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 maintaining biodiversity, and there are ongoing discussions over what is an appropriate global conservation area coverage target. To inform such debates, it is necessary 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, although data on privately and community-governed protected areas and 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 prioritization 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 by identifying a representative set of sampling units that cover 10% of the terrestrial realm, which included areas in only 25 countries. In contrast, selecting 10% of the terrestrial realm at random included areas across 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 more rapid and accurate estimates of global conservation area coverage and ecological representativeness, complementing existing international reporting systems.

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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 (2022) recently committed through the Kunming–Montreal Global Biodiversity Framework Target 3 to conserve at least 30% of the planet by 2030 through systems of protected areas and other effective area-based conservation measures. Progress towards this Target will be assessed using data from the World Database of Protected Areas and World Database of Other Effective Area-Based Conservation Measures. These databases are compiled and maintained by the UN Environment Programme World Conservation Monitoring Centre based on conservation area data approved by each national government or following an expert review and validation process (Bingham et al., 2019; Lewis et al., 2019; UNEP-WCMC & IUCN, 2021). These two databases therefore 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 protected areas to be included in these databases (UNEP-WCMC, 2019). More generally, non-state protected areas and other effective area-based conservation measures are under-represented in the databases (Bingham et al., 2017; Corrigan et al., 2018), partly because governments only recently started collecting data on conservation areas not governed 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). Investing in improving the quality of global conservation area datasets will address this; there is an ongoing process working with countries to increase

the accuracy of data from state protected areas and to collect information on non-state protected areas and other effective area-based conservation measures (UNEP-WCMC, 2019). Such work is important, but is a resource-intensive, long-term process (Juffe-Bignoli et al., 2016), so complementary, more rapid approaches could provide additional insights.

Such approaches are particularly needed to account for the new international focus on other effective area-based conservation measures (Maxwell et al., 2020; Gurney et al., 2021). However, we lack global data on these other types of conservation area. Thus, although there is a wealth of important literature on the effectiveness of state-governed protected areas (Venter et al., 2014; Geldmann et al., 2019; Maxwell et al., 2020), we cannot estimate current levels of conservation area coverage or accurately measure progress towards international area-based conservation targets. This also makes it difficult to measure how well the global network represents biodiversity, especially as recent work suggests that non-state conservation areas can play an important role in representing ecosystems that are missing from state protected areas (Garnett et al., 2018; Palfrey et al., 2022). In addition, more accurate data would help the international community better estimate funding requirements to improve management effectiveness (Geldmann et al., 2019) and inform ongoing debates regarding the social impacts of meeting Target 3 (Sandbrook et al., 2023).

Fortunately, the relevant conservation area data that we need are often collected at the nation-state level, so one complementary approach would be to base global analyses on information from a subset of countries. Collecting and analysing data from a smaller number of nations would have obvious benefits in terms of time and resources. Just as importantly, producing such estimates would not involve reporting results per country, so analyses could use the latest and most accurate national conservation area datasets without contradicting official data reported by governments. Using such an approach would provide additional insights on trends in global protected area and other effective area-based conservation measure networks alongside the existing official datasets countries maintain as part of their requirements as signatories to the Convention on Biological Diversity (UNEP-WCMC, 2019). However, the sample of countries needs to be selected carefully, minimizing the number of countries to allow rapid data collection whilst also ensuring they reflect the underlying global variation. 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 protected area and other effective area-based conservation measure networks meet 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, 2004). 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 targets for 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 amounts of these features (Kukkala & Moilanen, 2013).

Using this approach also involves choosing a cost metric, so that the prioritization process minimizes the cost whilst 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. Protected area and other effective area-based conservation measure 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 to collect and provide relevant data 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 main disadvantage, 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 overrepresented (Nhancale & Smith, 2011). However, this can be overcome by repeating the spatial prioritization 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 protected area and other effective area-based conservation measure datasets and produce more accurate measures of global patterns in conservation area coverage.

Methods

Our approach comprised three steps (Fig. 1), beginning with choosing socio-economic and biogeographical factors that represent drivers of conservation area extent and global biodiversity patterns, and defining and mapping the features that make up the categories within each factor. This was followed by a two-stage analysis: Stage 1 identified the minimum set of countries needed to meet the targets for each feature and Stage 2 identified sets of 10,000 km² 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 10 available global datasets that mapped these important factors: biomes, elevation, government effectiveness, islands and continents, land cover, latitude, income, human population density, realms and sub-regions (Table 1, Supplementary Fig. 1). We selected three of these factors 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 by choosing appropriate thresholds for continuous data (Table 1, Supplementary Table 1). We used the various datasets to produce a 1 × 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 meeting targets for each of the 89 features across the 10 factors whilst minimizing the number of countries selected (Fig. 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 km² 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 in which each analysis involves running the software multiple times

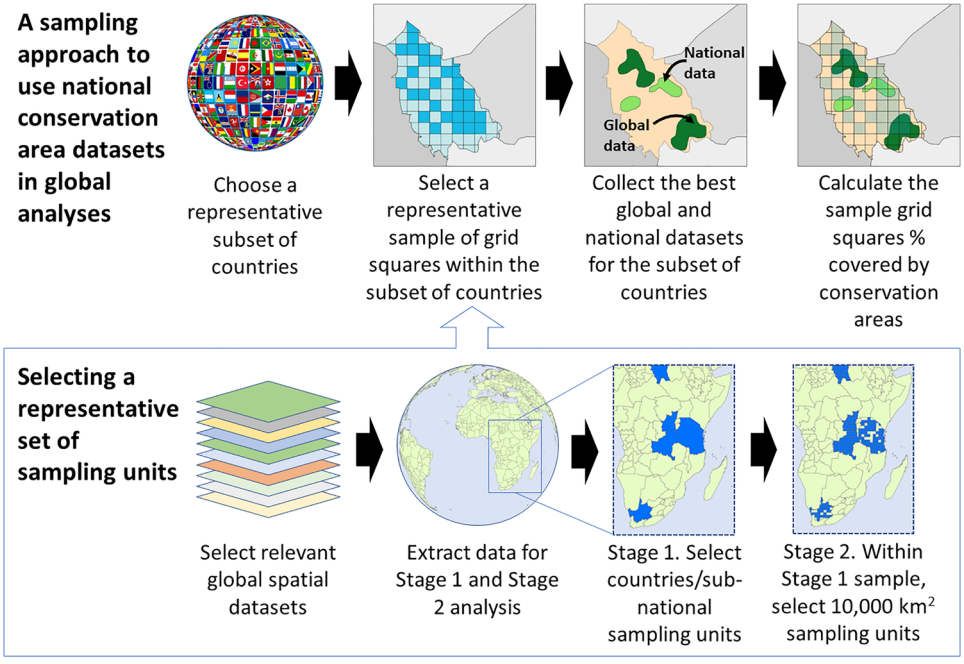

FIG. 1 Schematic illustrating the sampling approach for developing more accurate estimates of global conservation area coverage based on national datasets. (Readers of the printed journal are referred to the online article for a colour version of this figure.)

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

Factor	Features	Data source
Biomes	16 biomes	Olson et al. (2001)
Elevation	Five features: 0 < 300 m, 300 < 800 m, 800 < 1400 m, 1400 < 2000 m, ≥ 2000 m	Shuttle Radar Topography Mission
Government effectiveness	Four features: 0 < 25%, 25 < 50%, 50 < 75%, 75 < 100%	World Bank (2019b)
Income (per capita)	Four features: low-income, lower-middle-income, upper-middle-income, high-income countries	World Bank (2019a)
Islands & 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, 'Continent' (≥ 1,000,000 km^2)	GADM (2018)
Land cover	12 land-cover 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 < 1, 1 < 10, 10 < 100, 100 < 1000, ≥ 1000 people per km^2	UNPD (2013)
Realms	Eight realms	Olson et al. (2001)
Sub-regions	22 sub-regions	UNSD (2019)

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 we derived the sampling units from the Database of Global Administrative Areas (GADM, 2018) that comprised countries or nations with an area < 1,000,000 km² or the highest sub-national administrative-level polygons for larger countries (e.g. states, provinces, etc., which 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 minimize 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). We based the Stage 2 sampling units on a global set of 100 × 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 Stages 1 and 2 were representative of the terrestrial realm, we used *Marxan* to identify sampling units that, when combined, met the same per cent 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

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 per cent 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 & continents	5	0.36	94.23	14.95	11.61
Land cover	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
Sub-regions	22	< 0.01	15.95	22.18	13.87

coverage and minimizing 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 was more than two-fold greater (Supplementary Material 1, 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 of the targets and also minimized 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 of the targets.

Comparative analyses

To measure whether using our prioritization 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 × 100 km sampling units (analogous to the Stage 2 *Marxan* analysis but based on all of 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 sub-national) sampling units selected and therefore the effort needed to collect conservation area data. The third analysis compared the per cent of the terrestrial realm covered by any protected areas. The protected area data came from the publicly available World Database of Protected Areas dataset downloaded in May 2021 (UNEP-WCMC & IUCN, 2021). It should be noted that the publicly available World Database of Protected Areas data does not include most protected areas in China and India. We followed the standard protocol (UNEP-WCMC & IUCN, 2016) by excluding protected areas that are 'Proposed' or 'Not Reported' and UNESCO Man and the Biosphere Programme Reserves. We included point data if the protected area 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 protected areas for each country, used *QGIS* to calculate the total area in each grid square and then calculated the overall per cent protected area coverage for each of the *Marxan* and random sets.

Results

Stage 1 analysis

The best portfolio identified using *Marxan* comprised nine whole countries and territories and 33 of the sub-national sampling units within another 16 countries (Fig. 2a). These 25 countries and territories are Argentina, Australia, Brazil, China, Democratic Republic of the Congo, Dominican Republic, France, French Polynesia, Greenland, India, Indonesia, Italy, Kazakhstan, Kiribati, Mali, Mexico, Papua New Guinea, Russia, Saudi Arabia, South Africa, South Georgia and the South Sandwich Islands, Sudan, Sweden, Tanzania and the USA. We selected only 17 of these 42 sampling units in every one of the 1,000 portfolios identified by *Marxan* (Fig. 2b), 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 of the targets and contained 2,231 of the 3,377 sampling units found within the Stage 1 sample, covering 10.9% of the global terrestrial area (Fig. 3a). The combined area of the selected Stage 1 sampling units also selected in Stage 2 ranged from 31.5% for Australia to 100% for the Dominican Republic, with a median of 76.1% (Fig. 3a); only seven countries had less than half of their Stage 1 areas selected in Stage 2. The selection frequency results for Stage 2 mirror 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 (Fig. 3b).

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 16.8 ± SD 1.0% of the terrestrial realm and the mean selected area of the 1,000 Stage 2 *Marxan* outputs was 10.9 ± SD 0.006%. The global area of the different features varied between < 0.001% for the Micronesia sub-region and 94% for

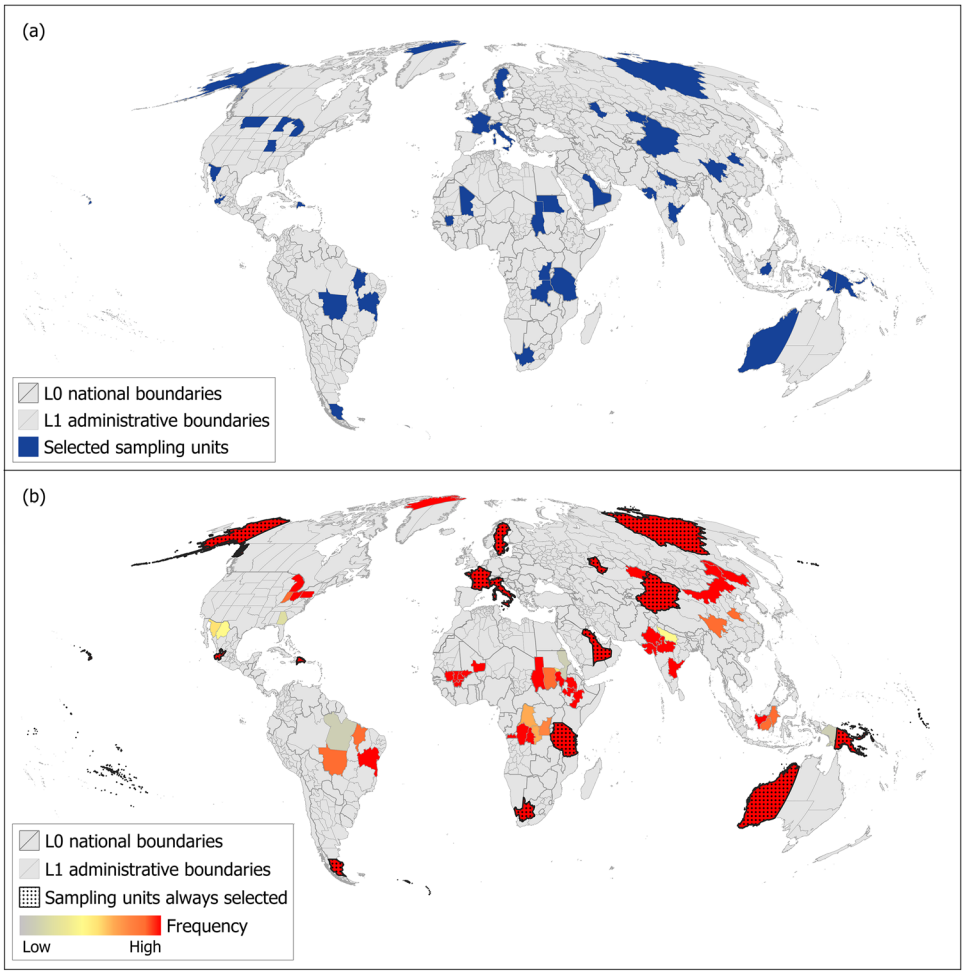

FIG. 2 (a) Sample of countries (national sampling units) and administrative units (sub-national sampling units) that meet 10% of targets selected based on 1,000 *Marxan* runs and selecting the result with the smallest number of sampling units, most even spread across the continents and with sampling 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.

continents. All of the Stage 1 and Stage 2 *Marxan* outputs met all of the 89 feature coverage targets (Table 1, Supplementary Table 4), whereas the Stage 1 random sets failed to meet a mean of 15.7 ± SD 4.0 targets and the Stage 2 random sets failed to meet a mean of 16.5 ± SD 3.6 targets.

Using the best *Marxan* output would require collecting protected area data from 25 countries and across 42 Stage 1 (national and sub-national) sampling units. In comparison, the Stage 1 random sets of sampling units covered a mean of 64.3 ± SD 7.4 countries (Supplementary Fig. 1) and 152.9 ± SD 20.6 national and sub-national sampling units. The Stage 2 random sets of sampling units covered a mean of 162.1 ± SD 4.9 countries (Supplementary Fig. 2) and 514.1 ± SD 10.3 national and sub-national sampling units.

The publicly available World Database of Protected Areas data showed that 15.3% of the terrestrial realm is under protection compared to a mean of 15.3 ± SD 2.2% for the Stage 1 *Marxan* outputs and a mean of 16.0 ± SD 0.3% for the Stage 2 *Marxan* outputs. This compares to a mean area under protection for the Stage 1 random sets of sampling units of 15.2 ± SD 2.5% and for the Stage 2 random sets of sampling units of 15.2 ± SD 0.572%.

Discussion

Choosing the factors and features

In this study we outline a framework for producing more accurate estimates of progress towards global conservation area targets, 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 (Fig. 1). 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, 2004). 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, previous studies have shown conservation area coverage is influenced by human population density and proxies of agricultural opportunity cost such as elevation and land cover (Loucks et al., 2008; Joppa & Pfaff, 2009) and the link between

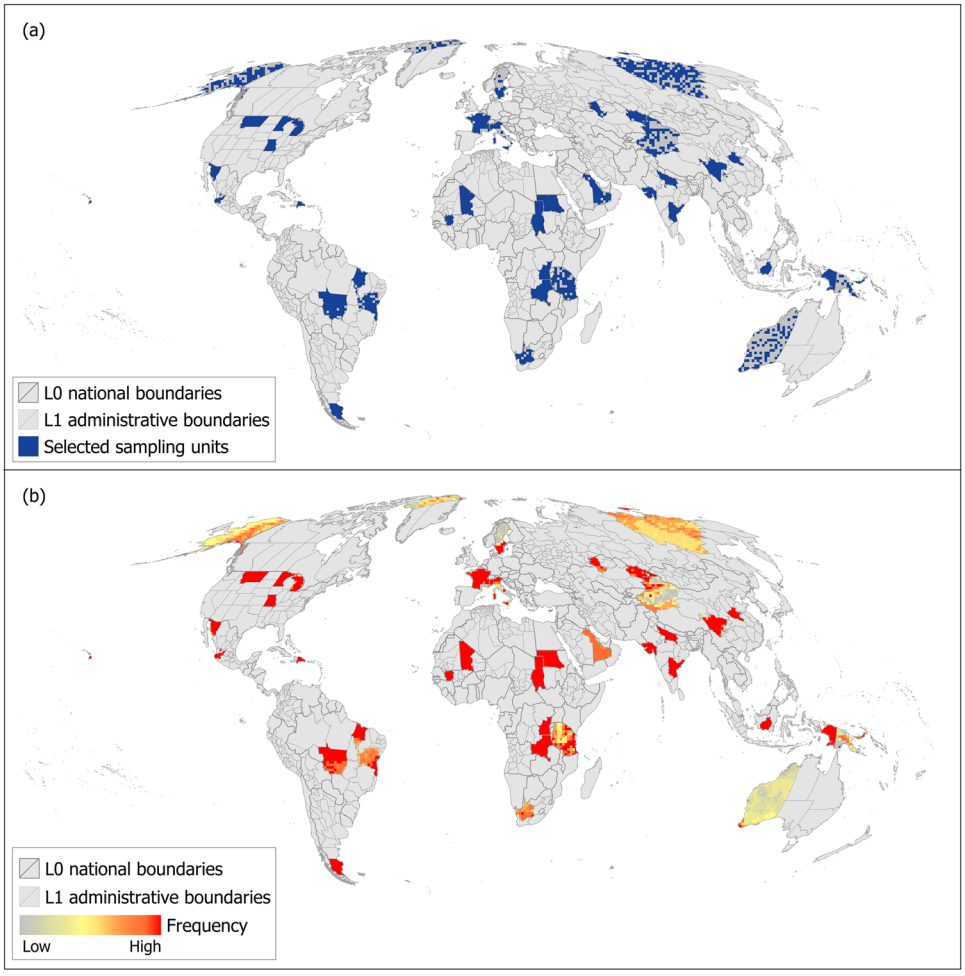

FIG. 3 (a) Sample of 100 × 100 km grid squares found in the focal countries (national sampling units) and administrative units (sub-national sampling units) selected by *Marxan* that best meets 10% of targets for biogeographical and conservation area extent factors whilst minimizing sample area. (b) 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.

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, could have an effect on conservation area establishment but global datasets focused on this factor were not available. This could be resolved in future through using polling data and citizen science initiatives (McKinley et al., 2017). Collecting data on national land tenure systems could also be important, as these are likely to have a large impact on the extent of privately and community-governed protected areas and other effective area-based conservation measures in each country (Bingham et al., 2017). However, we did broadly account for this, as well as other potential factors, by using the geographical sub-regions dataset, ensuring representation of countries with shared legal, cultural and historical backgrounds. Another issue is that although some of our datasets represent snapshots of the current situation, conservation area coverage reflects both past and current circumstances, although governments often add or remove conservation areas in response to current 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 represented 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 minimizing the number of countries in our sample we also minimized the number of agencies and organizations involved in data collection. For the largest countries we also assumed their conservation authorities would have a devolved structure involving national and sub-national agencies, hence our use of sub-

national areas 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 (Fig. 2b). 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). However, it is likely that some portions of the largest countries will have to be included to meet all of the targets. 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 (Fig. 3). 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, although features belonging to different factors have different spatial distributions and extents. This involved selecting $>$ 10% for some features that are found in many of the 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 affect 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 protected area coverage to the global figure. However, none of these random outputs also met all of the feature targets, so they would be less suitable for assessing to which extent a sample of conservation areas represented biodiversity. The Stage 1 and Stage 2 *Marxan* outputs met all of the feature targets, indicating they could be used to measure conservation area representativeness, but the mean protected area coverage for the Stage 2 outputs is 15.97% compared to the global figure of 15.25% calculated from the publicly available World Database of Protected Areas data. This overestimate could be a result of our sampling framework, and it was unexpected given that this dataset does not include every protected area from China and India. Thus, more research is needed to understand the reasons underlying 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 World Database of Protected Areas coverage data.

It could be argued that a better approach to 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 protected area coverage to the global figure but would require collecting data from 2–7 times more countries and across 3–12 times more national and sub-national sampling units than the *Marxan* outputs. Thus, our data collection framework based on minimizing the number of countries selected and minimizing biases in these countries by setting representation targets is 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 require 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 data from unofficial national datasets.

In this study we have shown that it is possible to identify such a representative sample of areas from across the globe within a small enough number of countries to make intensive data collection realistic. We have demonstrated a proof of concept and identified a sample of a 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 to non-marine conservation areas (Devillers et al., 2020).

The next step is to work with local experts to collect existing conservation area datasets covering the sample we have identified. 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 other effective area-based conservation measures, as national- and regional-scale data suggest they enhance protected area network connectivity and cover different biodiversity elements (Dudley et al., 2018). Future work

should then involve working with the sample countries to fill data gaps, which in many cases will involve identifying and recognizing existing areas as other effective area-based conservation measures (Gurney et al., 2021), and providing additional resources and support for the lower-income nations. More broadly, we suggest that this approach based on using data collected from a representative sample of countries could be used to produce global estimates of other conservation metrics. This is important because, as reflected in Target 3 of the Global Biodiversity Framework (Convention on Biological Diversity, 2022), increasing the effectiveness of conservation area networks involves more than expanding the area under management. In particular, our sampling approach could be used to collect data related to costs and management effectiveness (Coad et al., 2015; Iacona et al., 2018) and social impacts, governance and equity (Dawson et al., 2018; Naidoo et al., 2019), helping monitor progress towards meeting international conservation targets and policies.

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Conflicts of interest None.

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

Data availability Data are available from the authors on request.

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