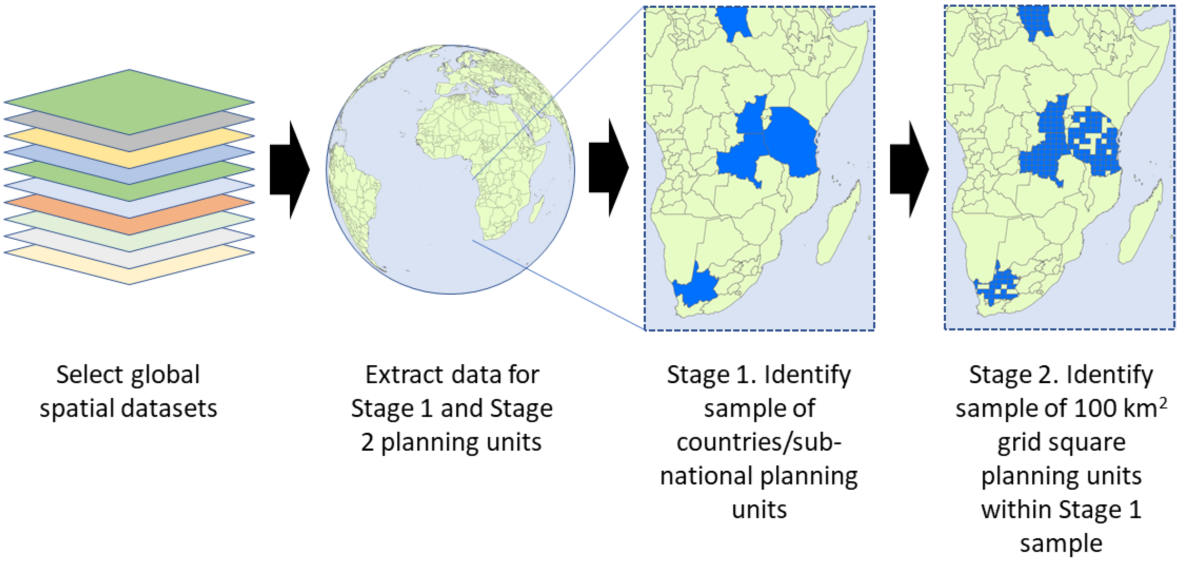


Figure 1: The four steps in the analysis involved: (i) identifying spatial datasets that represent the factors driving conservation area establishment and drivers of biodiversity patterns; (ii) defining and mapping the features that make up the categories within each factor, dividing the terrestrial realm into a series of planning units, calculating the extent of each feature in each planning unit, and setting targets for how much of each feature should be selected; (iii) in the Stage 1 analysis, identifying the set of countries and, for the larger countries, sub-national units that meet the targets for each of the features, and (iv) in the Stage 2 analysis, identifying the 100 km^2 grid squares within the selected countries that meet the targets for each of the features.

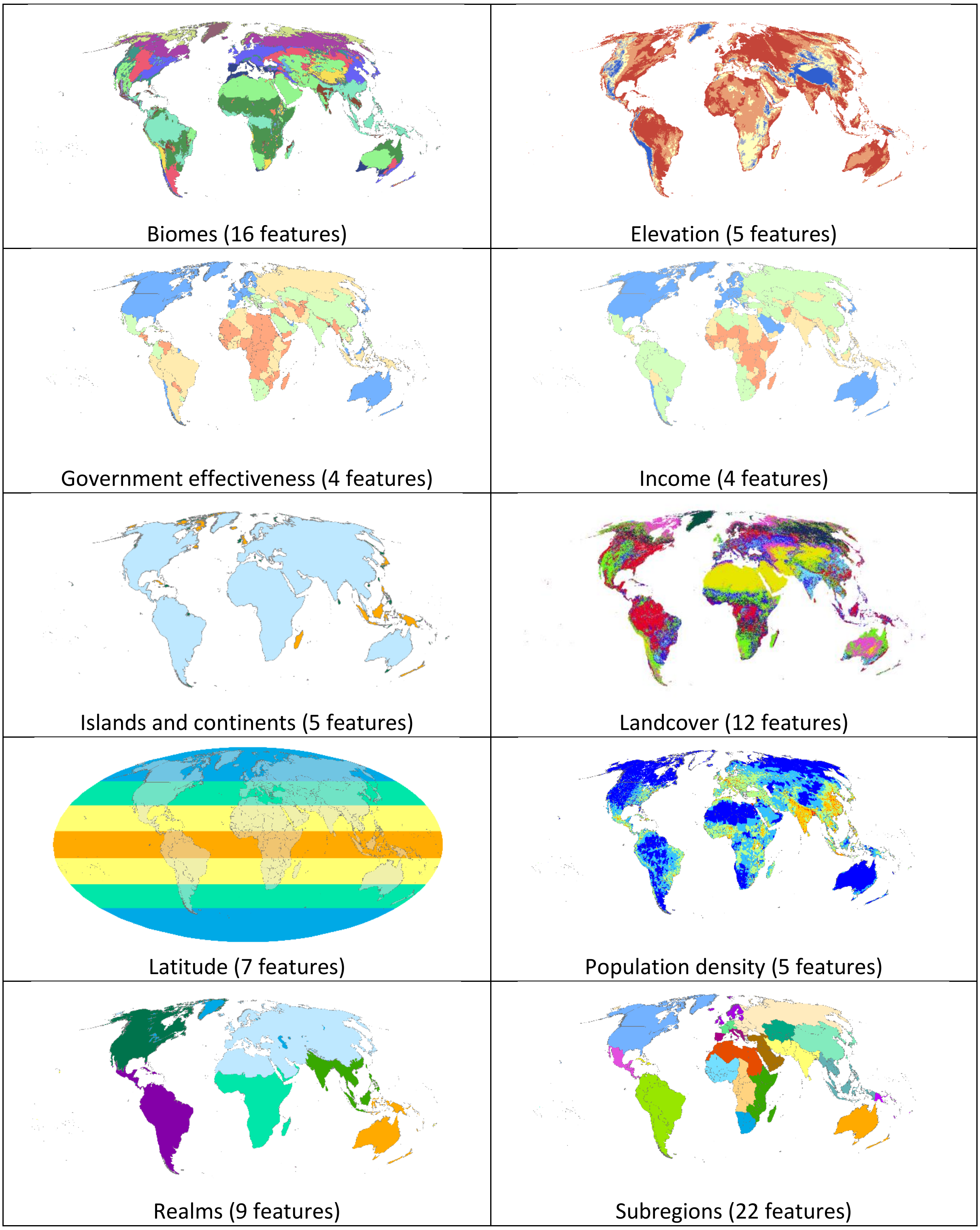
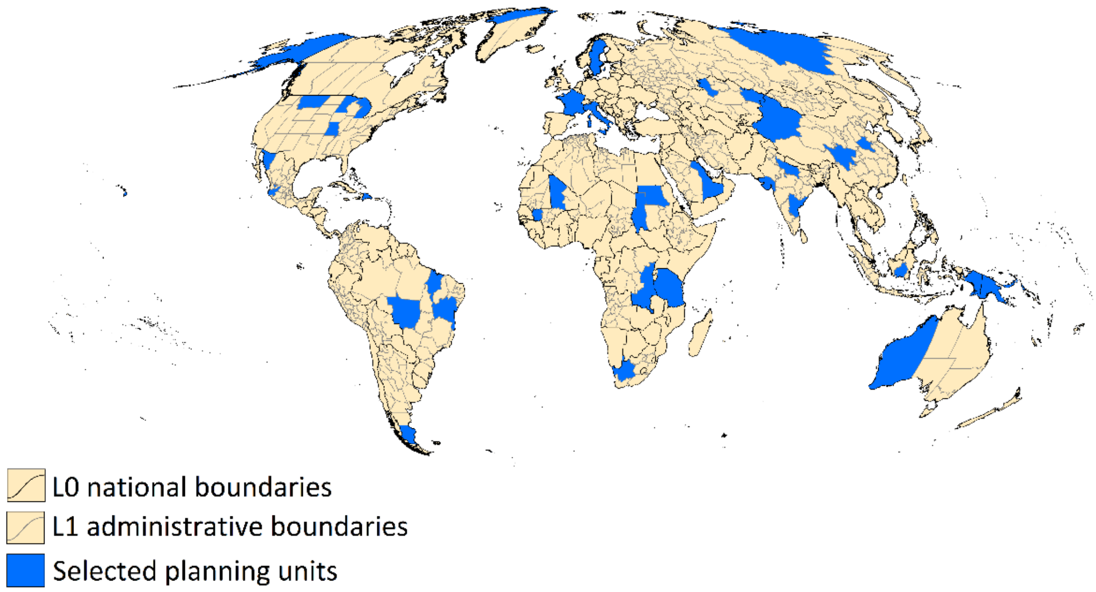


Figure 2: Maps of the ten factors used in the analysis to identify a representative sample of countries demonstrating drivers of conservation area extent and drivers of global biodiversity patterns. Details of the features that make up each factor are given in Supplementary Material Table S3.

(a)



(b)

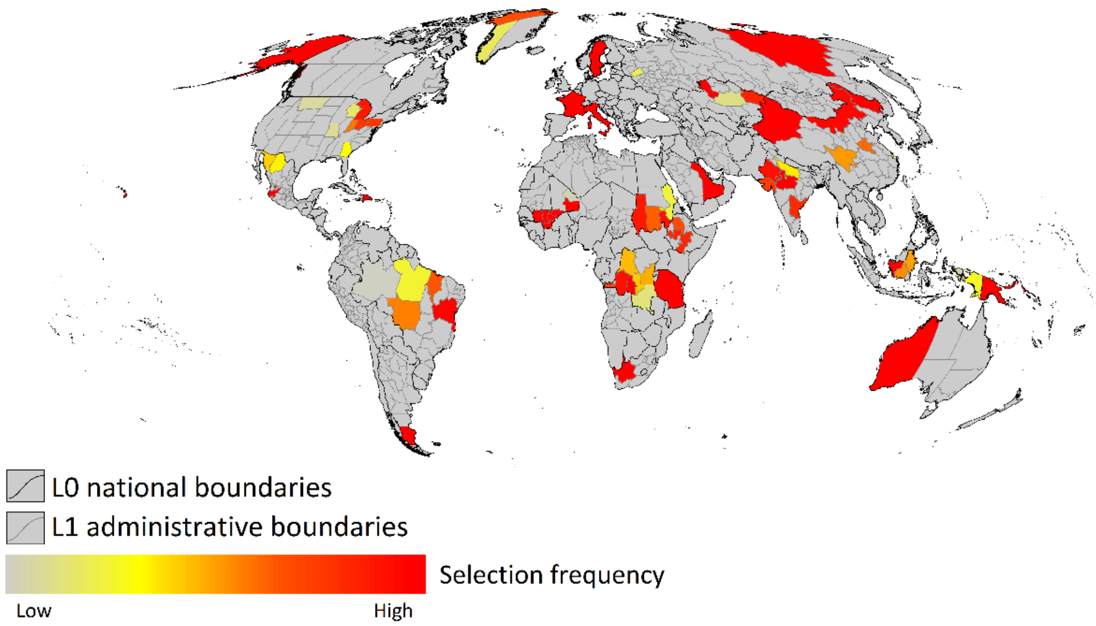
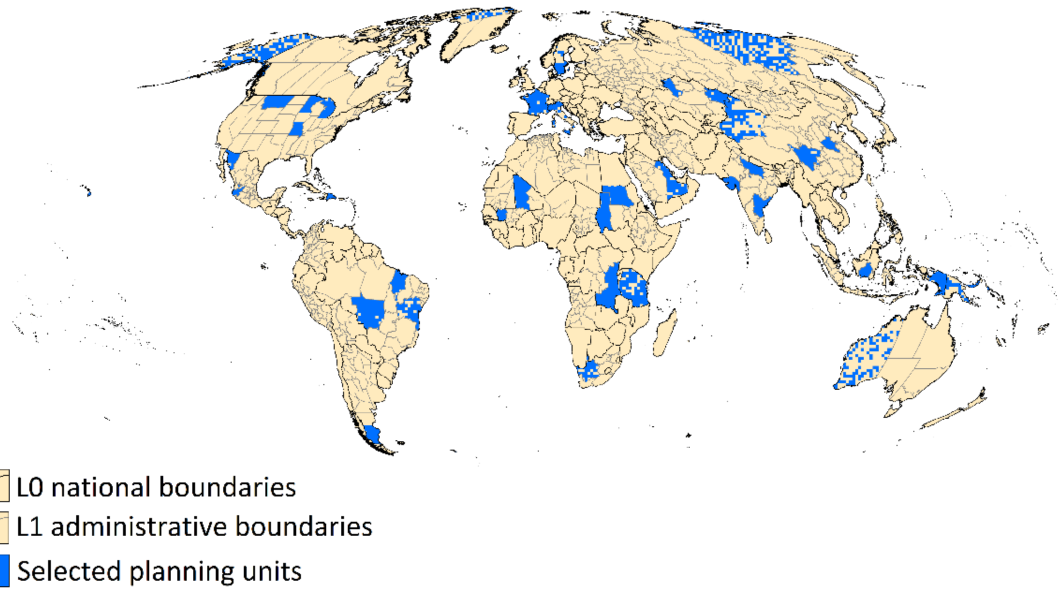


Figure 3: (a) Sample of countries (national planning units) and administrative units (sub-national planning units) that meet 10% targets, selected based on 1,000 Marxan runs and selecting the result with the smallest number of planning units, most even spread across the continents and with planning units with the highest mean selection frequency. (b) Selection frequency scores from Marxan showing the number of times each planning unit was selected across the 1,000 runs used to identify the sample.

(a)



(b)

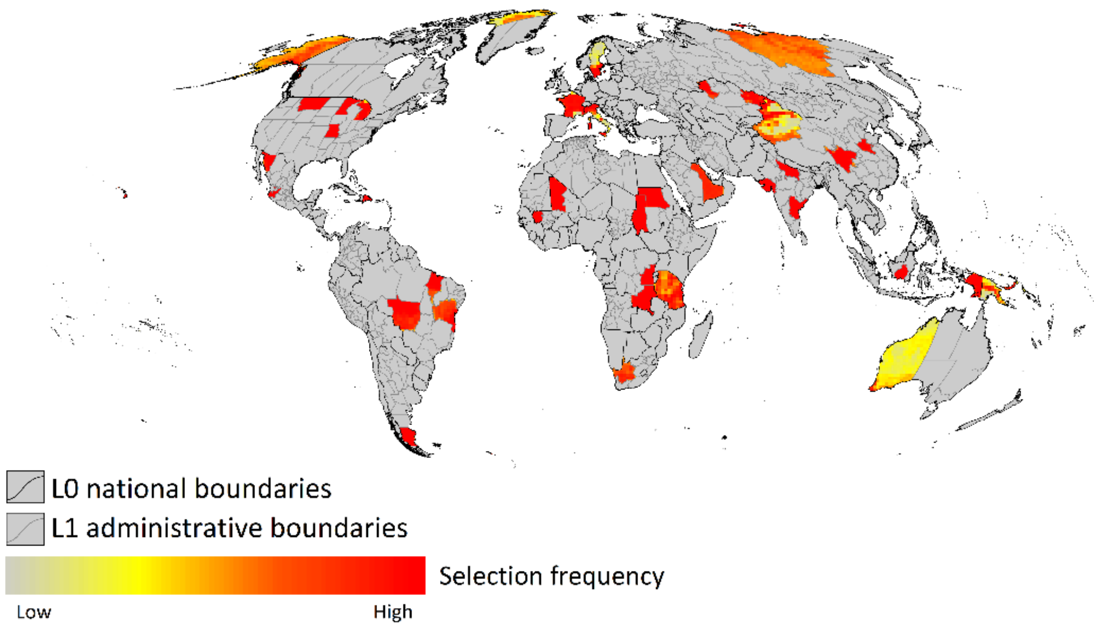


Figure 4. (a) Sample of 100 km² grid squares found in the focal countries (national planning units) and administrative units (sub-national planning units) selected by Marxan that best meets 10% targets for biogeographic and conservation area extent factors while minimising sample area. (b) Selection frequency scores from Marxan showing the number of times each planning unit was selected across the 1,000 runs used to identify the best sample.

Supplementary Materials

Initial list of factors to be included in spatial prioritisation

Table S1: Factors discussed in our expert workshop as potential drivers of conservation area establishment and drivers of biodiversity patterns

African, Caribbean and Pacific Group of States	Latitude
Age of PA network	Legal system type
Carbon payments	Major habitat types
Climate vulnerability indices	PA investment
Completeness of WDPA country records	PA management effectiveness
Continents	PA management record
Corruption	PA visitor numbers
Degraded and pristine areas	Political groupings (e.g. ex-Soviet, ex-colonial)
Ecoregions	Political stability
Endemism	Rates of forest loss
Freshwater	Rates of habitat conversion
Islands	Religious groupings
Land tenure	Sacred sites
Landcover trends	Size of country
Language groups	Within country variability

Sensitivity analysis to set targets

The sensitivity analysis explored the trade-off between the area of the terrestrial realm selected to be a potential sample for future studies on conservation area extent and representativeness, and the number of planning units selected (where each planning unit was a country or, for countries with an area ≥1 million km^2, sub-national units such as provinces and states). This was based on the premise that selecting a larger percentage of the planet would produce a more robust sample but selecting more countries and provinces would increase the time and resources needed to collect the conservation area data. So, we used the conservation planning system developed for Stage 1 to run eight Marxan analysis using the same percentage target for each feature in each analysis. These different targets were 1%, 2%, 5%, 10%, 20%, 30%, 40% and 50% of the total extent of each feature, and each analysis consisted of 100 runs of 10,000,000 iterations. We used a Boundary Length Modifier of 1.5 (Ball et al. 2009), a value that we determined through testing to best ensure that Marxan chose enough sub-national units from the same countries to meet the targets. We then counted the number of whole countries and the number of planning units in the 'best' solution for each of the eight analyses.

The number of planning units selected by Marxan to meet the targets for the 89 conservation features ranged from 23 for the 1% targets to 206 for the 40% targets (Table S2). The number of planning units more than doubled when comparing results from using 10% and 20% targets, with a levelling off when the targets were ≥ 30%. Based on these results, we decided to use 10% targets for the main analyses.

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Table S2. The number of planning units and countries selected to meet specific percentage targets for each of the 89 features. Planning units consisted of whole countries for nations with an area <1 million km^2 and highest level sub-national units (provinces, states, etc) for countries with an area ≥1 million km^2.

Conservation feature targets (%)	Number of planning units selected	Number of countries selected
1	23	22
2	24	22
5	30	24
10	50	25
20	117	27
30	204	32
40	206	32
50	205	32

Details of the features used in the analysis and their levels of representation in the selected samples

Table S3: Details of all the features used in the analysis, their total extent, the proportion of the Stage 1 and Stage 2 best outputs covered by each, and the proportion of the terrestrial realm covered by the Stage 1 and Stage 2 best outputs.

Category	Feature	Global extent (km^2)	Terrestrial realm covered by feature (%)	Stage 1 sample covered by feature (%)	Stage 2 sample covered by feature (%)	Global extent found in Stage1 sample (%)	Global extent found in Stage 2 sample (%)
Biomes	Tropical and subtropical moist broadleaf forest	19,847,759	14.67	10.78	13.49	11.40	10.00
Biomes	Tropical and subtropical dry broadleaf forest	3,017,092	2.23	1.92	2.54	13.36	12.41
Biomes	Tropical and subtropical coniferous forest	711,296	0.53	0.34	0.48	9.98	9.98
Biomes	Temperate broadleaf and mixed forest	12,772,448	9.44	6.64	8.68	10.91	10.00
Biomes	Temperate conifer forest	4,075,868	3.01	1.97	2.77	10.16	10.00
Biomes	Boreal Forest/taiga	15,046,636	11.12	14.11	10.99	19.68	10.75
Biomes	Tropical and Subtropical grasslands, savannas and shrubland	20,285,917	14.99	14.04	15.73	14.53	11.41
Biomes	Temperate grasslands, savannas and shrublands	10,098,291	7.46	4.92	6.86	10.22	10.00
Biomes	Flooded grasslands and savannas	1,094,839	0.81	0.63	0.83	12.03	11.13
Biomes	Montane grasslands and shrublands	5,203,199	3.85	3.28	3.58	13.23	10.13
Biomes	Tundra	8,206,496	6.07	9.22	7.90	23.59	14.16
Biomes	Mediterranean forests, woodlands and scrub	3,210,402	2.37	3.59	2.34	23.50	10.70
Biomes	Deserts and xeric shrublands	27,969,796	20.67	25.21	21.03	18.92	11.06
Biomes	Mangroves	320,823	0.24	0.21	0.23	13.99	10.51
Biomes	Inland water	1,039,692	0.77	0.84	0.96	16.96	13.54
Biomes	Rock and ice	1,973,619	1.46	1.99	1.34	21.16	10.00
Realms	Australasia	9,232,561	6.82	15.77	8.78	35.85	13.99
Realms	Antarctic	11,159	0.01	0.02	0.01	33.00	10.88

Realms	Afrotropics	21,769,183	16.09	13.08	16.22	12.62	10.96
Realms	Indomalay	8,513,981	6.29	4.08	5.79	10.06	10.00
Realms	Nearctic	20,398,341	15.08	12.92	13.86	13.30	10.00
Realms	Neotropics	19,368,174	14.31	10.32	13.16	11.19	10.00
Realms	Oceania	43,247	0.03	0.09	0.10	45.13	32.70
Realms	Palearctic	52,705,510	38.95	40.89	39.84	16.28	11.12
Realms	Snow and ice	2,832,017	2.09	2.52	2.01	18.66	10.44
Elevation	0 – 299 m	55,813,693	41.25	37.82	39.26	14.23	10.35
Elevation	300 – 799 m	43,299,328	32.00	35.59	33.97	17.26	11.54
Elevation	800 – 1399 m	19,827,397	14.65	16.57	15.77	17.54	11.71
Elevation	1400 – 1999 m	7,279,095	5.38	4.47	4.95	12.88	10.00
Elevation	>= 2000 m	8,627,189	6.38	5.32	5.86	12.94	10.00
Islands and continents	< 1,000 km^2	487,462	0.36	0.29	0.33	12.28	10.00
Islands and continents	1,000 to 10,000 km^2	660,808	0.49	0.60	0.50	18.95	11.07
Islands and continents	10,000 to 100,000 km^2	1,621,613	1.20	0.86	1.11	11.11	10.03
Islands and continents	100,000 to 1,000,000 km^2	5,009,245	3.70	4.04	3.95	16.92	11.60
Islands and continents	> 1,000,000 km^2	127,492,420	94.23	94.20	94.10	15.51	10.86
Landcover	Croplands	10,044,523	7.42	7.92	9.62	16.54	14.08
Landcover	Croplands mosaic	17,948,478	13.27	10.76	12.81	12.59	10.50
Landcover	Closed forest	25,436,142	18.80	13.85	17.29	11.43	10.00
Landcover	Open forest	12,323,377	9.11	12.82	11.32	21.85	13.51
Landcover	Mosaic grassland/shrubland	26,265,135	19.41	20.05	18.32	16.02	10.26
Landcover	Sparse vegetation	13,551,920	10.02	12.60	9.22	19.52	10.01
Landcover	Flooded forest/grassland	1,902,386	1.41	1.53	1.45	16.92	11.19
Landcover	Artificial surfaces	317,365	0.23	0.20	0.22	12.94	10.04
Landcover	Bare areas	21,608,578	15.97	15.35	15.53	14.91	10.57
Landcover	Water bodies	2,980,599	2.20	2.08	2.18	14.68	10.75
Landcover	Snow and ice	2,913,595	2.15	2.82	2.02	20.29	10.21
Landcover	No data	14,186	0.01	0.02	0.02	29.48	18.71

Latitude	50N to 90N	31,826,862	23.52	27.39	22.89	18.06	10.58
Latitude	30N to 50N	32,126,360	23.74	20.68	21.83	13.51	10.00
Latitude	10N to 30N	26,501,375	19.59	15.65	21.21	12.40	11.78
Latitude	-10S to 10N	20,617,051	15.24	13.90	16.00	14.15	11.42
Latitude	-30S to -10S	18,842,279	13.93	18.04	14.11	20.10	11.02
Latitude	-50S to -30S	5,146,310	3.80	4.04	3.54	16.48	10.13
Latitude	-90S to -50S	214,058	0.16	0.30	0.41	29.83	28.50
Income classification	Low income	14,417,961	10.66	11.06	14.00	16.10	14.29
Income classification	Lower middle income	22,038,475	16.29	12.63	15.92	12.03	10.63
Income classification	Upper middle income	60,767,325	44.91	40.77	41.32	14.08	10.00
Income classification	High income	38,082,584	28.15	35.54	28.76	19.59	11.11
Population density	0 to 0.9	53,883,215	39.82	46.44	39.53	18.09	10.79
Population density	1 to 9.9	39,359,881	29.09	28.03	31.21	14.95	11.67
Population density	10 to 99.9	27,781,643	20.53	16.15	18.89	12.20	10.00
Population density	100 to 999.9	9,292,487	6.87	5.54	7.02	12.52	11.11
Population density	1000+	1,070,380	0.79	0.56	0.73	11.05	10.10
Govt. Effectiveness	0 - 24.9	23,463,373	17.34	11.34	15.95	10.15	10.00
Govt. Effectiveness	25 - 49.9	48,702,809	35.99	33.62	34.59	14.49	10.45
Govt. Effectiveness	50 - 74.9	28,037,538	20.72	23.55	24.89	17.64	13.06
Govt. Effectiveness	75 – 100	35,102,625	25.94	31.49	24.58	18.83	10.30
Subregions	Australia and New Zealand	7,985,635	5.90	12.08	5.43	31.75	10.00
Subregions	Caribbean	233,427	0.17	0.23	0.33	20.70	20.62
Subregions	Central America	2,481,651	1.83	1.25	1.70	10.57	10.05
Subregions	Central Asia	4,380,003	3.24	2.29	2.98	10.99	10.00
Subregions	Eastern Africa	7,049,679	5.21	4.52	4.79	13.45	10.00
Subregions	Eastern Asia	11,598,707	8.57	10.87	9.46	19.68	12.00
Subregions	Eastern Europe	18,604,967	13.75	14.62	12.64	16.49	10.00
Subregions	Melanesia	544,908	0.40	2.22	1.38	85.63	37.36
Subregions	Micronesia	3,576	0.00	0.00	0.00	27.68	15.27

Subregions	Middle Africa	6,608,246	4.88	3.55	5.01	11.27	11.15
Subregions	Northern Africa	7,647,985	5.65	4.80	6.74	13.18	12.97
Subregions	Northern America	21,581,549	15.95	14.61	14.67	14.21	10.00
Subregions	Northern Europe	1,803,994	1.33	2.13	1.23	24.83	10.00
Subregions	Polynesia	8,613	0.01	0.02	0.01	46.37	14.01
Subregions	South America	17,845,353	13.19	9.80	12.40	11.53	10.23
Subregions	South-eastern Asia	4,483,416	3.31	2.24	3.05	10.50	10.00
Subregions	Southern Africa	2,681,065	1.98	1.73	1.82	13.54	10.00
Subregions	Southern Asia	6,710,677	4.96	3.35	4.75	10.49	10.41
Subregions	Southern Europe	1,316,461	0.97	1.43	1.11	22.85	12.38
Subregions	Western Africa	6,082,789	4.50	2.99	4.20	10.33	10.15
Subregions	Western Asia	4,528,985	3.35	2.62	3.08	12.16	10.00
Subregions	Western Europe	1,102,673	0.81	2.62	3.24	49.81	43.21