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Developing a framework to improve global estimates of conservation area coverage

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Abstract

Area-based conservation is a widely used approach for tackling biodiversity loss and there are ongoing discussions over what is an appropriate global conservation area coverage target. To inform such debates, we need to know the extent and ecological representativeness of the current conservation area network, but this is hampered by gaps in existing global datasets. In particular, while data on privately and communally managed protected areas (PAs) and OECMs (other effective area-based conservation measures) are often available at the national level, it can take many years to incorporate these into official datasets. This suggests a complementary approach is needed, based on selecting a sample of countries and using their national-scale datasets to produce more accurate metrics. However, every country added to the sample increases the costs of data collection, collation and analysis. To address this, here we present a data collection framework underpinned by a spatial prioritisation algorithm, which identifies a minimum set of countries that are also representative of 10 factors that influence conservation area establishment and biodiversity patterns. We then illustrate this approach to identify a representative set of sampling units that cover 10% of the terrestrial realm, selecting 25 countries (choosing the same 10% area at random selected a mean of 162 countries). These sampling units could be the focus of future data collation on different types of conservation area. Analysing these data could produce quicker, more accurate estimates of global conservation area coverage and ecological representativeness, complementing existing international reporting systems.

Keywords Aichi Target 11, conservation areas, other effective area-based conservation measures, OECM, protected areas, systematic conservation planning, conservation targets

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) and World Database of OECMs (WD-OECM). These databases are 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 and WD-OECM extremely important sources of information, which need long-term, sustained resourcing to maintain their 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 (Bingham et al., 2017; Corrigan et al., 2018), partly because governments only recently started collecting data on conservation areas not owned or managed by the state. Additionally, some custodians of non-state conservation areas lack the capacity or are wary of providing information to governments about their land (Clements et al., 2018).

These limitations make it difficult to accurately measure progress towards international area-based conservation targets. 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 ecosystems that are missing from state PAs (Palfrey et al., 2022). Both these issues 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; Visconti et al., 2019; CBD, 2021). Investing in improving the quality of global conservation area datasets will address this; 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 resource intensive and a long-term process (Juffe-Bignoli et al., 2016), so complementary approaches that can provide more rapid insights are also needed.

One complementary approach could be to develop an analogous methodology to that of the Sampled Red List Index, which was designed to produce a better measure of 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). 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). 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 national conservation area datasets without contradicting official data reported by governments. Using such an approach would give additional insights on trends in global PA and OECM networks, alongside the existing official datasets countries maintain as part of their CBD commitments (UNEP-WCMC, 2019). 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 units 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 influenced by a range of economic, political and social factors. For example, it is well known that conservation area coverage is higher on land of lower commercial value for agriculture or resource extraction (Loucks et al., 2008; Joppa & Pfaff, 2009). Drivers of biodiversity patterns include latitude and elevation, as species and ecosystems show strong variation across these gradients (Gaston & Spicer, 2013). Selecting a set of countries that best mirror these patterns is mathematically defined by the minimum set problem, so our framework is based on algorithms typically designed to solve these problems. This involves: selecting and mapping the features that influence conservation area extent and/or biodiversity pattern features; setting how much of each feature should be included in the sample, and; using complementarity-based algorithms to choose the best sets of countries that contain the specified amount of these features (Kukkala & Moilanen, 2013).

Using this approach also involves choosing a cost metric, so that the prioritisation process minimises the cost while achieving the feature representation goals (Naidoo et al., 2006). In our case this metric needs to reflect the substantial time and effort involved in collecting the conservation area data. PA and OECM datasets 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. 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 sub-national 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, to better match 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 objectives, 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 sampling units within the subset of selected countries. 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 three steps (Figure 1), 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 (iii) a two-stage analysis: Stage 1 to identify the minimum set of countries needed to meet targets for each feature, and Stage 2 to identify sets of 10,000 km^2 grid squares that meet these targets within this subset of countries.

Choosing factors affecting biodiversity patterns and area-based conservation efforts

We conducted a literature review to identify factors that influence 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 Table 1) before generating a final list. This 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 (Table 1, Figure 2). 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 (Supplementary Table 2).

Spatial analysis

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 (Table 1 and Supplementary Table 1). We used the different datasets to produce a 1 km x 1 km resolution raster layer for each factor based on the Mollweide projection.

We used the Marxan software package (Ball et al., 2009) for the Stage 1 and Stage 2 analyses to identify the best set of sampling units, based on identifying a representative sample of the terrestrial realm by meeting targets for each of the 89 features across the ten factors, whilst minimising the number of countries selected (Figure 1). This is a novel use of Marxan, which is generally used to identify priority areas for conservation, whereas our analyses identify priority areas for data collection. We used Marxan in Stage 1 to identify a representative set of countries and territories. In Stage 2 we then identified 10,000 km^2 grid squares within these countries (Table 2), thus refining the sample from Stage 1 to avoid over-representing larger nations.

Marxan uses a simulated annealing algorithm, where each 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 sampling unit appears in each of the portfolios. Sampling units with high selection scores are always needed to meet the targets; lower scoring sampling units can be swapped with similar sampling units without affecting target attainment (Ball et al. 2009).

For Stage 1, the sampling 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 sampling 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 collate data from a large number of expert groups. We followed established practice for reporting terrestrial coverage statistics by excluding Antarctica from our analyses (Butchart et al., 2015). The Stage 2 sampling units were based on a global set of 100 km x 100 km grid squares created in QGIS 3 (QGIS, 2019). We then clipped this global grid layer with the national and sub-national sampling units used in Stage 1 to produce the final sampling unit layer.

We used the CLUZ plugin (Smith, 2019) for QGIS to import the feature raster layers, calculate the area of each feature in each sampling unit and run Marxan. To ensure the sampling units selected in Stage 1 and 2 were representative of the terrestrial realm, we used Marxan to identify sampling units that when combined met the same percentage of total extent 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 sampling units. Based on this sensitivity analysis we chose a target value of 10%, as the number of sampling units required to meet higher targets increased more than two-fold (Supplementary Material 1 and Supplementary Table 3). Thus, the set of sampling units identified by Marxan contained 10% of the total area of each of the 89 features.

The Stage 1 and Stage 2 analyses both involved 1,000 Marxan runs (see Supplementary Material 2 for more details). The Stage 1 analysis was based on 900 national and sub-national sampling units. Each run consisted of 10 million iterations, and we set the costs so that Marxan ensured each portfolio met all the targets and also minimised the number of countries selected (Supplementary Material 2). The Stage 2 analysis was based on the 3,377 grid squares found within the national and sub-national sampling units selected in Stage 1. Each run consisted of 100 million iterations, and we set the costs so that Marxan ensured each portfolio met all the targets.

Comparative analyses

In order to measure whether using our prioritisation approach produced better results than sampling units at random, we created 1,000 randomly selected sets of national and sub-national sampling units (analogous to the Stage 1 Marxan analysis) and 1,000 randomly selected sets of the 100 km x 100 km sampling units (analogous to the Stage 2 Marxan analysis but based on all the sampling units across the global terrestrial realm, not only those found within the selected Stage 1 Marxan analysis areas). To do this, we used Python (Van Rossum & Drake, 2009) to randomly select sampling units until the set met or exceeded the mean of the combined areas of the 1,000 Stage 1 or Stage 2 Marxan outputs, and to calculate the characteristics of the Marxan and random samples.

We then undertook three analyses to compare the two Marxan and two random samples. The first analysis compared the extent to which the different samples met the feature targets and therefore represented the different factors linked to drivers of conservation area establishment and biodiversity patterns. The second analysis compared the number of countries and number of Stage 1 (national and subnational) sampling units selected, and therefore the effort needed to collect conservation area data. The third analysis compared the percentage of the terrestrial realm covered by any PAs. 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. Point data were included if the PA area 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, used QGIS to calculate the total area in each grid square, and then calculated the overall percentage PA coverage for each of the Marxan and random sets.

Results

Stage 1 analysis

The best portfolio identified using Marxan consists of nine whole countries and territories, and 33 of the sub-national sampling 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 sampling units were selected in every one of the 1,000 portfolios identified by Marxan (Figure 3b), meaning that each of the other 25 sampling units could be swapped for sampling units containing similar amounts of the different features to produce similarly efficient portfolios.

Stage 2 analysis

The best portfolio identified by Marxan met all the targets and contained 2,231 of the 3,377 sampling units found within the Stage 1 sample, covering 10.89% of the global terrestrial area (Figure 4a). The combined area of the selected Stage 1 sampling units also selected in Stage 2 ranged between 31.5% for Australia and 100% for the Dominican Republic, with a median of 76.1% (Figure 4a); only 7 countries had less than half their Stage 1 area selected in Stage 2. The selection frequency results for Stage 2 mirrors this pattern, with low scores for sampling units where Marxan only needed to select a smaller proportion of the national and sub-national sampling units (Figure 4b).

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.D. = 0.975) of the terrestrial realm and the mean selected area of the 1,000 Stage 2 Marxan outputs was 10.89%. (S.D. = 0.006). 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 (Table 1, Supplementary Table 4), whereas the Stage 1 random sets failed to meet a mean of 15.7 targets (S.D. = 4.02) and the Stage 2 random sets failed to meet 16.5 targets (S.D. = 3.62).

Using the best Marxan output would require collecting PA data from 25 countries and across 42 Stage 1 (national and subnational) sampling units. In comparison, the Stage 1 random sets of sampling units covered a mean of 64.3 countries (Supplementary Fig 1, S.D. = 7.44) and 152.9 national and subnational sampling units (S.D. = 20.6). The Stage 2 random sets of sampling units covered a mean of 162.1 countries (Supplementary Fig 2, S.D. = 4.91) and 514.1 national and subnational sampling units (S.D. = 10.3).

The publicly available WDPA data showed that 15.25% of the terrestrial realm is under protection, compared to a mean of 15.34% (S.D. = 2.20) for the Stage 1 Marxan outputs, and a mean of 15.97% (S.D. = 0.274) for the Stage 2 Marxan outputs. This compares to a mean area under protection for the Stage 1 random sets of sampling units of 15.23% (S.D. = 2.53) and for the Stage 2 random sets of sampling units of 15.24% (S.D. = 0.572).

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). To augment the existing reporting systems, we propose using an approach pioneered by the Sampled Red List Index and similar projects (Butchart et al., 2007; Baillie et al., 2008). In this study we outline 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 shape total conservation area network extent and patterns of global biodiversity (Figure 1).

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 shape 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 Table 1). 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 sampling 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 sampling 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 sampling unit was selected in each of the runs, showed that only 17 of these sampling units were chosen every time (Figure 3b). The other sampling 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 sampling units, mostly within the largest sub-national sampling units selected in Stage 1 containing additional land not needed to meet the targets (Figure 4). This Stage 2 result also shows the efficiency benefits of using a complementarity-based algorithm to select sample areas (Ball et al., 2009), as Marxan was able to meet the 10% targets for each feature in close to 10% of the sampling 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 sampling units and so are over-represented through meeting targets for other features (Table 1, Supplementary Tables 2 & 4). 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.

We found that the Stage 1 and Stage 2 random sets of sampling units had near identical levels of PA coverage as the global figure. However, none of these random outputs also met all of the feature targets, so they would be less suitable for assessing the extent to which a sample of conservation areas represented biodiversity. The Stage 1 and Stage 2 Marxan outputs met all the feature targets, indicating that they could be used to measure conservation area representativeness, but the mean PA coverage for the Stage 2 outputs is 15.97%, compared to the global figure of 15.25% calculated from the publicly available WDPA data. This over-estimate of PA coverage may be a result of our sampling framework, so more research is needed to understand the reasons for this difference, but its impact could be reduced in future by adjusting conservation area estimates from this sampled approach based on the difference between the global and sample WDPA PA coverage.

It could be argued that a better approach for choosing a sample is to select sampling units at random, avoiding the need to make assumptions about which factors drive conservation area extent and global biodiversity patterns. We investigated this and found that the Stage 1 and Stage 2 random sets of sampling units had near identical levels of PA coverage as the global figure, but would require collecting data from between two to seven times more countries and across three to twelve times more national and sub-national sampling units than the Marxan outputs. Thus, our data collection framework based on minimising the number of countries selected and minimising biases in these countries by setting representation targets is much more practical.

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 for conservation area coverage 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 intensive data collection realistic. 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 (O'Neill et al., in prep). 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 suggest this approach based on using data collected from a representative sample of countries could be used to produce global estimates 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; Naidoo et al., 2019). In doing so, our sampling approach could help monitor progress towards meeting international conservation targets and policies.

Author contributions

Conceptualization: RJS, ZD, NB, NK; Study design: RES, DJB, KM, PS, MS, PV, NB, NK, ZD, RJS; data analysis: RES, HON, RJS; writing: RES, HON, DJB, KM, PS, MS, PV, NB, NK, ZD, RJS

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Conflicts of interest None.

Ethical standards This research abided by the *Oryx* guidelines on ethical standards.

Data availability The files used in this analysis are available from DOI:10.32942/osf.io/sxmk5

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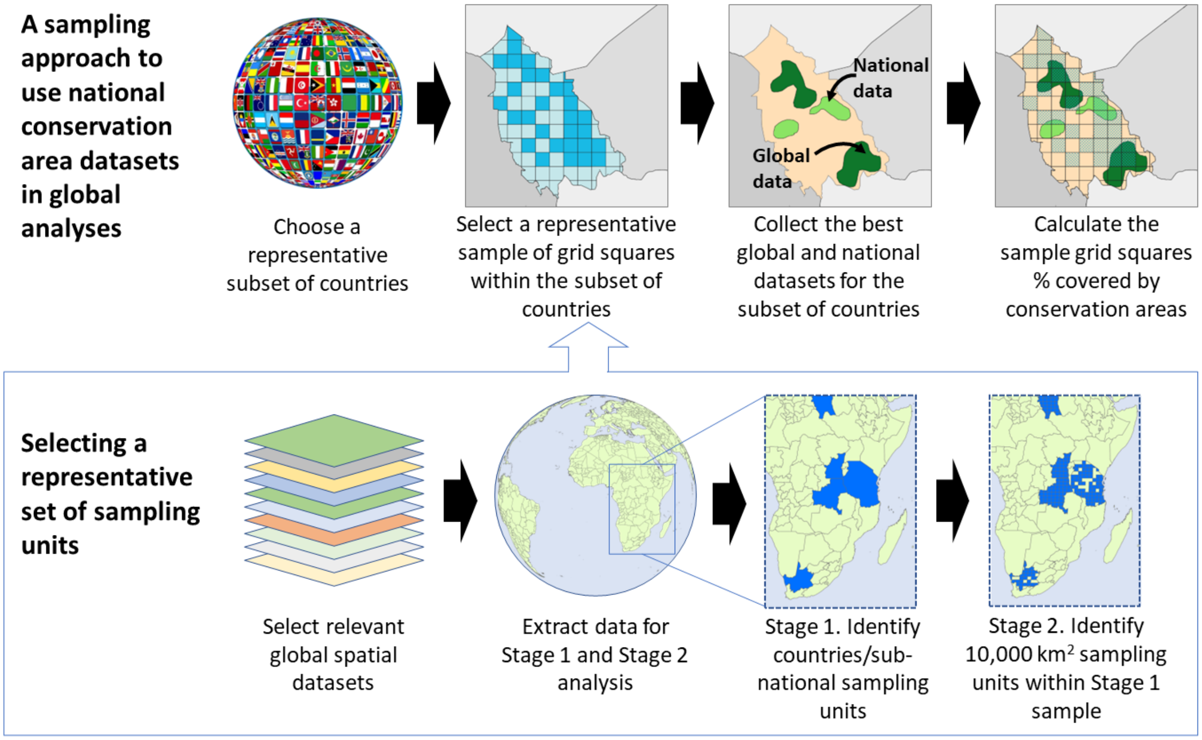
TABLE 1 Details of how the features used in the analysis were defined and their data sources.

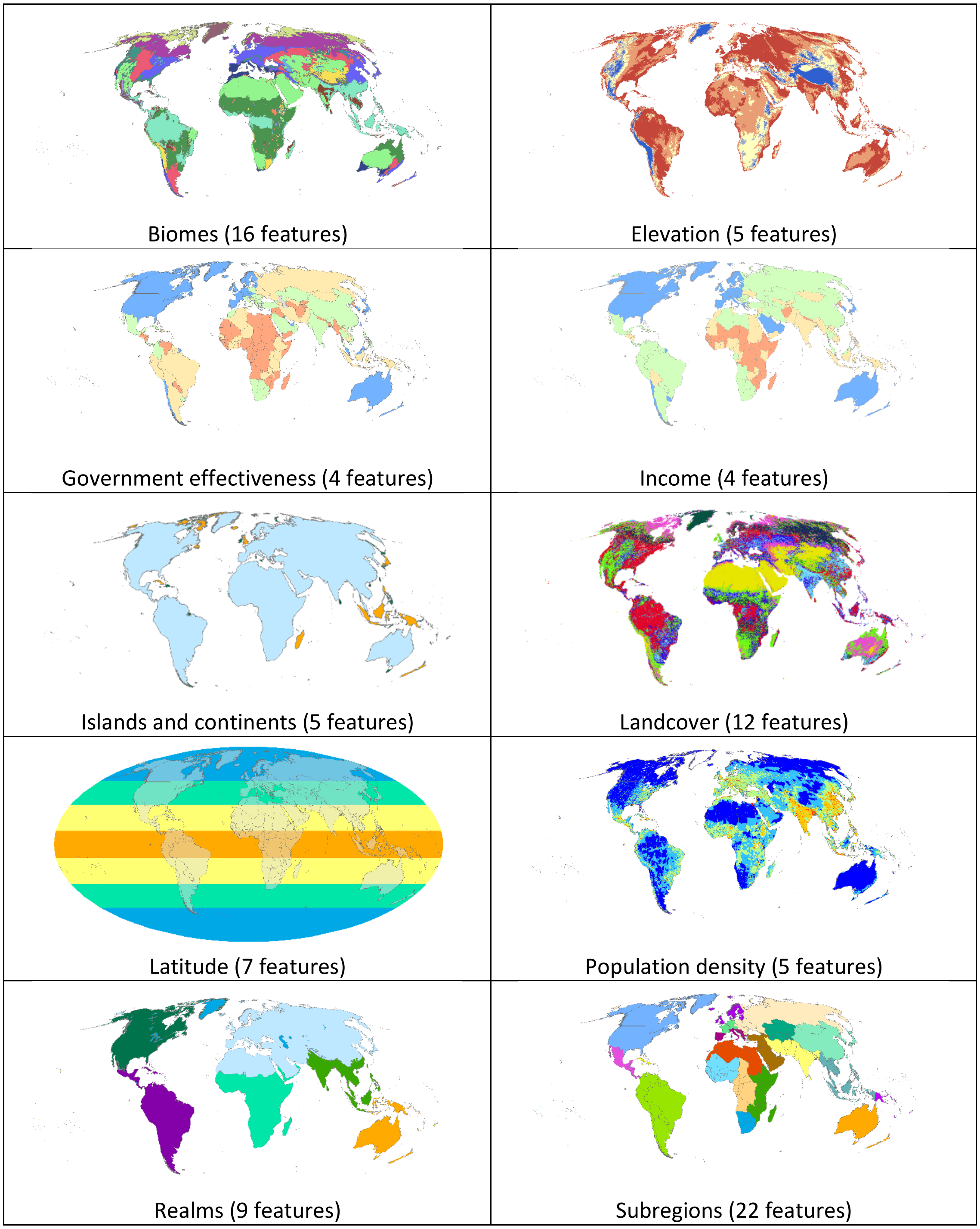
Factor	Features	Data source
Biomes	16 biomes	Olson et al., 2001
Elevation	Five features: 0 – 299 m, 300 – 799 m, 800 – 1399 m, 1400 – 1999 m, ≥ 2000 m	Shuttle Radar Topography Mission
Government effectiveness	Four features: 0 - 24.9, 25 - 49.9, 50 - 74.9 and 75 - 100	World Bank, 2019a
Income (per capita)	Four features: low, lower-middle, upper-middle and high income countries	World Bank, 2019b
Islands and continents	Five categories: < 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)	GADM 2018
Landcover	12 landcover types	ESA GlobCover Project 2009
Latitude	Seven features: five 20° bands; two 40° bands at the poles to avoid over-representation of these smaller regions	
Population density	Five features using a logarithmic scale: 0 - 0.9, 1 - 9.9, 10 - 99.9, 100 - 999.9 and > 1000 people per km^2	UNPD, 2013
Realms	Eight realms	Olson et al., 2001
Subregions	22 subregions	UNSD 2019

TABLE 2 Details of the factors used in the analysis that are likely to shape 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	10.92
Elevation	5	5.38	41.24	12.94	10.73
Government effectiveness	4	17.34	35.99	15.28	11.01
Income	4	10.66	44.91	15.45	10.60
Islands and continents	5	0.36	94.23	14.95	11.61
Landcover	12	0.01	19.41	17.26	11.04
Latitude	7	0.16	23.74	17.79	13.87
Population density	5	0.79	39.82	13.76	10.59
Realms	9	<0.01	38.95	21.79	14.82
Subregions	22	<0.01	15.95	22.18	13.87



580 FIG. 1 Schematic illustrating the sampling approach for developing more accurate estimates of global conservation area coverage based on national datasets.



585 FIG. 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 Table 4.

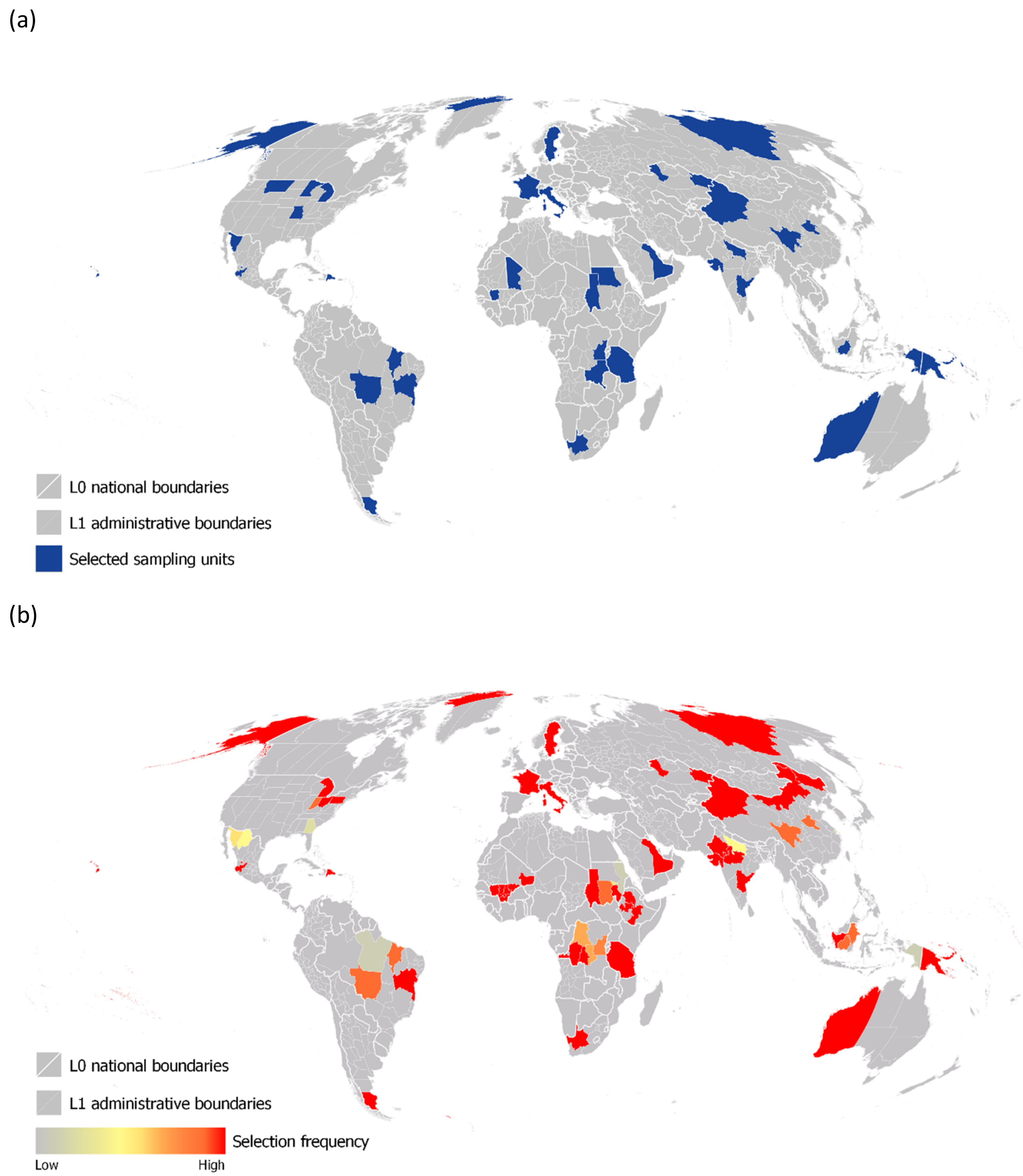


FIG. 3 (a) Sample of countries (national sampling units) and administrative units (sub-national sampling units) that meet 10% targets, selected based on 1,000 Marxan runs and selecting the result with the smallest number of sampling units, most even spread across the continents and with sampling units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

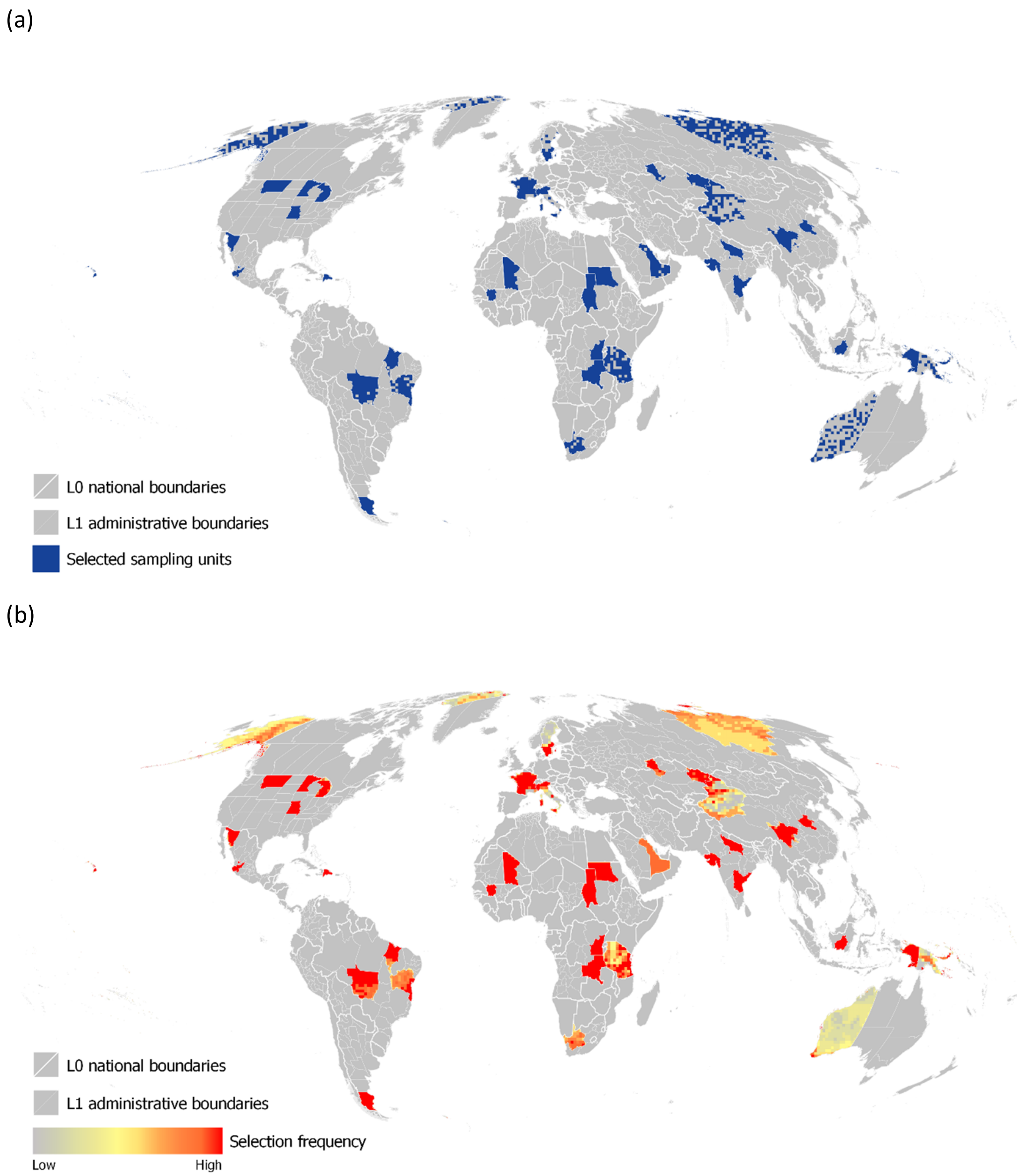


FIG. 4 (a) Sample of 100 x 100 km grid squares found in the focal countries (national sampling units) and administrative units (sub-national sampling units) selected by Marxan that best meets 10% targets for biogeographic and conservation area extent factors while minimising sample area. (b) Selection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

Developing a framework to improve global estimates of conservation area coverage

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SUPPLEMENTARY TABLE 1 Initial list of factors which were discussed in our expert workshop as potential drivers of conservation area establishment and drivers of biodiversity patterns for possible inclusion in spatial prioritisation

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

SUPPLEMENTARY TABLE 2 Factors that drive global biodiversity patterns and conservation area extent which were included in our spatial prioritisation 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).

SUPPLEMENTARY MATERIAL 1 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 sampling units selected (where each sampling 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 sampling units in the 'best' solution for each of the eight analyses.

The number of sampling 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 S3). The number of sampling 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.

SUPPLEMENTARY TABLE 3 The number of sampling units and countries selected to meet specific percentage targets for each of the 89 features. Sampling 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 sampling 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

SUPPLEMENTARY MATERIAL 2 Marxan analysis

We used Marxan for a two-stage analysis: Stage 1 identified the minimum set of countries needed to meet targets for each feature and Stage 2 identified sets of 10,000 km^2 grid squares that meet these targets within this subset of countries. This involved setting Species Penalty Factors to ensure that all the targets were met and we used a value of 10 for every feature for both analyses, as our initial testing showed this value produced efficient results.

For the Stage 1 analysis, we sought to select a set of national and sub-national sampling units that represented all the features, while also minimising the number of countries selected. To do this we set the combined sampling 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 sampling units, based on the sub-national administrative units, we set the sampling 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 sampling unit cost of 0.111. In addition, we needed to ensure that Marxan met targets by selecting the sub-national sampling units from the same countries whenever possible. To do this we manipulated the Marxan boundary cost file so it appeared that every sub-national sampling unit in the same country shared a boundary. This meant that if Marxan selected one sub-national sampling unit in a particular country then it would be less costly to select subsequent sub-national sampling 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 sampling units are more likely to be selected together, even when they are not physically adjacent (Possingham et al., 2005; Hermoso et al., 2011).

We 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 sampling units selected. Of the resulting 1,000 portfolios, 284 had equally low costs, i.e., contained exactly the same number of countries and sampling 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 sampling 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 sampling 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 x 100 km sampling 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 but we used 100,000,000 iterations after carrying out a sensitivity analysis that showed more iterations were needed to produce efficient results because Stage 2 involved a larger number of planning units than Stage 1. For Stage 2 we used a Boundary Length Modifier value of 0 because we were not interested in selecting adjacent sampling units. For this finer-scale analysis we used the sampling unit area as the cost metric. 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 sampling units neighbour each other.

SUPPLEMENTARY TABLE 4 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.

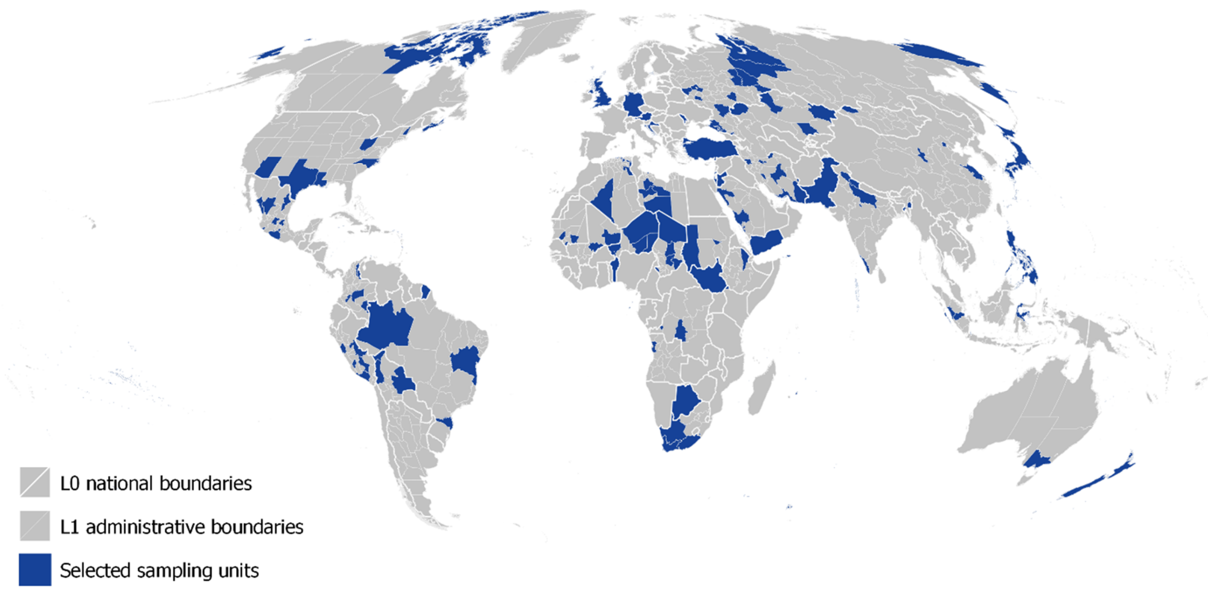
Category	**Feature**	**Global extent (km^2)**	**Terrestrial realm covered by feature (%)**	**Stage 1 sample covered by feature (%)**	**Stage 2 sample covered by feature (%)**	**Global extent found in Stage 1 sample (%)**	**Global extent found in Stage 2 sample (%)**
Biomes	Tropical and subtropical moist 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	12.32
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	10.01
Biomes	Temperate conifer forest	4,075,868	3.01	1.97	2.77	10.16	10.01
Biomes	Boreal Forest/taiga	15,046,636	11.12	14.11	10.99	19.68	10.73
Biomes	Tropical and Subtropical grasslands, savannas and shrubland	20,285,917	14.99	14.04	15.73	14.53	11.29
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	11.58
Biomes	Montane grasslands and shrublands	5,203,199	3.85	3.28	3.58	13.23	10.19
Biomes	Tundra	8,206,496	6.07	9.22	7.90	23.59	14.10
Biomes	Mediterranean forests, woodlands and scrub	3,210,402	2.37	3.59	2.34	23.50	10.00
Biomes	Deserts and xeric shrublands	27,969,796	20.67	25.21	21.03	18.92	11.13
Biomes	Mangroves	320,823	0.24	0.21	0.23	13.99	10.95

Biomes	Inland water	1,039,692	0.77	0.84	0.96	16.96	12.47
Biomes	Rock and ice	1,973,619	1.46	1.99	1.34	21.16	10.05
Realms	Australasia	9,232,561	6.82	15.77	8.78	35.85	13.82
Realms	Antarctic	11,159	0.01	0.02	0.01	33.00	15.72
Realms	Afrotropics	21,769,183	16.09	13.08	16.22	12.62	10.99
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	41.67
Realms	Palearctic	52,705,510	38.95	40.89	39.84	16.28	11.07
Realms	Snow and ice	2,832,017	2.09	2.52	2.01	18.66	10.15
Elevation	0 – 299 m	55,813,693	41.25	37.82	39.26	14.23	11.61
Elevation	300 – 799 m	43,299,328	32.00	35.59	33.97	17.26	11.88
Elevation	800 – 1399 m	19,827,397	14.65	16.57	15.77	17.54	10.07
Elevation	1400 – 1999 m	7,279,095	5.38	4.47	4.95	12.88	10.08
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	12.22
Islands and continents	1,000 to 10,000 km^2	660,808	0.49	0.60	0.50	18.95	10.02
Islands and continents	10,000 to 100,000 km^2	1,621,613	1.20	0.86	1.11	11.11	11.27
Islands and continents	100,000 to 1,000,000 km^2	5,009,245	3.70	4.04	3.95	16.92	10.84

Islands and continents	> 1,000,000 km^2	127,492,420	94.23	94.20	94.10	15.51	13.69
Landcover	Croplands	10,044,523	7.42	7.92	9.62	16.54	10.47
Landcover	Croplands mosaic	17,948,478	13.27	10.76	12.81	12.59	10.00
Landcover	Closed forest	25,436,142	18.80	13.85	17.29	11.43	13.02
Landcover	Open forest	12,323,377	9.11	12.82	11.32	21.85	10.50
Landcover	Mosaic grassland/shrubland	26,265,135	19.41	20.05	18.32	16.02	10.16
Landcover	Sparse vegetation	13,551,920	10.02	12.60	9.22	19.52	10.66
Landcover	Flooded forest/grassland	1,902,386	1.41	1.53	1.45	16.92	10.21
Landcover	Artificial surfaces	317,365	0.23	0.20	0.22	12.94	10.64
Landcover	Bare areas	21,608,578	15.97	15.35	15.53	14.91	10.18
Landcover	Water bodies	2,980,599	2.20	2.08	2.18	14.68	10.21
Landcover	Snow and ice	2,913,595	2.15	2.82	2.02	20.29	15.85
Landcover	No data	14,186	0.01	0.02	0.02	29.48	10.53
Latitude	50N to 90N	31,826,862	23.52	27.39	22.89	18.06	10.00
Latitude	30N to 50N	32,126,360	23.74	20.68	21.83	13.51	11.75
Latitude	10N to 30N	26,501,375	19.59	15.65	21.21	12.40	11.31
Latitude	-10S to 10N	20,617,051	15.24	13.90	16.00	14.15	11.09
Latitude	-30S to -10S	18,842,279	13.93	18.04	14.11	20.10	10.12
Latitude	-50S to -30S	5,146,310	3.80	4.04	3.54	16.48	28.55
Latitude	-90S to -50S	214,058	0.16	0.30	0.41	29.83	14.29
Income classification	Low income	14,417,961	10.66	11.06	14.00	16.10	10.56

Income classification	Lower middle income	22,038,475	16.29	12.63	15.92	12.03	10.00
Income classification	Upper middle income	60,767,325	44.91	40.77	41.32	14.08	11.07
Income classification	High income	38,082,584	28.15	35.54	28.76	19.59	10.78
Population density	0 to 0.9	53,883,215	39.82	46.44	39.53	18.09	11.62
Population density	1 to 9.9	39,359,881	29.09	28.03	31.21	14.95	10.02
Population density	10 to 99.9	27,781,643	20.53	16.15	18.89	12.20	11.12
Population density	100 to 999.9	9,292,487	6.87	5.54	7.02	12.52	10.13
Population density	1000+	1,070,380	0.79	0.56	0.73	11.05	10.00
Govt. Effectiveness	0 - 24.9	23,463,373	17.34	11.34	15.95	10.15	10.42
Govt. Effectiveness	25 - 49.9	48,702,809	35.99	33.62	34.59	14.49	13.09
Govt. Effectiveness	50 - 74.9	28,037,538	20.72	23.55	24.89	17.64	10.23
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	20.70

Subregions	Central America	2,481,651	1.83	1.25	1.70	10.57	10.11
Subregions	Central Asia	4,380,003	3.24	2.29	2.98	10.99	10.02
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	11.95
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	34.56
Subregions	Micronesia	3,576	0.00	0.00	0.00	27.68	10.26
Subregions	Middle Africa	6,608,246	4.88	3.55	5.01	11.27	11.25
Subregions	Northern Africa	7,647,985	5.65	4.80	6.74	13.18	12.96
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	18.77
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	10.01
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	13.23
Subregions	Western Africa	6,082,789	4.50	2.99	4.20	10.33	10.06
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	40.67



SUPPLEMENTARY FIGURE 1 Representative example of the countries (national sampling units) and administrative units (sub-national sampling units) selected when using a random sampling approach

SUPPLEMENTARY FIGURE 2 Representative example of the 100 km x 100 km sampling units (analogous to the Stage 2 Marxan analysis but based on all the sampling units across the global terrestrial realm)

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