Assessing the biogeographical and socio-ecological representativeness of the ILTER site network

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ABSTRACT

The challenges posed by climate and land use change are increasingly complex, with rising and accelerating impacts on the global environmental system. Novel environmental and ecosystem research needs to properly interpret system changes and derive management recommendations across scales. This largely depends on advances in the establishment of an internationally harmonised, long-term operating and representative infrastructure for environmental observation. This paper presents an analysis evaluating 743 formally accredited sites of the International Long-Term Ecological Research (ILTER) network in 47 countries with regard to their spatial distribution and related biogeographical and socio-ecological representativeness. “Representedness” values were computed from six global datasets. The analysis revealed a dense coverage of Northern temperate regions and anthropogenic zones most notably in the US, Europe and East Asia. Significant gaps are present in economically less developed and anthropogenically less impacted hot and barren regions like Northern and Central Africa and inner-continental parts of South America. These findings provide the arguments for our recommendations regarding the geographic expansion for the further development of the ILTER network.

1. Introduction

Human impacts on the environment can present major global environmental risks leading to new information needs by management and policy. Resulting research challenges frequently require a broader and deeper understanding of ecosystem dynamics and behaviour at regional, continental and global scales. These challenges include the needs (i) to describe and predict mass flows and energy balances at the ecosystem level, taking into account the multiple interactions and complex feedbacks between environmental compartments, (ii) to detect and distinguish signals from natural variability at a wide range of spatial and temporal scales, and (iii) to predict the consequences of human interaction with natural systems. In order to meet these needs, integrated multi-scale monitoring and modelling approaches are required (Ali et al., 2013; Bloschl and Sivapalan, 1995; Haberl et al., 2006; Kirchner, 2006; Levin, 1992; Lin, 2003; Montgomery et al., 2007; Parr et al., 2002).

The development and enhancement of integrated observation systems to foster inter- and transdisciplinary research is one of the Grand Challenges of Earth System Science for global sustainability (Reid et al., 2010). However, this poses critical demands on spatial and observational designs, i.e. coverage, and capabilities of monitoring technologies.
(Reid et al., 2010; Vihervaara et al., 2010; 2013; Zoback, 2001) and calls for the “next generation of ecosystem research” (Mirtl, 2010). Responses to similar requests were explored in frameworks for the organisation of continental and global scale research infrastructures like the Group of Senior Officials (GSO) on Global Research Infrastructures (GSO, 2020) and the European Research Infrastructure Consortium (ESFRI, 2020). However, the time horizon for such formalised implementations is in the range of a decade. Therefore, it is expedient to explore – and where possible, capitalise on - existing initiatives and investments in the domain, like the Long-Term Ecosystem Research (ILTER). ILTER is one component of worldwide efforts to better understand the current state and dynamics of various ecosystems. Through long-term research and monitoring, ILTER seeks to improve our knowledge of the structure and functions of ecosystems and their response to environmental, societal and economic drivers.

The International Long-Term Ecological Research Network (ILTER) was founded in 1993 to meet a growing need for communication and collaboration among long-term ecosystem researchers (Mirtl et al., 2018; Kim et al., 2018). ILTER is a global network of networks consisting of research sites in a wide array of ecosystems that focuses on long-term, site-based research, and builds on a “bottom-up” governance structure (ILTER, 2020). As of October 2020, the ILTER network covers 743 sites globally (DEIMS-SDR, 2020; see Fig. 1).

This represents a substantive potential in meeting one of the most demanding requirements of continental- and global-scale environmental in-situ research infrastructures, namely representative coverage of key environmental and geographic gradients (e.g. altitude, climate, landforms, geology, land cover, biogeography), and social and economic gradients such as demography and economic density (Mollenhauer et al., 2018) at larger, international scales. Although there are a large number of ILTER sites, this alone does not ensure good representativeness since there may be over-representation of certain areas or biases in site selections. For this reason, carefully assessing the degree of representative coverage of site networks like ILTER is important. Is the coverage of world regions suitable for global comparative studies and meta-analyses? Is this constrained by biases common to terrestrial ecological study sites (Martin et al., 2012)? From our assessment of the representativeness and coverage of the global ILTER in-situ site network with respect to multiple biogeographical and socio-ecological gradients, we derived recommendations for the extension of the ILTER site network for closing identified gaps.

2. Material and methods

In order to assess the representativeness of the ILTER site network, we chose six global datasets describing biogeographical, ecological and anthropogenic patterns that were intersected with the locations and boundaries of the ILTER sites following the statistical concepts described by Schmill et al. (2014) as well as extending these concepts with additional analyses tailored to this study. We chose classifications that were both available as global high-quality geospatial datasets and suitable to match the scientific scope of the ILTER site network (ILTER, 2020). The data sources used and the individual geoprocessing steps conducted for each dataset are outlined below. The ILTER sites datasets as used for this work (see 2.1.1) as well as all data derived by the outlined processing and analyses are available online (Ohnemus and Wohner, 2020). All R scripts associated with this work are also available online (Ohnemus, 2021).

2.1. Used datasets

2.1.1. ILTER sites

Location data of the ILTER sites was obtained from the web service DEIMS-SDR. DEIMS-SDR is developed by the European regional LTER network and used by ILTER and its member networks as their official site registry (Wohner et al., 2019). DEIMS-SDR enables environmental monitoring or experimental sites to be described and their spatial extent defined as complex geometries. As of October 2020, the geographic information available for ILTER sites includes both a point-based geospatial dataset of the centroid or representative coordinates of all 743 officially accredited and active ILTER sites (see Fig. 1) and the boundary information of exactly 500 accredited and active ILTER sites as a multipolygon based geospatial dataset. For the sites reporting only a point representation, 242 specified a numeric size value. The one site for which no indication of the actual size was reported is described as a marine buoy and is located outside of the extent of the used datasets and was consequently excluded from analysis. For the 242 sites with only a point representation and a size value, applying the function buffer of the package raster (Hijmans, 2019) in R v. 3.6.0 (R Core Team, 2019) allowed us to calculate circular polygons with the reported size in order to approximate the extent of these sites. This resulted in a multipolygon geospatial dataset for a total of 742 ILTER sites, which was the basis for the further analysis.

The registered sites show a wide range in their given geographical extent, from a few square metres to several hundreds of square
kilometres. The smallest sites are single sampling stations e.g. for rivers, while the largest sites represent platforms that carry out a whole-systems approach combining environmental and socio-ecological aspects consisting of multiple subsites and plots. While DEIMS-SDR defines the boundaries of a site as “The geographic extent covering the area of all measurement infrastructures including measurement devices (e.g. hydrological observations, soil respiration chambers) as well as permanent plots (e.g. vegetation surveys, soil sampling)” (DEIMS-SDR Data Models, 2020), it can be assumed that the provided boundaries do not always follow that definition and that for some sites the geographic extent of the hydrological catchment was provided instead. As a result, 11 sites are registered with an extent of over 100,000 km². By applying a logarithmic weighting of the geographical extent, this inconsistency in the information was largely eliminated in the analysis. A detailed description of the applied weighting procedure is provided in the analytical methods section in 2.2.

2.1.2. Anthromes

In order to account for human influences on ecosystems, we decided to include a dataset describing anthropogenic biomes. Anthropogenic biomes or simply anthromes describe the terrestrial biosphere in its contemporary, human-altered form using global ecosystem units defined by global patterns of sustained direct human interaction with ecosystems (Ellis and Ramankutty, 2008). For the analysis, we used the dataset by Ellis et al. (2020). At the time of writing this paper, this was the most recent development in a series of global anthrome datasets, providing 20 categories of human influence as raster data with a resolution of 5 arcminutes in the World Geodetic System (WGS) 84 Mercator projection. This dataset was reprojected to the equal-area Mollweide projection using the function “rasterProject” (Hijmans, 2019) with a resulting spatial resolution of 8350 m × 10300 m.

2.1.3. Biomes

Biomes delineate ecoregions summarising macroscale patterns of flora and fauna (Olson et al., 2001). For the analysis of the representativeness across biomes, we used the depiction of the 846 ecoregions produced by Dinerstein et al. (2017), available as polygon data but without exact information on the spatial resolution. Some of the datasets used by Dinerstein et al. (2017) have a resolution of 30 m but it is unclear how much of that remained in the final product. For the purpose of this analysis, we deemed this uncertainty as acceptable. Using the function “rasterize” (Hijmans, 2019) we converted the vector information to raster data with the same origin, extent, and resolution as the anthromes data. The function “mask” (Hijmans, 2019) was used with the extent of the anthromes dataset as the mask. As a result, Antarctica was removed from the biome raster data to achieve comparability of the statistical analyses between the different datasets.

2.1.4. Bioclimatic zones

Bioclimatic zones are depictions of the clustering of a wide range of climatic zones (Metzger et al., 2013). To assess the representativeness across bioclimatic zones, we used the raster dataset provided by Metzger et al. (2013). In contrast to the biomes dataset, this dataset was derived solely based on statistical analyses, not on expert judgement. The dataset represents 125 environmental strata with a 30 arcseconds resolution (equivalent to 0.86 km² at the equator), which can be aggregated into 18 global environmental zones. The dataset was reclassified (Hijmans, 2019) to represent these global environmental zones in order to allow for correct statistical estimations of the chi²-tests of homogeneity (see 2.2) and comparable results. Using “rasterProject” (Hijmans, 2019) the data was reprojected to the Mollweide projection with a resulting spatial resolution of 818 m × 1020 m. Using “resample” (Hijmans, 2019) the bioclimatic raster was transformed to have the same origin, extent and resolution as the anthromes dataset.

2.1.5. Economic density

Similar to the motivation for the anthromes dataset, we included a dataset describing the so-called Economic Density (ED) in order to assess socio-ecological representativeness. This parameter was chosen in particular as it was already used for a similar study of LTER sites in Europe (Mollenhauer et al., 2018). The ED is defined as the gross domestic product (GDP) per square kilometre, combining economic power and population density as two critical measures for human influence in one parameter (Metzger et al., 2010).

\[ ED = \frac{GDP}{\text{Capita} \times \text{Population Density}} \]

Rummu et al. (2018) provide a raster dataset with the average GDP per capita of the years 1990–2015 with the reference unit of the US Dollar from 2011 in the WGS84 Mercator projection with a spatial resolution of 0.083° × 0.083°. Additionally, a population density raster dataset for the year 2020 representing people per km² was available in WGS84 Mercator projection with a spatial resolution of 0.25° × 0.25° (CIESIN, 2016). Using “rasterProject” (Hijmans, 2019) both datasets were projected to the Mollweide projection. The population density data was then resampled (Hijmans, 2019) to the same origin, extent and resolution as the GDP data. With the function “resample” with the method “bilinear” (Hijmans, 2019) Eq. (1) was applied to derive ED in US$ per km². Using the function “resample” with the mask “land” (Hijmans, 2019) the ED dataset was transformed to have the same origin, extent and resolution as the anthromes dataset. The resulting ED raster was then split into six classes using the function “cut” (Hijmans, 2019). Class limits in million US $/km² are 0, 0.01, 0.1, 1, 10, 30. For the most economically dense class, 30 was chosen as the lower limit to allow for correct chi² approximation (see 2.2). The other classes vary one to the next by an order of magnitude.

2.1.6. Land cover

Land cover is a feature on the interface of human and natural interaction, vastly influencing ecological spatial patterns. The European Space Agency (ESA) provides a raster dataset with 37 land cover categories at a spatial resolution of 300 m based on WGS84 (ESA, 2017). This dataset was chosen since it was published recently and provides a fine categorical resolution. Since the category “water” was not subdivided into terrestrial and marine waters, “extract by mask” in ArcMap v. 10.7 (ESRI, 2019) was used with the “medium scale physical land surface” dataset (Natural Earth, 2020) as the mask to remove the oceans, the Black Sea and the Caspian Sea. Next, a 3 nautical mile buffer (Hijmans, 2019) around the land surface shapefile was created to produce a polygon representing “transitional waters” (Mollenhauer et al., 2018). This polygon was transformed into a raster and merged with the land cover raster before it was projected to the Mollweide projection using the functions “rasterize”, “merge” and “rasterProject” (Hijmans, 2019), respectively.

To allow for correct computation of the statistical analyses, the aggregation of scarcely present categories was also necessary. Therefore, the function “reclassify” (Hijmans, 2019) was used to combine a total of 12 categories to 4 new categories (see Table 1). This raster was resampled (Hijmans, 2019) to have the same origin, extent and resolution as the anthromes dataset. Ultimately, the function “mask” (Hijmans, 2019) with the anthromes raster dataset as a mask was used to remove Antarctica from the dataset in order to establish comparability with the other datasets.

2.1.7. Landforms

Landforms are an essential feature determining ecological processes by influencing inter alia the pedosphere as well as macro- and micro-climates. For assessing the representativeness across landforms, the dataset by Karagülle et al. (2017) with 16 different landform categories was used, which itself is an update to the dataset by Sayre et al. (2014). The dataset with a resolution of 1500 m × 1500 m in the Mollweide Projection was obtained using the ArcGIS Online interface in ArcMap.
and resolution but without spatial coverage of Antarctica to be used for the equal-area Mollweide projection with the identical origin, extent and resolution as the anthromes dataset.

Reclassification table for the land cover dataset.

| Original Category (ESA 2017)               | Area [% of dataset] | Reclassified Category                      | Area [% of dataset] |
|-------------------------------------------|---------------------|--------------------------------------------|---------------------|
| Tree Cover: needleleaf (sic) evergreen - closed | 0.48                | Tree Cover: needleleaf (sic) evergreen - closed | 0.48                |
| Tree Cover: needleleaf (sic) evergreen - open | <0.01               | or open                                    |                     |
| Tree Cover: needleleaf (sic) deciduous - closed | 0.99                | Tree Cover: needleleaf (sic) deciduous      | 0.99                |
| Tree Cover: needleleaf (sic) deciduous - open | <0.01               | or open                                    |                     |
| Sparse Vegetation                         | 1.66                | Sparse Vegetation                          | 1.74                |
| Sparse Tree                                | <0.01               |                                            |                     |
| Sparse Shrub                               | 0.01                |                                            |                     |
| Sparse Herbaceous Cover                    | 0.07                |                                            |                     |
| Bare Areas                                 | 3.75                | Bare Areas                                 | 3.79                |
| Consolidated Bare Areas                    | 0.02                |                                            |                     |
| Unconsolidated Bare Areas                  | 0.02                |                                            |                     |

10.7 (ESRI, 2019) and was resampled (Hijmans, 2019) to have the same origin, extent and resolution as the anthromes dataset.

These processing steps resulted in six harmonised raster datasets in the equal-area Mollweide projection with the identical origin, extent and resolution but without spatial coverage of Antarctica to be used for the subsequent analysis outlined below.

2.2. Analytical methods

To determine the representativeness of the ILTER site network, we applied statistical concepts as defined by Schmill et al. (2014) to the harmonised datasets as well as the ILTER sites dataset. These statistical concepts, which are described in detail below, are based on the approach of the Global Collaborative Engine (GLOBE, 2020). GLOBE is an online collaborative environment that enables land change researchers to share, compare and integrate local and regional studies with global data to assess the global relevance of their work. The programming language and software environment R v. 3.6.0 (R Core Team, 2019) was used for all subsequent analyses. Initially, the provided spatial extent of each ILTER site was used for the analysis. However, if all sites had been included in the analysis with a weighting proportional to their extent, around 150 of 742 ILTER sites would have accounted for 99% of the total spatial coverage. The reason is that for some sites, the recorded geographical extent does not correspond to the actual distribution of the existing infrastructure as outlined earlier. In some cases other reference criteria, such as the catchment area was given as the site area, despite being significantly larger than the studied area (see chapter 2.1.1). Thus, in order to reduce the weight of extreme outliers, the logarithm of the area of each site was used instead to represent the relative weight of each single site. The distribution of cumulative percentages of the total area for all ILTER sites by different weighting methods is outlined in Fig. 2.

With the log-weighted site data, a chi²-test of homogeneity was conducted comparing the count of all raster cells of each analysed category in a dataset to the corresponding count of all raster cells of the ILTER sites for each category. This was done in order to assess the deviation of the expected cell count based on each dataset’s classification compared to the actual cell count based on the ILTER sites. To obtain the count of raster cells in the entire dataset the R-function “freq” (Hijmans, 2019) was used, generating a table with the cell count per category. To obtain the count of raster cells within ILTER sites the R-function “extract” (Hijmans, 2019) was used, generating a table with all cell values within the ILTER polygons, with the parameter “small = true”. With this configuration, for ILTER sites with boundaries smaller than the extent of a single raster cell, one raster cell matching the location of the site was extracted from the dataset. The output of this analysis generated a chi² value, a p value and enabled the comparison of observed and expected counts of cells for each category of any dataset. If the expected cell count for any category in a dataset was below five and reclassifying such a category was not possible, the chi² approximation may be incorrect and the generated chi² value and the p value were omitted from the results.

Next, a second chi²-test of homogeneity was conducted for each category within a given dataset. For each category of a dataset the expected cell count and the observed cell count of the ILTER sites were compared, resulting in a p value for each category. Based on the expected (exp) and observed (obs) cell count and the p value for each category, Schmill et al. (2014) introduced a numerical parameter called “representedness”. To emphasise that this value is computed based solely on spatial distributions, we refer to it as “Geographic Representedness” (GR). Table 2 provides an overview of how the GR value is calculated, which conditions apply, the meaning of the values and the value range. Values above 0.00 indicate “Geographic Overrepresentedness” and values below 0.00 indicate “Geographic Underrepresentedness” (see also Fig. 3a). If a category was not covered by any ILTER site no GR value was computed.

Next, every dataset was reclassified (Hijmans, 2019) so that each raster cell is assigned a GR value. When no GR value could be computed for a given category, we argue that this category is not covered at all and must therefore be underrepresented. In such cases, the value −1.00 was assigned.

It should be stressed that for every class in a dataset, exactly one GR value is calculated. These values are then mapped to the original input raster (Fig. 3b). However, the resulting spatial dataset does not actually take the spatial distribution of ILTER sites into further consideration.

After calculating the GR for each dataset, we calculated a summation parameter, which we refer to as “Aggregated Representedness” (AR), by adding (Hijmans, 2019) all six individual GR raster datasets that were overlaid and aggregating each corresponding raster cell value (Fig. 3c). This resulted in an additional raster dataset with a value range from −6.00 to + 6.00. The value −6.00 represents areas that feature
categories underrepresented in all of the six input datasets whilst $+6.00$ represents areas featuring categories that are overrepresented in all six input datasets. Using this method AR values around 0 do not necessarily indicate good representation, instead they can represent regions where overrepresented categories from one dataset cancel out underrepresented categories from other datasets. In our case AR values of around zero are always the result of overrepresented and underrepresented categories cancelling each other out. Thus, it is hard to make clear recommendations for these areas. However, identifying clearly over- and underrepresented areas is sufficient to achieve the aim of this work.

In addition, based on the AR raster, we derived the so-called “priority regions”. They are intended to indicate regions that are of higher or lower priority for extending the ILTER site network, to mitigate the outlined downsides of the AR dataset and - for some non-scientific stakeholders – to translate the potentially abstract statistical measures into a more intelligible representation. For this purpose, a hexagon grid was created using QGIS 3.4 (“create grid”, grid type “hexagon” with vertical and horizontal spacing of 5° in the WGS84 Mercator projection). The AR raster layer was reprojected using “warp (reproject)” utilising QGIS 3.4 to also be in the WGS84 Mercator projection. Next, the hexagon grid layer was combined with the AR layer using “zonal statistics”. Thus, every hexagon cell was assigned a mean value based on all AR raster cell values within the feature. The resulting mean values per grid cell were further reclassified to indicate where additional sites should be established (Table 3).

For hexagon cells below a mean value of 0.00, we assigned a “medium” to “very high” priority depending on the degree of underrepresentedness. For hexagon cells equal to or above 0.00, we assigned a
In addition to the six GR datasets used in the representedness analysis, the Euclidian distance of each investigated grid cell to the next existing site was also examined. This is to take into account the fact that it is not only the number and spatial extent of the sites that are decisive for the assessment of representedness, but also the spatial distribution of the sites within a classification’s category. Especially for categories that have a very large spatial extent, the spatial distribution of sites should be optimised in order to minimise information redundancies, e.g. with regard to climate data. For this, the “Euclidean Distance” algorithm with the distance method “geodesic” and the polygon representation of the 742 ILTER sites as the input layer was executed in ArcGIS v. 10.8 (ESRI, 2020). This algorithm, however, ignored a few small polygons. To account for these, the same algorithm was executed with the point representation of the 742 ILTER sites (Ohnemus and Wohner, 2020) as the input layer. The algorithm did not ignore any point geometries. Both resulting datasets were clipped to the global land surface, using “extract by mask” in ArcGIS v. 10.8 (ESRI, 2020) with the administrative boundaries of the world (GADM, 2018) as the mask. Using the function “overlay” (Hijmans, 2019) in R v. 3.6.0 (R Core Team, 2019) both raster datasets were combined with the function “min”, hence the minimum value of two corresponding input raster cells was assigned to a new dataset. Therefore, the resulting Euclidean Distance raster accounts for the point representation of ILTER sites only if the polygon representation was ignored by the algorithm. Since only a few small polygons were ignored the computed distance to the point representation is similar to the distance to the polygon representation, thus, this approximation is satisfactory.

Table 3
Reclassification of “Aggregated Representedness” (AR) values.

| Mean Aggregated Representedness (AR) | Priority for additional sites |
|--------------------------------------|-------------------------------|
| 3.00 to 6.00                         | low                           |
| 1.99 to 3.00                         | medium                        |
| 0.99 to 2.00                         | high                          |
| 0.00 to –0.99                        | very high                     |
| –0.99 to –4.00                       | very low                      |
| –6.00 to –4.00                       | very very low priority        |

“low” or “very low” priority. Additionally, in case a single ILTER site was located in a hexagon cell and if the mean was below 3.01, we automatically assigned a “low” priority for this cell. For hexagon cells with more than one ILTER site, we automatically assigned a very low priority.

Fig. 4. “Geographic Representedness” (GR) per classification following Schmill et al. (2014).
3. Results

The analysis revealed a significantly different distribution of relative cell counts per category for ILTER sites compared to the global distribution for all datasets, with hardly any category of any dataset being well represented (see Supplement Fig. S1 - S6). Based on the GR per input dataset several spatial biases could be detected as outlined below.

The analysis of the anthromes dataset revealed a bias towards more anthropogenically developed areas, with an undersampling of all wild and less anthropogenically influenced semi-natural and rangeland areas (Supplement Fig. S1). Thus, overrepresentation is evident for the Eastern parts of the United States, Southeast-Asia, the Indian subcontinent, the Brazilian coastline, parts of Bolivia, Southern and Central Africa, regions north of the Gulf of Guinea and most of Europe, in particular the so-called ‘Blue Banana’ (Brunet, 1989), a discontinuous corridor of urbanisation spreading over Western and Central Europe (Fig. 4a). The analysis of the Economic Density indicates a bias towards wealthy regions (Supplement Fig. S4) and further displays a spatial pattern similar to the anthromes data (Fig. 4d). Here, regions in Asia, India and Australia are almost congruent to the anthromes dataset. More regions in Africa are underrepresented (Supplement - Fig. S5). The categories of croplands and shrublands, tablelands categories. The pattern and distinctly more regions in Africa are underrepresented as a whole (Supplement Fig. S2).

Bioclimatic data revealed a clear underrepresentation of “hot” and “extremely hot” regions while “temperate” regions are strongly overrepresented as a whole (Supplement Fig. S2). “Cool temperate and dry” regions, however, are well represented. For cold regions no clear pattern emerges, with e.g. “extremely cold and mesic” bioclimates being clearly underrepresented and the bioclimatic “cold and mesic” being clearly overrepresented. There is almost no coverage of arctic regions in the ILTER network. For biomes, the pattern is clearer with the Mediterranean region and “temperate conifer forests” being slightly overrepresented and “temperate broadleaf and mixed forests” being strikingly overrepresented while any other biome is underrepresented (Supplement Fig. S3). Hence, both of these datasets reveal a bias towards the temperate and Mediterranean regions and towards the Northern hemisphere with only coastal regions in Australia, South Africa and South America and, due to their bioclimate, elevated regions in South America, Africa and the Indo-Malayan archipelago being overrepresented and every other region being underrepresented in the Southern hemisphere (Fig. 4b and 4c).

The analysis of the landform data revealed a strong underrepresentation of “nearly flat plains” and a slight bias towards the different categories of hills and a more pronounced bias towards the different tablelands categories. The “scattered” regions are rather underrepresented while “scattered low mountains” are well represented.

The land cover data reveals biases towards “urban areas”, “grasslands”, “evergreen needleleaf trees”, “areas with herbaceous cover”, “water bodies” as well as “transitional waters”, while e.g. different categories of croplands and shrublands, “bare areas” and “sparse vegetation” are underrepresented (Supplement - Fig. S5). The categories “needleleaf deciduous trees”, “evergreen shrubland” and “lichens and mosses” are not covered by ILTER sites. For both datasets the geographical patterns are not as pronounced as for the other datasets, though a bias towards the Northern hemisphere is detectable (Fig. 4e and 4f). It should again be emphasised that the method used assigns exactly one GR value to each category. Therefore, for some datasets overrepresentedness can be the case in areas that are not covered by ILTER sites as it does not take the actual proximity of ILTER sites to each raster cell into consideration. An example for this is the bioclimatic category “cold and mesic”, which in its entirety is overrepresented. Thus, based on the bioclimatic alone Siberia is overrepresented, even though the ILTER network does not have any sites that are located in Siberia.

These individual effects are less obvious in the AR dataset, which is illustrated in Fig. 5. Here, we regard areas as overrepresented with a value of + 3.00 or higher, since this value means at least three categories are overrepresented if simultaneously three categories are well represented. However, since only one category in each of the bioclimatic, the land cover and the landforms datasets obtained a GR value of around 0.00, an AR value of + 3.00 generally equates to four overrepresented, one underrepresented and one well-represented category. So, AR values of + 3.00 and higher clearly reveal a dominance of overrepresented categories. The inverse is true for the values of −3.00 and lower. Thus, the AR values can be seen as a summation parameter of the coverage of biogeographical and socio-ecological global patterns by the ILTER network, and hence can reflect the state of the entire ILTER network regarding these global patterns. The AR shows a pattern where overrepresentation is much more prominent in the Northern hemisphere, i.e. the East and West Coast of the United States, Europe, Japan, the Korean peninsula, vast parts of China and a corridor covering Northern India, Nepal and Bhutan. Overrepresentation in the Southern hemisphere can only be found in parts of the Andes, the Chilean coast, parts of South Africa and on the Australian Southern coast. 7.2% of all cells show a value of 3.00 and higher.

Underrepresented areas are more widespread with 52.9% of all cells revealing a value of −3.00 or lower. Most parts of South America, Africa and Australia are underrepresented. Thus, underrepresentation is more pronounced in the Southern hemisphere. However, vast parts of the Northern hemisphere are also underrepresented, e.g. the Mid-Western United States, Alaska, Northern parts of Central and Northern Asia, Greenland and the northernmost parts of Europe. While 11% of all cells show an AR value of around zero, there are no areas where all six parameters individually are well represented, since, for the anthromes, economic density and biomes datasets, all the categories are either over- or underrepresented (i.e. GR values of exactly + 1.00 or −1.00). Values of around zero therefore mean that Geographic Overrepresentedness in some datasets is counterbalanced by Geographic Underrepresentedness in others. These regions are mostly found dispersed across the United States, Asia, India, Eastern Europe, Africa except for the Sahara, coastal regions of Australia as well as coastal, mountainous and urban regions in South America. In addition to the Representedness analysis, we derived so-called priority regions that can be seen as recommendations for extending the ILTER site network in order to counteract the detected biases and compensate for underrepresented regions (Fig. 6).

Low priority regions for the extension of the site network are located in Europe, Japan, South Korea, Eastern China, Eastern USA and South Eastern Australia. Regions that are of high priority for extending the network are Greenland, Canada, Northern Russia as well as Central Asia, Northern and Central Africa, and also inner continental parts of South America and Western Australia.

Comparing the priority regions to the Euclidean distance (Fig. 7) reveals substantially different spatial patterns. Most notably, the high priority regions reveal a different spatial pattern than the Euclidean distance would suggest. Some regions that are in the proximity of ILTER sites still show a high or even very high priority for additional sites, e.g. parts of Australia, the Sahara and the Amazon Basin. Also regions over 2000 km away from any ILTER site do not necessarily show a high or very high priority for new sites as is evident for e.g. the Indo-Malayan archipelago and a corridor from the Kara Sea in the North to the Arabian Sea in the South. Areas a great distance from an ILTER site can be overrepresented in this analysis nevertheless, as is evident for a small corridor covering Northern India, Nepal and Bhutan. The combination of high economic density, strong human influence, the hilly landforms and the urban land cover results in this overrepresentation, even though this part of the globe as a whole is underrepresented. Consequently, over- and underrepresented areas are not necessarily related to the proximity to ILTER sites.
4. Discussion

The results revealed a strong geographical bias of site locations towards regions with higher economic density (see also Fig S4). This result is both consistent with findings for Europe obtained by Metzger et al. (2010) and Mollenhauer et al. (2018) as well as findings on the global scale by Martin et al. (2012), who, among other aspects, also examined the socio-ecological representativeness of long-term environmental monitoring infrastructures. These analyses also showed that regions of lower economic density are underrepresented - most probably due to less favourable funding options for environmental research. However, such regions often have significant relevance in both a regional and a global context concerning the sensitivity of ecosystems and socio-ecological relationships. Such areas are, in many cases, habitats for animal or plant species that have already disappeared or that are threatened in landscapes that are more strongly influenced by human activity. Often these are also landscapes of critical importance with regard to global feedbacks and interrelationships of the climate system such as the permafrost regions of the northern hemisphere or the Amazon rainforest. In other underrepresented regions with less wealthy countries, the livelihoods of residents are much more directly impacted by changing environmental conditions than in wealthier regions.

While a clear spatial bias was detected for anthromes and economic density, a striking spatial bias was also detected for biomes and bioclimates. Temperate and Mediterranean regions are clearly overrepresented which again seems to be largely driven by comparatively substantial funding resources. For landforms, the bias tends toward hilly and mountainous areas as well as tablelands, with plains being underrepresented. One well known bias for the location of research sites is accessibility, with sites tending to be placed in easily accessible areas. Here, a contrary bias is apparent. However, accessibility is again related to the funding resources and not to the landform alone. Thus, with the European Alps and Japan in particular showing a dense site network and vast plain areas, e.g. vast parts of Russia and Australia, being almost devoid of ILTER sites, this bias again appears to be related to the economic density. Economic density is an important factor for the
accessibility of sites, and in a study area with vastly differing economic density, accessibility appears not to be related to the landform. Regarding land cover, interpretation of the results is difficult. While the fine categorical resolution allows us to more clearly define priority regions, interpretation of the biases is aggravated. More in-depth analysis would be required to see the influence of the aforementioned biases on this dataset. Recapitulating, these results suggest that, currently, ILTER sites are largely placed in economically dense and strongly anthropogenically influenced areas, rather than along biogeographical and socio-ecological gradients.

Improving the collection of environmental data from these underrepresented areas and hence, representing all biogeographical and socio-ecological gradients is an important goal. Still, the challenges to be met are manifold. In addition to the challenges arising directly from national differences in the funding of environmental research, the situation is often aggravated by the fact that underrepresented regions are often sparsely populated and locations of interest are difficult to reach, further hampering long-term operation of in-situ research infrastructures. Scientific institutes are often concentrated in areas with relatively higher income and many of the underrepresented areas are located at great distances from such hotspots of scientific activities and funding. To successfully operate instruments in sparsely populated, remote regions permanently and over the long term, a number of technological criteria must be met: robustness, low power consumption, low maintenance needs and wireless data transmission. Furthermore, such sensor technology has to be globally available at affordable prices. Initiatives like TAHOME, the Trans-African Hydro-Meteorological Observatory (van de Giesen et al., 2014), show the potential that can be tapped by developing such technical solutions.

Another important potential solution to increase representativeness is satellite-based remote sensing. The earth observation missions of e.g. NASA or ESA provide a wealth of information that can be used for model-based predictions and the interpolation of environmental information. Despite the great progress made in recent years to make data from satellite-based remote sensing usable for ecological research, the potential is far from being fully exploited. This is due in part to the scarcity of suitable in-situ data for ground-truthing. An optimised design of the in-situ networks with respect to the type of variables collected, the measurement protocols used and their spatial design can create the basis for better integration between in-situ data and remote sensing and validation exercises. This can lead to new ways of information acquisition that go far beyond what can be achieved by the traditional way of data collection in environmental research and will help to close some of the critical data gaps.

As already indicated in the results section, there are some challenges in interpreting the results due to uncertainties in the underlying information. In order to partially counteract some of the outlined downsides of the approach used and to provide a clearer picture of the status quo, the results for the individual data sets were combined and a global map of the so-called priority regions was synthesised. The priority regions map depicts regions and countries where additional ILTER member networks should ideally be established or existing networks should extend their site network. Based on this synthesis, we recommend establishing LTER networks for example in Arctic regions, e.g. Iceland, Canada or Russia, in Central Asia, e.g. Kazakhstan, Uzbekistan or Turkmenistan, in large parts of Africa, e.g. Egypt, Mauritania, Namibia or Botswana as well as inner-continental regions of South America, e.g. Peru or Bolivia. However, several ILTER member networks currently have a small presence in some less covered regions and expanding on this is likely to help close the most critical gaps. Examples are LTER France for West Africa and LTER Brazil for the inner-continental parts of South America. Placing additional sites in such high priority regions would help mitigate weaknesses and gaps in a cost- and time efficient way. However, if ILTER wants to address specific weak points like the low-coverage of the biomes “Tropical & Subtropical Coniferous Forests”, “Flooded Grasslands & Savannas” or “Mangroves” the recommendations shift towards countries or regions with strong coverage of these biomes. The low coverage of mangroves could be mitigated by systematically establishing sites in that biome in general or in countries where such mangroves are common in particular, e.g. Indonesia. However, such recommendations should be done purposefully for each respective gap.

While a strong case can be made for selecting additional or different classifications and indices for our analysis, we were limited by the general availability of global geospatial datasets meeting the necessary requirements. The selection of datasets was primarily motivated by the requirements regarding the spatial extent and resolution. To improve the priority regions map in the future, a more refined analysis with reference parameters in higher spatial resolution could help to examine regional or national biogeographical and socio-ecological patterns, if such datasets are available. Furthermore, the “priority map” approach could be expanded to include additional information e.g. regarding the current infrastructural configurations. This can help to uncover gaps not only in the geographical distribution but also in the availability of data for certain parameters. Such a refined approach is recommended for national and regional networks with high site density such as Japan or Europe. Even though ILTER encompasses a smaller number of marine sites, only terrestrial ecosystems were taken into consideration for the present study. Additionally, Antarctica was not included in the study.
However, by selecting different datasets or extending the used datasets, the approach could be extended to incorporate marine regions and Antarctica in the future. The limitations also lie in partially incorrect spatial information about the boundaries of ILTER sites hindering higher accuracy.

In spite of the detected biases in site distribution, the ILTER site network is still likely capable of conducting global studies that are representative of biogeographical and socio-ecological patterns by choosing suitable subsets of ILTER sites for given analyses. ILTER also has the potential to close the most critical gaps by extending existing national networks or establishing additional national networks.

We are positive that our recommendations will support the ILTER network in time efficiently reducing biases and closing gaps. Especially when repeating this analysis over the coming years, the development of the ILTER site network could be quantified and evaluated based on transparent and reproducible criteria. Furthermore, our analytical approach could be applied in analyses of regional or national ILTER network representativeness. Further iterations at the global scale might prompt more customized recommendations for developing the ILTER network.

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CRediT authorship contribution statement

Christoph Wohner: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. Thomas Ohnemus: Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing - original draft, Writing - review & editing. Steffen Zacharias: Methodology, Supervision, Validation, Writing - original draft, Writing - review & editing. Hannes Mollenhauer: Conceptualisation, Project administration, Supervision. Erle C. Ellis: Project administration, Supervision. Hermann Klug: Validation. Hideaki Shibata: Funding acquisition, Resources, Writing - original draft. Michael Mirtl: Funding acquisition, Resources, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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