

Global disparity of research allocation and the Aichi biodiversity conservation targets

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Abstract

Tracking progress towards global biodiversity conservation targets requires appropriate allocation of research and monitoring efforts. We conducted a global review of camera trap research on mammals as a proxy for biodiversity research and monitoring over the last two decades. We assessed how 3395 research locations from 2324 studies tracked priority regions for attaining the 2020 Aichi Biodiversity Targets. We used a geospatial distribution modelling approach to predict the spatial allocation of biodiversity research and to identify its key drivers. We show that conservation research in the past two decades has often failed to target areas important for conservation, and that 76.8% of the global research allocation can be attributed to country income, biome, mammal richness and accessibility. We predicted lowest probabilities of research allocation in low income countries. The Amazon and Congo Forest basins — two highly biodiverse ecosystems facing unprecedented human alteration — received inadequate research attention. Even in the most researched regions, an average of 51.4% of the research locations were outside the top 20% most important areas for the global biodiversity Aichi Targets. To support biodiversity conservation targets, policy and practice, more research and monitoring is required in regions with high importance for conservation.

Introduction

We are experiencing a biodiversity crisis with estimated global extinction rates 100-1000 times greater than pre-human rates (Chapin et al., 2000; Ceballos et al., 2020). Biodiversity loss has altered ecological communities with impacts on ecosystem functioning (Bello et al., 2015) and on livelihoods of billions of people (Cardinale et al., 2012). To mitigate these processes, 196 nations signatory to the Convention on Biological Diversity ratified the Aichi Biodiversity Targets in 2010 (hereafter “Aichi Targets”) (Convention on Biological Diversity, 2010). The aim was to halt global biodiversity loss by 2020. Target 12 envisioned that: “*by 2020, the extinction of known threatened species has been prevented and their conservation status, particularly of those most in decline, has been improved and sustained*”. This, and other Aichi Targets, underline that biodiversity assessment and monitoring is crucial to track progress (Andelman & Willig, 2004).

Despite commitments, the international community has struggled to track progress towards achieving the Aichi Targets (Tittensor et al., 2014). One challenge is our incomplete understanding of how biodiversity is being impacted across the world (Andelman & Willig, 2004; Ahumada et al., 2011; Beaudrot et al., 2016). The assessments required to report progress on the Aichi Targets are difficult to achieve, particularly for terrestrial mammals (hereafter “mammals”), which often occur at low densities and can be difficult to detect (Bush et al., 2017). Previous attempts to assess disparities in biodiversity research allocation compared either the number of published studies (Lawler et al., 2006; Wilson et al., 2016; Hickisch et al., 2019) or research impact (Meijaard et al., 2015) among biomes (Christie et al., 2020) or countries and their constituent provinces. However, the quantity of research in previous studies is tied to a country (and provinces) or biome as a whole and does not reveal the nuances in research allocation across countries or biomes or across the global landscape. Further, we don’t understand how anthropogenic activity, biodiversity, economics and geography determine relative research allocation. Understanding how well research allocation aligns with the Aichi targets can inform future global conservation research allocation policy.

Here, we spatially predict the global allocation of biodiversity research using an established geospatial distribution modelling approach (maximum entropy, MaxEnt) (Elith et al., 2011; Phillips et al., 2006), which combines a global dataset of camera trap research locations on mammals published between 2000 and 2019 (see Methods; Figure 1) with ten spatial datasets (hereafter “predictors”) representing anthropogenic, biological, economical and topographic factors thought to relate with biodiversity research allocation (Table 1). We use camera trap research on mammals as a proxy for biodiversity research because mammals indicate ecosystem health (Ahumada et al., 2011), and support ecosystem functioning with benefits for human wellbeing (Cardinale et al., 2012), climate (Brodie & Gibbs, 2009) and carbon stocks (Bello et al., 2015).

Mammals are also disproportionately impacted by anthropogenic activities (Schipper et al., 2008; Ceballos et al., 2015; Ceballos et al., 2017; Allan et al., 2019). For over two decades, camera traps have revolutionized the way scientists and conservation stakeholders survey mammals globally even in the remotest areas (Ahumada et al., 2011; Gibson et al., 2011; Skidmore et al., 2015; Beaudrot et al., 2016; Tilker et al., 2019), as camera traps operate continuously for months at a time without the need for observer presence.

Our goals were to: 1) reveal the global patterns of biodiversity research allocation, and spatially predict its distribution across the global landscape, 2) identify the key predictors of global biodiversity research allocation, and 3) quantify the associated disparity of research allocation in relation to the Aichi Targets. Our assumption is that research allocation should be driven by the conservation policy needs reflected in the Aichi Targets and the key predictors of research allocation would be those linked with the Aichi Targets (Table 1). We hypothesise that the selected research locations in the past two decades often failed to overlap areas most important for achieving the Aichi Targets, for instance, where biodiversity is high and anthropogenic threats are most prevalent.

Materials and Methods

A systematic search of camera trap studies.

On 09.09.2019, we conducted an extensive systematic literature search on the Web of Science™ (WoS, Science Citation Index Expanded) and Google Scholar (GS) databases, for both peer-reviewed and grey literature published between 1900 and August 2019 that used camera traps as a research tool. We followed standard guidelines for conducting a systematic literature search in conservation and environmental management (Pullin & Stewart, 2006). We used a priori selected search string: (camera trap* OR camera-trap* OR remote camera* OR photo trap* OR photo-trap* OR camera NEAR/1 trap* OR trail camera* OR automatic camera* OR remotely triggered camera* OR game camera* OR motion-activated camera* OR infrared camera* OR wildlife camera*) AND (wildlife* OR animal* OR mammal* OR vertebrate* OR terrestrial vertebrate*). For the WoS, we specified the search within the biological research categories: environmental sciences, ecology, zoology, biodiversity conservation, behavioral sciences, forestry, evolutionary biology, remote sensing, reproductive biology and anthropology.

We checked the searches returned from WoS and GS for duplicate records and those not in English, which we removed (Lawler et al., 2006). Where possible, we then downloaded the studies as .pdf or MS Word or HTML files. Using the title, abstract and main text, we identified studies based either wholly or in part on-field use of camera traps to study wild animals for ecological and/or conservation research purposes. We then subjected these studies to a priori designed inclusion/exclusion criteria (Figure 1). We excluded non-camera trap studies and books, book chapters and reviews. We also excluded studies that did not provide research location name(s), those which provided

research location name(s) but, either the location could not be georeferenced or the geospatial information (longitude and latitude) was erroneous, and finally studies on non-mammalian terrestrial wildlife. In the remaining studies, we extracted the location information (longitude and latitude) where the study was conducted. We excluded research locations for studies conducted before year 2000 to ensure that research location data matched the temporal extent of the predictors. We also removed locations not on land, as well as duplicates.

Collating of and processing predictor datasets.

Based on our own research experience, study objectives and published literature, we selected ten spatially explicit environmental predictors for their potential importance to the research location selection. These predictors included those that represented anthropogenic threats to biodiversity, those related to biodiversity, and those related to economical and topographic aspects. We downloaded predictor datasets from the web in both vector and raster formats. A detailed description of the covariate datasets is given in Table 1.

The geospatial data were processed in the R statistical language (R Core Team, 2019). Because our predictors' data originated from different sources, we harmonized projections, grid cell size and alignment, and the spatial extent to ensure consistency across all predictor data layers using appropriate functions from the “raster” package (Hijmans & Robert, 2020). We chose a geographical latitude / longitude projection at 30 arc-second resolution (ca. 1 km at the equator) for this analysis. We plotted the research location data on a global map to locate where research has been conducted. We then used the *spsample* function and the Fibonacci sampling type argument in “sp” package (Pebesma & Bivand, 2005) to create 50,000 random points for which, together with each of the research locations, extracted the associated predictor data. We used the *extract* function of the “raster” package for the extraction of the raster values. We then computed a Spearman's rank correlation matrix to test for multi-collinearity among predictors (Figure S1). We assumed predictors with a correlation value $r < -0.7$ or $r > 0.7$ to be correlated. If predictors were found to be collinear, only one of them was included in the subsequent models. We used raincloud and bar plots in the “ggplot2” R package (Wickham, 2009) to visualize the data distribution of the continuous and categorical predictors respectively, between research locations and a random sample of available land surface (Figure S2).

MaxEnt Modelling.

We used the MaxEnt models to 1) identify the key predictors of research allocation, and 2) predict the spatial probability for research allocation, given the relationship of research allocation and predictors. We implemented the MaxEnt models using the *maxent* function in the “dismo” package in R (Hijmans et al., 2017). Before modelling, we used the

ENMevaluate function in the “ENMeval” package to tune our models, i.e. identify the optimal feature classes and regularization multiplier values needed to maximize model predictive ability while avoiding overfitting (Muscarella et al., 2014). We split the research locations into two separate partitions (80% for model training and 20% for model testing). We ran five MaxEnt models. 1) One global model (using all research locations), and 2) four biome specific models for biomes with the highest number of research locations (hereafter “most researched biomes”). We used feature classes and regularization multiplier value of the model with the lowest Akaike Information Criterion (AIC) value as returned by the *ENMevaluate* process. We set the number of background points to 10,000 for all models. We used the value of the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curves on the test data to assess model performance. We assumed models with an AUC value of > 0.70 to be of good model fit (Phillips et al., 2006; Hijmans et al., 2017). We used the jackknife procedure and permutation importance to assess variable importance and to identify the most important predictors of research allocation (Phillips et al., 2006).

Quantifying disparity in research location selection.

We used bivariate choropleths to assess the relationship between the probability of research allocation and Aichi Targets at the four most research biomes. We first developed a global “Aichi map” for each of the biomes to identify areas across the landscape of high Aichi value (ranging between 0 and 1). We generated the Aichi map by identifying from our set of predictors those related to Aichi Targets (see Table 1). We then normalized the predictors to range from 0 to 1. For country income which may be negatively associated with Aichi Targets, i.e. low income countries have higher biodiversity and face higher anthropogenic alteration, we calculated the inverse. We then weighted the predictors with 2, 1 or 0 based on their importance to Aichi Targets (0 = no importance (not used for the map); 1 = low importance; 2 = high importance). Finally, we generated the Aichi map by calculating a weighted mean of the predictors’ Aichi importance.

To generate a bivariate choropleth, we used a customised R function that divided the probabilities of research allocation and the Aichi value datasets into five classes each containing 20% of the available values (quintiles). The bivariate choropleth indicates the spatially explicit strength of associations between two variables and results in: (1) high□high values, here, areas with high Aichi value and high predicted probability of research allocation, (2) high□low values, high Aichi value and low predicted probability of research allocation, (3) low□high values, low Aichi value and high predicted probability of research allocation, and (4) low□low values, low Aichi value and low predicted probability research allocation. We then used the *extract* function of the “raster” package to extract the Aichi quintile for each of the research locations in the four

most researched biomes. We used the accruing data to calculate the percentage of research locations in each of the Aichi quintiles.

Results

Searches from WoS and GS returned 4350 and 7047 studies respectively. After removing duplicate records and those not in English, we obtained a combined list of 7001 studies. From the 7001 studies, we excluded 2176 as non-camera trap studies, and 79 books, book chapters and reviews. In the remaining 4746 records, we excluded 174 studies that did not provide research location name(s), 839 which provided research location name(s) but, either the location could not be georeferenced or the geospatial information (longitude and latitude) was erroneous, and 239 studies on non-mammalian terrestrial wildlife. We thus remained with a total of 3494 studies for which we extracted the studies' longitude and latitude information. As some studies were conducted at multiple research locations, the 3494 studies represented a total of 5158 research locations. We then excluded 64 research locations for studies conducted before 2000 to ensure that research location data matched the temporal extent of the predictors. We also removed 214 locations not on land, as well as 1485 duplicated research locations. We thus remained with 3395 research locations from 2324 studies for use in the subsequent analyses.

The most researched biomes were; Tropical and Subtropical Moist Broadleaf Forests (hereafter “tropical moist forests”, $n = 1075$); Temperate Broadleaf and Mixed Forests (hereafter “temperate forests”, $n = 711$); Tropical and Subtropical Grasslands, Savannas and Shrublands (hereafter “tropical grasslands”, $n = 311$) and Mediterranean Forests, Woodlands and Scrub (hereafter “Mediterranean forests”, $n = 228$). The discriminative performance of our models gave an average model Area Under Curve (AUC) measure of ≥ 0.8 ; hence, the models were particularly useful to identify the most important predictors (Table S1) and specific areas of research allocation (Figure 3 and 4).

Global patterns of research allocation.

Studies were conducted in 130 countries (Figure 2c). The countries with highest number of studies (in descending order) were; the USA, Brazil, Australia, India, Mexico, China and Malaysia (Figure 2d and Table S1). Of the large countries (area >1 million km^2), Mauritania, Democratic Republic of Congo, Niger, Angola, Libya, Kazakhstan, Algeria, Ethiopia and Egypt received less than five studies (Table S1). The top five countries with the highest density of studies were Singapore, Belize, Mauritius, Costa Rica and Panama (Figure 3c and Table S1). Similarly, North America, continental Europe, United Kingdom and Japan had a high probability of research allocation (Figure 3c). African countries generally had some of the lowest density of research locations and probabilities of research allocation (Figure 3c and Table S1).

The biomes with the highest density of studies, research locations and predicted probability of research allocation were mangroves, Tropical and Subtropical Coniferous

Forests (hereafter “tropical coniferous forests”), Mediterranean forests, tropical moist forests and Tropical and Subtropical Dry Broadleaf Forests (hereafter “tropical dry forests”) (Figure 3b and Table S2). Boreal forests/Taiga and Tundra biomes had the lowest density of studies and predicted probability of research allocation (Figure 3b and Table S2).

Within the tropical moist forests biome, we predicted a higher probability of biodiversity research allocation in Malaysia, Thailand and Indonesia, while tropical African countries had a much lower probability of research allocation (Figure 4c). In South and Central America, the Brazilian Atlantic dry forests had the highest probability of research allocation (Figure 4c). In the tropical grasslands biome, the Cerrado and the Llanos in Colombia and Venezuela had the highest probability of research allocation (Figure 4c). Apart from some areas in East Africa, African savannahs, grasslands and shrublands had a disproportionally low probability of biodiversity research allocation, while grasslands and shrublands in Australia had a higher probability of research allocation (Figure 4g). In the Mediterranean forests, California, South Africa and Southern Europe particularly Italy, Greece and southern France had a higher probability of research allocation (Figure 4). Lastly, in the temperate forests biome, Japan, the United Kingdom and South-Eastern Australia had the highest probability of research allocation, while areas in Eastern Europe and those in Russia or the Caspian region had a lower probability of research allocation (Figure 4o).

Predictors of research allocation.

Globally, country income was the most important predictor of research allocation (23.5%) followed by biome (22.6%), mammal richness (16.5%) and accessibility (14.2%) (Figure 3a). Country income decreased the global model AUC the most when omitted, suggesting that it has the most important information that isn't present in the other predictors (Figure S4a). The probability of research allocation was higher in high income countries and lower in low income countries (Figure 3b). Among biomes, the probability of research allocation was higher in the mangroves, tropical dry forests, tropical coniferous forests, Mediterranean forests; and tropical moist forests. Boreal forests/Taiga and Tundra biomes had the lowest probability of research allocation (Figure 3b). There was a strong positive trend in research allocation with mammal richness and accessibility (Figure 3b).

In addition to the global analysis, we analysed the four most researched biomes independently to get further insights on the biome specific predictors. High country income and IUCN protected area status were the only predictors consistent in all four biomes (Figure 4a, e, i, m and Table S3), with research allocation being twice as high within protected areas than outside. Accessibility was a key predictor in three (tropical moist forests; Mediterranean forests and temperate forests) of the four most researched biomes, with higher research allocation in more accessible areas (Figure 4a, i, m and

Table S3). The number of species impacted by at least one human activity was a key predictor in three (tropical moist forests, tropical grasslands and Mediterranean forests) of the four most researched biomes (Figure 4a, e, i and Table S3). There was a positive trend towards more research allocation in areas with higher threat to species particularly in the two tropical biomes (Figure 4a, e), while the trend was less clear in the Mediterranean forests (Figure 4i). Lastly, mammal richness, which had a clear positive trend at the global level (with high species areas receiving a higher research allocation, Figure 3b), was a key driver only in the tropical grasslands (Figure 4e). In line with the global trend, we saw a general trend towards more research in more species-rich landscapes, although in contrast to the global level, research allocation in the grassland regions actually decreased again above 160 mammal species (Figure 4e).

Disparity in research allocation.

In all the four most researched biomes, the Aichi values of the researched locations were consistently higher than for the random locations (Figure 5e, h, k, n), particularly in the tropical grasslands biome. Out of the total number of research locations in the tropical moist forests biome, 40.8 % (n = 439) of those were in the top 20% of the most important areas for Aichi Targets (Figure 5c, f); 66.8 % (n = 208) in the tropical grasslands biome (Figure 5c, i); 43.8 % (n = 100) in the Mediterranean forests biome (Figure 5c, l) and 42.9 % (n = 306) in the temperate forests biome (Figure 5c, o). On the other hand, 5 % (n = 54) of all locations in the tropical moist forests biome were in the 20% least important areas for Aichi Targets (Figure 5c, f); 0.3 % (n = 1) in the tropical grasslands biome (Figure 5c, i); 1.2 % (n = 2) in the Mediterranean forests biome (Figure 5c, l) and 2 % (n = 14) in the temperate forests biome (Figure 5c, o).

We observed high research allocation in the high Aichi value areas of the Brazilian Atlantic dry forests, Central Europe and large parts of Southeast Asia (Figure 5b). But there was a disparity in research allocation and Aichi value particularly in the Central Amazon basin, Eastern Europe, Russia, the Caspian region and some areas of Africa including Liberia, Central African Republic, Democratic Republic of Congo and Mozambique, all regions which have a high Aichi value (Figure S5) but received low research allocation (Figure 5b).

Discussion

Our results indicate that biodiversity research allocation is uneven with distinct biases (Figures 3, 4 and 5). These biases are apparent at the global and biome levels and appear primarily associated with country income, with only a minor amount associated with Aichi Targets' related predictors such as species richness and number of species impacted. Thus, for the past two decades camera trap research has often failed to target areas important for biodiversity conservation.

At the country level, the probability of research allocation was highest in high income countries and lowest in low income countries. The importance of country income for research allocation is in contrast to objective research location selection for attaining the Aichi Targets; many of the world's most biodiverse and high Aichi value regions (Figure S5) occur in the lower middle and low income countries where much of the current global environmental degradation (Laurance & Balmford, 2013; Hansen et al., 2013, Laurance et al., 2014) and associated biodiversity loss is concentrated (Dirzo et al., 2014; Beaudrot et al., 2016). A notable example are the rainforests of the Congo Basin which are impacted by road expansion, mining, intensive timber extraction, commercial hunting and other developments (Wilkie et al., 2000; Edwards et al., 2014; Kleinschroth et al., 2017), along with unprecedented smallholder clearing for agriculture associated with increasing human population (Tyukavina et al., 2018). Such developments offer financial gains in a region suffering severe poverty, but without care this has negative implications for biodiversity conservation (Edwards et al., 2014) and attaining the Aichi Targets.

The importance of country income for conservation is well established. For example, ineffective protected area management is often associated with insufficient equipment, staff and other financial resources within poorer nations (Wolf et al., 2021). Our observation that research allocation differs among country income groups corroborates the important role of financing in global biodiversity conservation (see Aichi Target 20) (Waldron et al., 2013; Meijaard et al., 2015), as is the case in the medical and technology research fields (Vinkler, 2008; Iyer, 2018). High income countries typically invest more in scientific research, foster innovation and technological advancement, have established scientific infrastructure, expertise, training, and a long-term tradition and culture of scientific inquiry (Vinkler, 2008; Waldron et al., 2013; Meijaard et al., 2015).

Country income is also often related with other factors that may play a role when selecting research locations including political stability, good governance, safety and security, presence of strong domestic research programs and institutions, and infrastructure development (e.g. availability research stations among others). Accessibility, for example, is often limited in low income countries (Weiss et al., 2015), making areas critical for conservation in these countries hard-to-reach for researchers. This is clearly seen in our findings insofar as research allocation probability decreased rapidly with accessibility both at the global level (Figure 3) and in three of the four most researched biomes (Figure 4a, i and m). From a conservation perspective, effort and allocation should reflect conservation needs and biological interest rather than country wealth (Meijaard et al., 2015).

Biome-specific biases in conservation allocation have previously been reported in identifying global conservation priority areas (Myers et al., 2000; Wilson et al., 2006), allocating conservation research (Lawler et al., 2006; Meijaard et al., 2015; Wilson et al.,

2016), research funding allocation (Halpern et al., 2006) and in the establishment of protected areas (Hoekstra et al., 2005; Jenkins et al., 2009). This likely reflects how both biological diversity and level of threats differ among biomes (Lawler et al., 2006; Dinerstein et al., 2017). Currently, we see a shift in conservation priorities, from threatened species to threatened biomes (Hoekstra et al., 2005). For example, the IUCN protected area coverage, as a cornerstone for biodiversity conservation (Tilman et al., 2017; Wolf et al., 2021), has expanded greatly in the last decades, as part of the overall global increase in conservation allocation in the biomes at risk (Hoekstra et al., 2005; Jenkins & Joppa, 2009; Wolf et al., 2021). We also recorded high research location densities and probabilities of research allocation in some of the biomes at risk (Hoekstra et al., 2005; Jenkins & Joppa, 2009); Mediterranean forests; tropical dry forests; tropical coniferous forests; and tropical moist forests. This finding is therefore in line with the Aichi Targets — that regions facing the highest anthropogenic threats should receive greater research allocation partnering with increased conservation effort. Our findings further show that, even within the biomes, spatial disparities in research allocation in relation to Aichi Targets occur (Figure 5b).

Biodiversity and the threats to its persistence are unevenly distributed, and if we were focused on the Aichi Targets, these distributions should guide research allocation (Wilson et al., 2016). However, we only found such a positive association only in specific regions. For example, Southeast Asian tropical moist forests are both of high Aichi value (Figure S5) and have received substantial research allocation, likely as a result of their rich biodiversity (Sodhi et al., 2004), relative accessibility (compared to the Amazon or Congo), political stability and economic growth. At the same time, these forests are also among the world's major deforestation (Achard et al., 2002; Hansen et al., 2013) and hunting hotspots (Dirzo et al., 2014; Tilker et al., 2019), supporting the great research needs to assess and monitor the consequences of these threats on biodiversity. Our finding from Southeast Asia inspires optimism that with additional and targeted efforts, similar high research allocation can be achieved in other areas where Aichi value is high, charismatic species are present (Marshall et al., 2016), but research allocation is currently low.

The Amazon and Congo forest basins — two highly biodiverse ecosystems facing unprecedented human alteration (Wearn et al., 2012; Dirzo et al., 2014; Pimm et al., 2014) — received inadequate attention. Our findings indicate low levels of research in these regions despite their key role in climate regulation (Malhi et al., 2004) and biodiversity conservation (Pimm et al., 2014). This shortfall has substantial implications, not only for attaining the Aichi Targets, but also for the effective implementation of international and national conservation policies and payment schemes. For example Payment for Ecosystem Services (PES) schemes or the United Nations' Reducing Emissions from Deforestation and Forest Degradation (REDD+) require robust

biodiversity assessment and monitoring to quantify the biodiversity co-benefits associated with these payments (Lindenmayer et al., 2000; Sollmann et al., 2017).

Outside the tropics, we also observed a research shortfall (Figure 5b) and a low probability of research allocation in Eastern Europe (Figures 3c and 4o), despite this region's dominant biome, the temperate forest, possessing some value under the Aichi Targets (Figure S5). This again reflects a difference in country income across this biome (Figure 4m). Research allocation was much lower in lower middle income Ukraine, compared to the high probability of research allocation in the neighboring higher income countries of Poland, Slovakia, Hungary and Romania (Figures 3c and 4m). On the other hand, we also found some areas in the most researched biomes to have high research allocation but low Aichi value (Figures 5b and S5). These areas were mainly in the temperate forest biome in the USA, United Kingdom, China, Australia and Japan where relative research intensity is often determined by national conservation priorities, for example, presence of high conservation value charismatic species such as pandas in China or koalas in Australia.

Conservation policy implications.

To our knowledge, this is the first quantitative assessment of the degree to which research allocation matches global priorities for biodiversity conservation. Research allocation being lowest in low income countries both globally and in all the four most researched biomes (Figures 3 and 4) is unsurprising considering the financial and training investment needed for research—yet given how long this has been recognized (United Nations, 1992), the pace of progress remains disappointing. While economic growth may facilitate the expansion of research allocation in the places where it is most needed, this may be too late given we are losing biodiversity at a precipitous rate (Chapin et al., 2000; Cardinale et al., 2012; Bello et al., 2015). It will be challenging to understand and track the impacts of anthropogenic activity on biodiversity and ecosystem functioning if we don't take urgent action to expand and strengthen research and conservation in areas where it is most needed but lacking (Sheil, 2001; Lawler et al., 2006).

Aichi Target 19 states that “*By 2020, knowledge, the science base, and technologies relating to biodiversity, its values, functioning, status and trends, and the consequences of its loss, are improved, widely shared and transferred, and applied*”. It's 2022, and although our understanding has improved, many aspects of this target have not been achieved. Our understanding remains poor in many regions where research allocation has been low. Because country income was the most important predictor of research allocation, we suggest that the global conservation community (including governments and non-governmental organizations (NGOs)) explore available ecosystem-based financing mechanisms. Notable are the proposed financing through the REDD+ framework (Miles & Kapos, 2008; Harvey et al., 2010) and certification schemes (e.g. the Forest Stewardship Council) (Gullison, 2003), where the implementation of such

initiatives may enhance the assessment and monitoring of biodiversity's extent and status in low income countries.

As an alternative to ecosystem-based financing for biodiversity research, we suggest that high income countries, that ratified the Aichi Targets, fund research and conservation in countries where these are hampered by low income. However, any form of support should be provided with critical awareness for equity, inclusion and diversity, to ensure equal participation and empowerment of local research institutions and individuals (Wilson et al., 2016). This will require that the global research community adopts a more equitable research culture where research collaborators from host and international nations have mutual trust and respect. Such a culture demands the elimination of “parachute science”—whereby researchers from higher-income countries conduct research in lower income countries without engagement and investment in local research capacity or infrastructure (Bockarie et al., 2018; Stefanoudis et al., 2021). Truly collaborative research practices and effective engagement of researchers in host countries enhances local research capacity, eliminates dependency on external scientists, ensures sustainable continuation of monitoring and conservation programs when international researchers return to their home countries, and ensures that the research addresses local conservation challenges to deliver desired conservation outcomes.

Quantifying the relationship between research allocation and Aichi Targets (Figure 5) represents a first step towards identifying research and conservation shortfalls. We believe that our findings can be used to set specific targets for biodiversity research allocation—an important consideration for the Post-2020 Global Biodiversity Framework of the Conference of the Parties to the CBD, which aims to have “... *focused, concrete and measurable Action targets...*” which will be implemented and their impacts can be monitored and assessed. Some Aichi Targets have set quantifiable targets, but Aichi Target 19, which speaks directly to biodiversity conservation knowledge creation (through biodiversity research), does not have specific, quantifiable targets. The expansion of research to areas where biodiversity conservation is needed will depend on whether or not the Post-2020 framework will include specific targets that can be readily measured and directly linked to biodiversity conservation policy and practice.

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Conflict of interest

The authors declare no competing interests.

Author contributions

B.M. and A.W conceived the project; B.M. collected the data; B.M conducted the data analysis with input from A.W, S.K.S, J.N, A.P and D.S. B.M drafted the manuscript with input from A.W; All authors commented and reviewed the final manuscript.

Data accessibility statement

We will make the data for this study available at a central public repository and we will archive all model code and R scripts on GitHub. The authors declare no competing interests.

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Table 1. The final ten predictors used in the analysis, their description, associated Aichi Target and their importance to the Aichi Targets.

Predictor	Description	Aichi Target	Aichi Importance	Data type	Comment	Reference
Accessibility	Enumerates land-based travel time to the nearest densely-populated area at 1 km ² resolution. Each grid cell represents the modeled shortest time from that location to a city.	-	1	Continuous	Accessibility has been linked to anthropogenic threats (Benítez-López et al., 2019) Accessibility hence has an indirect link to Aichi Targets.	Weise et al. (2018)
Number of species impacted by human activity	Indicates the number of species in a grid cell impacted by at least one anthropogenic threat at a 30 km × 30 km spatial resolution.	7	2	Continuous	Similar to IUCN threatened species but more directly linked to the threats.	Allan et al. (2019)
Forest loss	Indicates forest loss during the study period, defined as a stand-replacement disturbance (a change from a forest to non-forest state) at a 30 m resolution.	5	1	Continuous	Directly linked to biodiversity loss and Aichi Target 5. We treat this with the same importance as other threats.	Hansen et al. (2013)
Country income	Country income groups are based on country's Gross Net Income (GNI) and are classified into four groups by the World Bank. We used an	20	1	Categorical	Aichi targets highlight that low income countries should receive financial support to attain their targets. But as it does	

		average of the country's GNI data for the period 2000-2020.				not directly refer to achieving the targets, we treat this with the same importance as the threats. Low income countries are areas of high Aichi importance.	
Terrestrial mammal species richness	Identifies centers of terrestrial mammal species richness at 10 × 10 km spatial resolution.	13	2	Continuous	A direct measure of mammal biodiversity.	Jenkins et al. (2013)	
IUCN protected area	IUCN protected areas were obtained from the World Database on Protected Areas (WDPA).	11	0	Categorical	Directly related to Aichi targets, but a clear guidance on whether to survey more in or out of protected areas is missing.		
Intact Forest Landscape (IFL)	Identifies intact forest landscapes (IFL), defined as a seamless mosaic of forest and naturally treeless	NA	0	Categorical	Not related to the Aichi targets.	Potapov et al. (2017)	
Biomes	Biomes were extracted from the terrestrial ecoregions of the world, as areas with distinct assemblages of natural communities and species.	NA	0	Categorical	Not related to the Aichi targets.	Dinerstein et al. (2017)	
Elevation	NASA's Shuttle Radar Topography Mission (SRTM) digital elevation dataset which provides	NA	0	Continuous	Not related to the Aichi targets.		

Terrain Ruggedness Index (TRI)	high-quality global elevation data.	A measure of the elevation difference between adjacent cells of a digital elevation grid, calculated as the square root of the average difference in elevation values from a center cell and the eight cells immediately surrounding it.	NA	0	Continuous	Not related to the Aichi targets.
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The Aichi importance is scored as 0 = no importance (not used for the analysis); 1 = low importance; 2 = high importance.

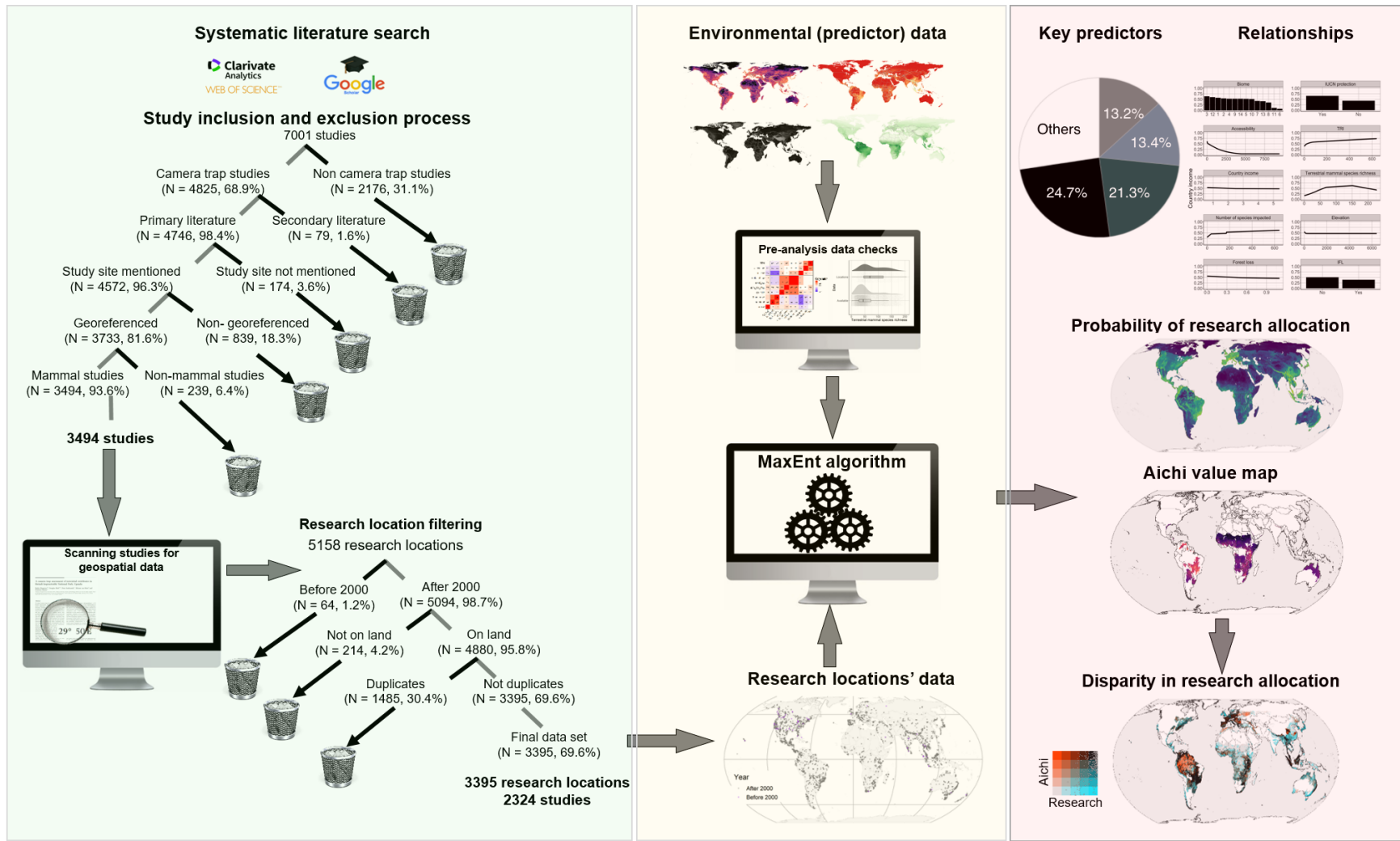


FIGURE 1 Step-by-step schematic representation of data collection and modelling workflow.

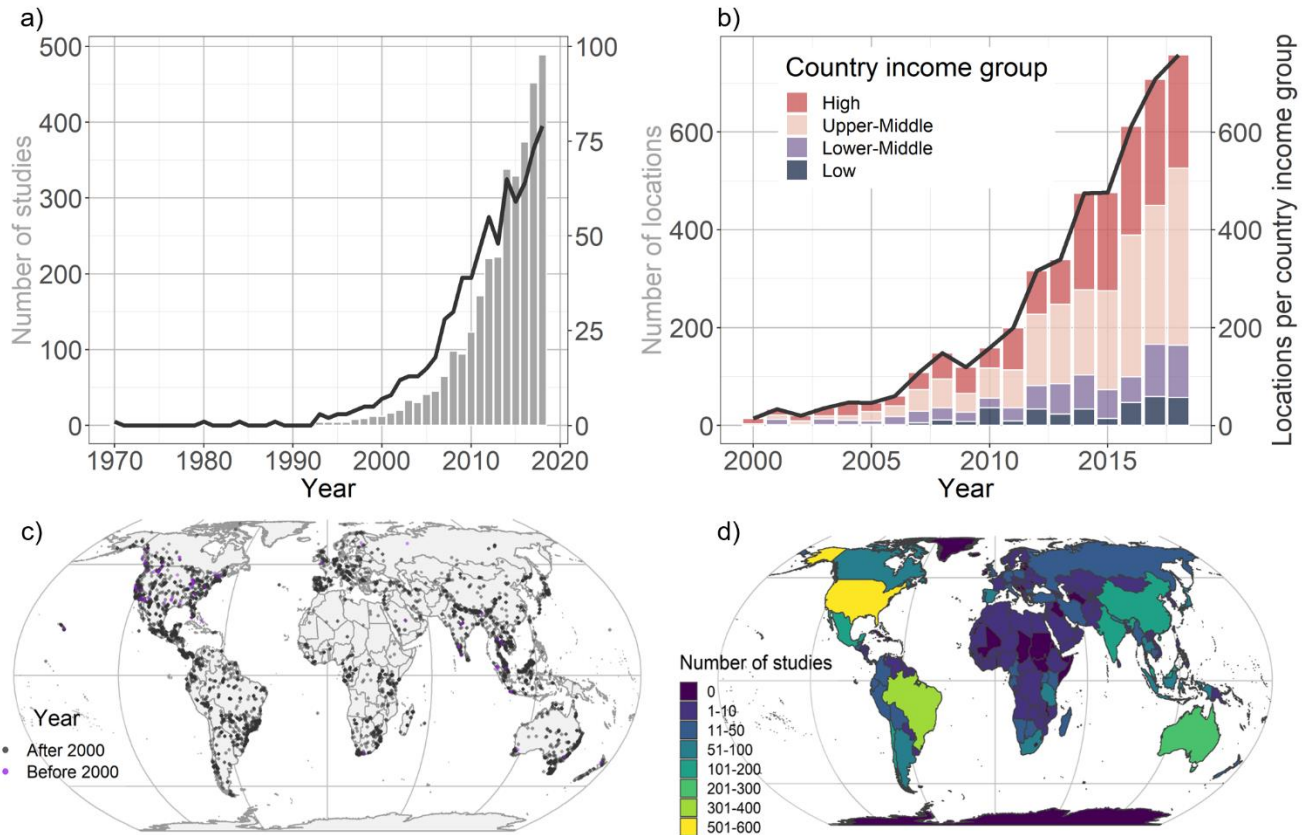


FIGURE 2 Temporal and spatial patterns of camera trap research. (a) Number of studies that used camera traps as a research tool (left axis and bar graph) and number of countries where the research was conducted (right axis and line graph) between 1970 and 2019. (b) Number of locations in the past two decades (right axis and line graph) compared among country income groups (left axis and stacked bar graph). (c) Global research locations before and after year 2000. (d) Number of studies that used camera traps as a research tool per country.

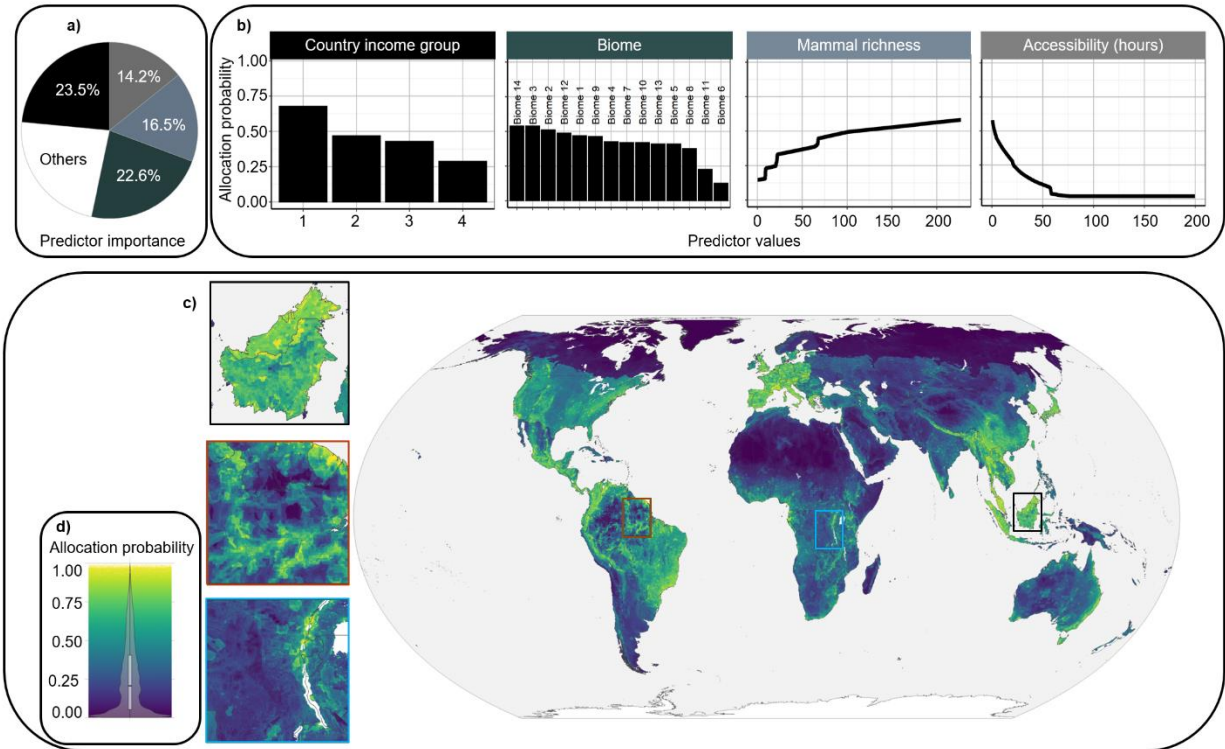


FIGURE 3 The most important predictors of global research allocation. (a) Permutation importance of the top four predictors (and others combined). (b) Relationships between the probability of research allocation and the top four most important predictors. (c) Probability of research allocation and three zoomed-in areas (insets) of the tropical moist forest biome; Southeast Asia (Borneo), South America (Amazon) and Africa (Congo Basin) and (d) Violin plot showing the probability of research allocation values and the colour ramp as a legend for the maps. The violin plot shows the median and the interquartile range of the probability of research allocation.

The biomes are: **1 = Tropical and Subtropical Moist Broadleaf Forests**, **2 = Tropical and Subtropical Dry Broadleaf Forests**, **3 = Tropical and Subtropical Coniferous Forests**, 4 = Temperate Broadleaf and Mixed Forests, 5 = Temperate Conifer Forests, 6 = Boreal Forests/Taiga, 7 = Tropical and Subtropical Grasslands, Savannas and Shrublands, 8 = Temperate Grasslands, Savannas and Shrublands, 9 = Flooded Grasslands and Savannas, 10 = Montane Grasslands and Shrublands, 11 = Tundra, **12 = Mediterranean Forests, Woodlands and Scrub**, 13 = Deserts and Xeric Shrublands and **14 = Mangroves**. The top five biomes with the highest probability of research allocation in bold.

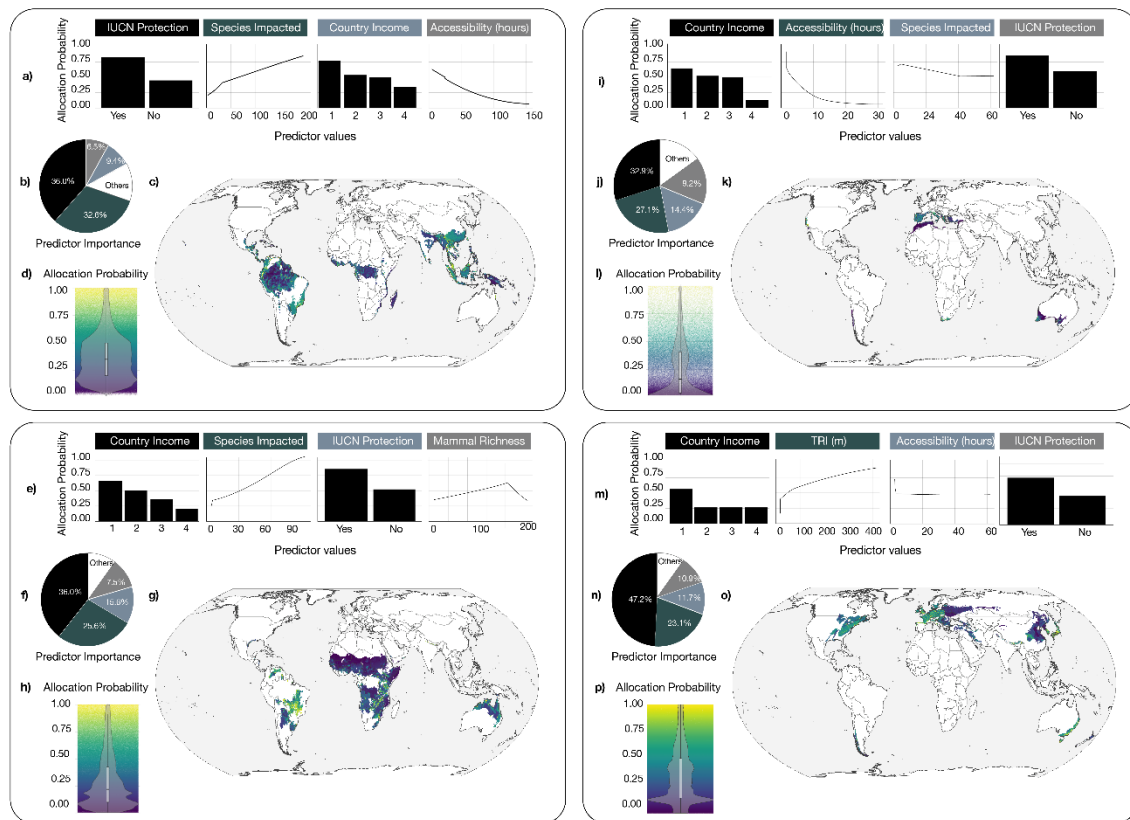


FIGURE 4 The most important predictors and probability of research allocation in the four most researched biomes; the tropical moist forests (top left), tropical grasslands (bottom left), Mediterranean forests (top right), and temperate forests (bottom right). (a), (e), (i) and (m) Relationships between the probabilities of research allocation and the top four most important predictors. (b), (f), (j), and (n) Permutation importance of the top four predictors (and others combined). (c), (g), (k), and (o) Probability of research allocation for each of the biomes. (d), (h), (l) and (p) Violin plots showing the probabilities of research allocation values for each of the four biomes also used here as a legend. The violin plots show the median and the interquartile range of the probability of research allocation.

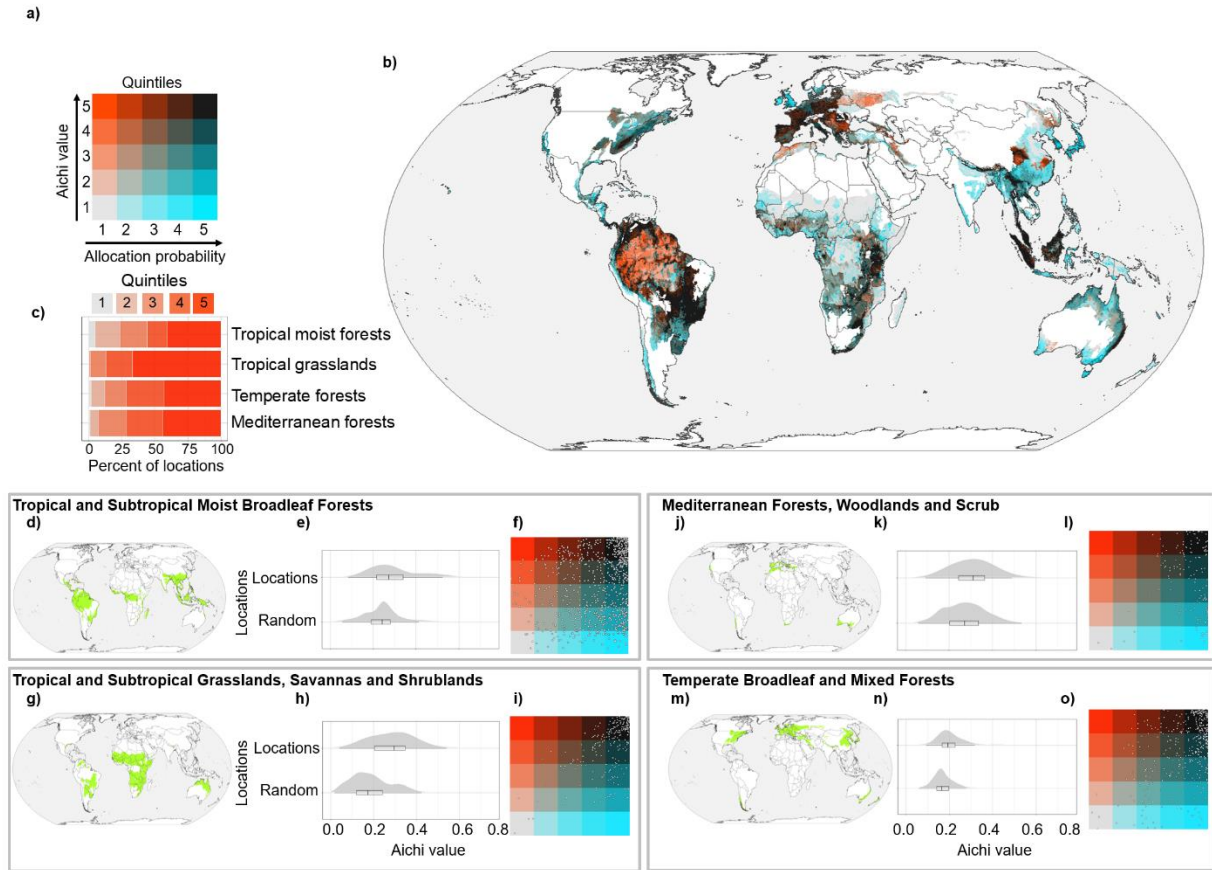


FIGURE 5 Disparity in the probability of research allocation and the Aichi Targets. (a) Bivariate choropleth showing the relationship between the probability of research allocation and the Aichi Targets. Numbers 1 to 5 on the bivariate choropleth depict quintiles. Each colour change means a 20% quintile change in probability of research allocation and Aichi value. (b) Disparity in the probability of research allocation and Aichi Targets. Notable, areas in orange are of high Aichi value. These areas would be the best targets for research aimed at meeting the Aichi Targets and hence informing actions to halt biodiversity loss. (c) Percentage of research locations in quintiles of areas important for Aichi Targets. (d), (g), (j) and (m) Extent of the four most researched biomes; tropical moist forests, tropical grasslands, Mediterranean forests, and temperate forests. (e), (h), (k) and (n) Aichi values of research locations compared to a random sample. (f), (i), (l) and (o) depict legends for the bivariate choropleth in (a); overlaid with research locations (dots).