Environmental and Sustainability Indicators 23 (2024) 100456

Contents lists available at ScienceDirect

Environmental and Sustainability Indicators

journal homepage: www.sciencedirect.com/journal/environmental-and-sustainability-indicators

The eLTER research infrastructure: Current design and coverage of environmental and socio-ecological gradients

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A R T I C L E I N F O

Keywords:
Representativity
Long-term
Observation
Network
Development
Social-ecology

A B S T R A C T

Addressing global change requires standardised observations across all ecosystem spheres. To that end, the distributed Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure (eLTER RI) strives for an optimal observational design of its over 200 in-situ facilities. Their spatial distribution should be unbiased to scale local data to its continental target region.

Therefore, we assessed biases in the emerging eLTER RI in-situ facility network. We (i) conducted a survey describing the emerging eLTER RI, (ii) detected critical *gaps* in its coverage of Reference Parameters by identifying biases in a six-dimensional thematic space and determined regions, where these biases cluster spatially, and (iii) derived recommendations to further develop the eLTER RI network.

Three distinct *gaps* were identified: the Iberian, Eastern and Nordic Gap. They resulted mainly from underrepresentation of agricultural lands, mesic and dry regions with low economic density and the Mediterranean, Continental and Boreal biogeoregions. The patterns of underrepresentation are driven by various factors including the thematic context of site establishment over the past decades, operations logistics and funding constraints. We consider closing these *gaps* of highest priority for spatial network development.

Mitigating the biases in the eLTER RI network is crucial to enable confident scaling of local data to the European scale. This will allow the eLTER RI to provide a comprehensive foundation for scientists, policy and decision makers to face global change. Next, a comprehensive dataset of possible additional research sites over Europe must be analysed to derive site- and country-specific recommendations for cost-efficient gap mitigation.

1. Introduction

Global change affects all spheres of the environmental and socio-ecological system, posing great challenges for humanity (Reid et al., 2010; Rounsevell et al., 2012; Kulmala, 2018). It occurs on different spatial scales and its manifestations are heterogenous, therefore, single-site observations are not sufficient to adequately describe its features (Futter et al., 2023) and impacts on ecosystems (Hobbs et al.,

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https://doi.org/10.1016/j.indic.2024.100456
Received 18 March 2024; Received in revised form 29 July 2024; Accepted 8 August 2024
Available online 8 August 2024

2006). To synthesise and scale single-site data to regional, continental or global scales, meta-studies are widely used (Forster, 2014; Li et al., 2017; Wolf et al., 2022). However, observational protocols of single sites are often not standardised (Futter et al., 2023) reducing comparability or even leading to contrasting conclusions (Gould et al., 2023). In addition, many meta-studies are spatially biased (Martin et al., 2012; Metcalfe et al., 2018) and fail to comprehensively describe whether their study sites represent their target region. Thus, meta-study conclusions are often limited by non-standardized and biased data.

Research infrastructures serve as overarching entities coordinating and standardising sites and their observations (Mirtl et al., 2018; Futter et al., 2023). While research infrastructures allow for standardised observations, analyses of the representation of their target regions are scarce. When such analyses were conducted in the past, differences between the characteristics of the target region and the characteristics of in-situ facility locations manifested as what we would describe as sampling bias (Metzger et al., 2010; Mollenhauer et al., 2018; Wohner et al., 2021). However, research infrastructures need to be well designed both in terms of the observational design of in-situ facilities and the distribution of these in-situ facilities across a larger spatial scale (i.e. spatial network design) to collect meaningful data with little or no bias.

Hence, to enable upscaling of in-situ data to the regional, continental or even global scales and to robustly and holistically understand human-environmental interactions, the spatial design of research infrastructures must be crafted carefully and biases must be uncovered (Schmill et al., 2014; Mahecha et al., 2017; Mollenhauer et al., 2018; Ohnemus et al., 2021; Wohner et al., 2021). Several data-driven approaches were developed and applied already to estimate optimal spatial network design (Diogo et al., 2023), which can be generalised to approaches following concepts of transferability (Václavík et al., 2016; Piemontese et al., 2020) and concepts of representativity (Meyfroidt et al., 2014; Schmill et al., 2014; Malek and Verburg, 2017; Ohnemus et al., 2021; Wohner et al., 2021). Concepts of transferability are rather designed to uncover conditions of a study region that are not represented in a research infrastructure, while representativity approaches are rather designed to uncover unequal representations of conditions of a study region within a research infrastructure.

The distributed Integrated European Long-term Ecosystem, critical zone and socio-ecological Research Infrastructure (eLTER RI) will integrate in-situ facilities into a pan-European, distributed research infrastructure with a target size of over 200 in-situ facilities. These in-situ facilities are the fundamental building blocks of the eLTER RI and will benefit from a harmonised design and instrumentation. They will be managed within national research infrastructures, but operations and research will be supported by central services. One of the distinguishing characteristics of all eLTER RI in-situ facilities is the design alignment with the "**W**hole-system **A**pproach for **I**n-situ research on **L**ife supporting **S**ystems" (**WAILS,** Mirtl et al., 2021). WAILS implies a holistic approach for observation and research at compliant in-situ facilities covering characteristics of (i) ecosystem structures (abiotic characteristics, biotic heterogeneity), (ii) ecosystem functions (balance of energy, water, and matter), (iii) the human dimension in an ecological meaningful manner. The according requirements are reflected by mandatory criteria for a set of site categories. These criteria include a selection of harmonised and standardised observation variables for each of the five ecosystem spheres - sociosphere, atmosphere, geosphere, hydrosphere, biosphere. The composition of these Standard Observations is customised for the respective habitat (Zacharias et al., 2021). These are considerable changes implemented in the eLTER RI compared to its last analysis of geospatial representativity (Mollenhauer et al., 2018). Thus, eLTER RI implements a whole-systems approach at an unprecedented scale (Zacharias et al., 2024). The data collected at eLTER RI in-situ facilities was already used for the development of large-scale models (Baatz et al., 2018; Forsius et al., 2023). Therefore, the eLTER RI observational design will allow measurements of global change impacts on all ecosystem spheres in a standardised manner, providing a sound basis for scientists, policy and decision makers.

Since the observational design was already crafted carefully, the scalability of data gathered at eLTER RI facilities depends on the bias manifesting in the spatial distribution of eLTER RI in-situ facilities. Thus, in this work we conducted a representativity analysis (Wohner et al., 2021) which, in effect, identifies biases in a six-dimensional thematic space and maps these biases in the spatial dimension. We aimed to infer clear recommendations for the spatial network development of the eLTER RI. Consequently, three tasks had to be fulfilled.

i) Characterise the current state of the eLTER RI network of in-situ facilities
ii) Identify the most critical spatial *gaps* within the eLTER RI regarding its coverage of environmental and socio-ecological gradients
iii) Derive recommendations for the further development of the eLTER RI

2. Data and methods

All subsequent analyses were conducted in R v. 4.3.0 (R Core Team, 2023), with all illustrations based on the package ggplot2 (Wickham, 2016). The R scripts associated with this work are available online (Ohnemus, 2023).

2.1. Material

2.1.1. Scope and in-situ facilities of the eLTER research infrastructure

eLTER RI comprises terrestrial, freshwater and transitional water habitats. In the past, eLTER RI defined the habitat types that are of highest relevance to be covered by its in-situ facilities. The specification of these habitats types is based on the EUNIS (European Nature Information System) Habitat Classification, developed by the European Topic Centre for Biodiversity for the European Environment Agency (EEA, 2022a).

- Wetlands (mires, bogs, fens)
- Grasslands and lands dominated by forbs, mosses or lichens
- Heathlands, shrub and tundra
- Forests and other wooded land
- Vegetated man-made habitats (regularly or recently cultivated agricultural, horticultural and domestic habitats)
- Inland surface standing waters
- Inland surface running waters
- Coastal (transitional) waters including coastal littoral zones
- Sparsely vegetated habitats and deserts

For each habitat type, customised mandatory criteria for a set of site categories were developed (Zacharias et al., 2021). Based on the fulfilment of these criteria, eLTER's in-situ facilities are assigned to a defined category – (i) eLTER Site Category 1 (Site Cat 1), (ii) eLTER Site Category 2 (Site Cat 2), (iii) eLTER Site Category 3 (Site Cat 3) and (iv) eLTSER platform (Platform). In addition to other criteria, Sites Cat 1 and 2 cover all five ecosystem spheres following the WAILS approach. Sites Cat 2 employ only the basic observation program as defined by the Standard Observations. Sites Cat 1, which are the top-tier sites, have the requirement of specialising in at least two of four ecosystem spheres - geosphere, atmosphere, hydrosphere, biosphere - including an extended set of Standard Observations and advanced methods. Sites Cat 3 do not comply with the holistic approach of covering all spheres. They are therefore not part of the formal eLTER RI, but could be considered as 'associated' or 'candidate' sites. By completing their observation programmes and complying with the other mandatory criteria, these in-situ facilities can upgrade to a Site Cat 2 or 1. Therefore, Sites Cat 3 bear the potential for expansion or modification of the spatial network of eLTER RI. The site category concept is an update to the ecosystem integrity components approach used earlier, e.g. Mollenhauer et al. (2018) analysed a selection of 224 LTER Europe in-situ facilities, but without considering a possible future categorization as eLTER RI sites.

eLTSER Platforms are spatially explicit living laboratories for conducting transdisciplinary, long-term, socio-ecological research and for implementing eLTER RI's WAILS approach. They are designed and operated with the specific goal of harnessing scientific research on human-environment interactions for addressing environmental challenges and facilitating sustainability transitions. Research is conducted at the landscape scale using diverse disciplinary, interdisciplinary, and transdisciplinary approaches in close coordination with local and regional stakeholders. Research and policy at platforms are supported by long-term environmental, social and economic data.

2.1.2. *Survey on the Status Quo of the eLTER research infrastructure*

eLTER developed bottom-up as a network of networks. These networks are nationally coordinated and eLTER RI functions as an overarching continental-scale infrastructure. However, in-situ facilities that are part of a national LTER network do not necessarily participate in eLTER RI.

Thus, a survey was developed to gain an overview of the current state of the eLTER RI and to be able to assess the development potential of the network with regard to the future eLTER RI. The Site and Platform Coordinators (SPCs) from all European LTER countries were asked via the eLTER National Coordinators to provide information about their sites and platforms in the first eLTER pre-screening during February and March 2023. A second consolidating screening was carried out in August and September 2023. This information included the focal habitat according to the eLTER habitat classification, geographic information and the assignment to a current and anticipated future category based on the above-mentioned criteria.

These screening data formed the data basis for the present analysis. For this study, the eLTER RI was defined as entailing all sites that anticipated compliance with Site Cat 1 or Site Cat 2 criteria in the future. Platforms were not considered in the present study. Sites that did not meet the requirements for a holistic approach in terms of their research programme and sites that did not provide information on current or anticipated categories were classified as Sites Cat 3.

2.1.3. *Geographic information*

The survey also requested geographical information on the location and extent of sites and platforms. The majority of the sites that responded to the screening were already registered in the eLTER site registry service (DEIMS-SDR, Dynamic Ecological Information Management System - Site and dataset registry; deims.org; Wohner et al., 2019), where their geographical information is stored. Sites in DEIMS-SDR can be associated with a point geometry or a boundary, i.e. a complex geometry. Sites and platforms not previously registered in DEIMS-SDR provided information directly in the form of geographic coordinates for inclusion in the analysis as a point geometry. For subsequent analysis, all sites associated with a point geometry, rather than geographic boundaries, were buffered to a circular 1 ha polygon. This was oriented on the area and shape of a typical site in the ICP Forest research infrastructure (International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forest, icp-forests.net), which can be seen as a realistic spatial extent for an intense environmental in-situ research facility.

2.1.4. *Reference Area*

For all analyses of spatial representativity the relevant Reference Area (RA) to cover needs to be defined. For the present study of the eLTER RI, the RA was defined to consist of the 26 countries of Europe contributing to the LTER network (Fig. 1). The geospatial data for these countries was obtained using the function “gadm” from the package geodata (Hijmans et al., 2022).

It is important to note that all non-Mediterranean islands connected

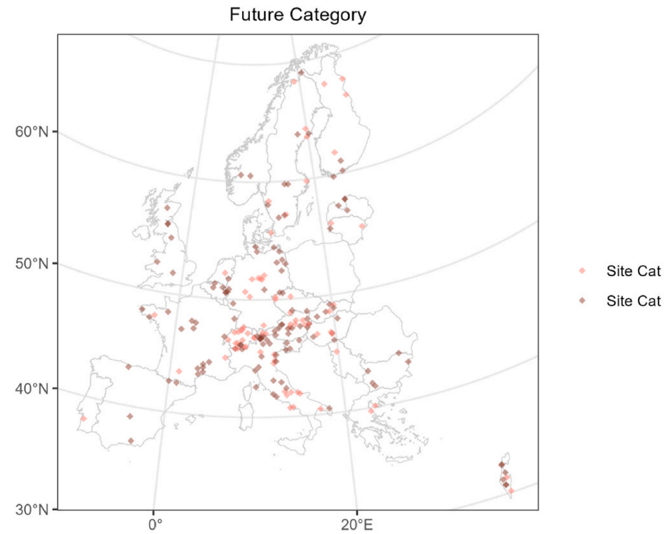

Fig. 1. Spatial distribution of the sites contributing to the eLTER Research Infrastructure with their anticipated future category as indicated by the eLTER National Coordinators in the 2023 survey, illustrated as dots with the respective colour. Grey country boundaries depict the RA. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

to the gadm data for Spain and Portugal, specifically the Canaries, the Azores and Madeira, were excluded. The multipart polygons were therefore disaggregated (Hijmans, 2023b), and the shapefiles were once again aggregated after eliminating the islands that were irrelevant for the analysis (Hijmans, 2023b). This exclusion was carried out for two reasons. First, these islands fall outside the geographical scope of the eLTER RI. Second, data were not available for all Reference Parameters (see below). The gadm country data did not include any additional overseas islands.

2.2. *Analysis*

2.2.1. *Habitat analysis*

The habitat analysis was based on the eLTER habitat classification described above. The data basis for the analysis was the information provided by the European Nature Information System (EUNIS). EUNIS habitats were obtained as raster data with a spatial resolution of 100 × 100 m (EEA, 2019). The EUNIS raster data was projected to the equal-area Mollweide coordinate system (Wohner et al., 2021) to allow a comparison of spatial coverage simply by counting cells. The raster dataset was masked with the RA using the "terra" package as implemented by Hijmans (2023b). Then, the raster dataset was reclassified (Hijmans, 2023b) such that it only entailed the categories defined in the eLTER habitat classification. Eventually, the "freq" function (Hijmans, 2023b) was employed to obtain the distribution of eLTER habitat categories within the RA.

The relative share of each habitat within Sites Cat 1 and 2 was extracted from the survey by dividing the number of instances of each focal habitat by the total number of instances of any habitat. Finally, the proportion of sites covering a specific habitat was compared to the proportion of area covered by that habitat within the RA.

2.2.2. *Representativity analysis*

The aim of the present study was to analyse the eLTER RI, i.e. the Sites Cat 1 and 2, for existing *gaps* in the geographical representation of the most important environmental and socio-ecological gradients based on the survey described above. For this purpose, the representativity analysis as described in Wohner et al. (2021) with adaptations by Ohnemus et al. (2021) was applied.

In brief, six so-called Reference Parameters (RPs) were acquired that collectively depict environmental and socio-ecological gradients: (i) anthromes describing anthropogenic biomes (Ellis et al., 2020), (ii) bioclimatic zones (Metzger et al., 2013), (iii) economic density (Wohner et al., 2021) calculated based on the datasets GDP per capita (Kummu et al., 2018) and population density (CIESIN, 2017), (iv) land cover (ESA, 2017), (v) landforms (Karagulle et al., 2017), and (vi) biogeographical regions of Europe (EEA, 2016). The latter are referred to as biogeoregions in this study. These RPs were processed as detailed by Wohner et al. (2021) with a resulting size of 8350 m × 10300 m for each cell in an equal-area Mollweide projection.

For this analysis, all datasets were masked (Hijmans, 2023a) with the RA. The masking procedure partly removed a three nautical mile buffer around the landcover dataset embodying transitional waters, which was introduced by Wohner et al. (2021) based on the work by Mollenhauer et al. (2018). Removed raster cells were not reinstated, since the other RPs displayed no values in these areas, thus these areas did not influence the result of the subsequent analysis.

Then, the distribution of all categories of each RP for the RA was compared to the distribution on the survey sites. For this purpose, the relative weight of each site in the analysis was calculated using the logarithm of the geographical area of the sites, and a chi-square test of homogeneity was performed to compare the RP category distributions for the RA with those of the Sites Cat 1 and 2 (Wohner et al., 2021). This test generated a x^2 value, a p value and the expected and observed cell count for each category of every RP. Schmill et al. (2014) introduced the numerical parameter “representedness”. This parameter was calculated based on the expected (exp), the RP category distribution of the RA, and the observed (obs), the RP category distribution given by the Sites Cat1 and 2, cell counts as well as the p value for each RP category (Table 1). Following Wohner et al. (2021) we refer to this parameter as “geographic representedness” (GR). A GR value of +1 indicates an overrepresentation of a RP category within the eLTER RI compared to the RA, while −1 indicates an underrepresentation and a value of 0 an ideal representation. Therefore, for this manuscript a GR of 0 means that there is no sampling bias of eLTER RI in-situ facility locations for a certain RP category, while other values indicate a biased representation, with +1 and −1 indicating strongest biases.

Then, the rasters depicting RPs were classified so each cell displayed the corresponding GR value. Ultimately, the six reclassified rasters depicting GR values were summed up to a dataset called “aggregated representedness” (AR, Wohner et al., 2021), which has a value range of −6 to +6. Cells with an AR value of −6 were underrepresented in all RPs, while cells with an AR value of +6 were overrepresented in all RPs. Importantly, over- and underrepresented features on the same cell balance each other out, e.g. a cell with three underrepresented and three overrepresented RP categories would have an AR value of 0. In this study, all observed AR values of around 0 could be attributed to this effect. Thus, in effect, the analysis investigates and compiles biases in site locations in six thematic dimensions and maps these biases in space.

A hexagonal grid with a cell area of 10,000 km^2 was computed using the "make_grid" function (Strimas-Mackey, 2020) to cover the entire RA. The function "extract" (Hijmans, 2023a) was then used to assign the mean of all underlying AR cells to each hexagonal grid cell. This allowed to derive "priority regions" based on the classification introduced by Wohner et al. (2021), with slight modifications (Table 2). Due to the above described effect of over- and underrepresented RPs balancing each other out, an AR around 0 is still classified as a low to medium priority, since usually underrepresented features are still present on these cells. Nonetheless, the lower the aggregated representation of an AR of a cell, the higher the strategic importance of that cell in terms of filling existing gaps in the geographic design of eLTER. Therefore, cells with high or very high priority for the establishment of new in-situ facilities should be regarded as most critical. Hereafter, priority always refers to the priority for the establishment of additional sites to densify the eLTER RI. An ideal representation of environmental and socio-ecological gradients within the eLTER RI would neither include any high priority nor very low priority regions, but medium and low priority regions would be considered an acceptable bias. This statistically-based approach is again an improvement to the simple comparison of value distributions without implementation of a sound statistical test used in the last analysis of the eLTER in-situ facility distribution by Mollenhauer et al. (2018).

Table 1
The conditions and the calculation, meaning and resulting value range of the geographic representedness, taken from Wohner et al. (2021).

Condition	Geographic Representedness (GR)		
	value calculation	meaning	value range
If obs = = exp	0.00	Well represented	0.00
If obs < exp	−1.00 + p value	Underrepresented	−1.00 to < 0.00
If obs > exp	+1.00 – p value	Overrepresented	>0.00 to +1.00

Table 2
Mean aggregated representedness of a hexagon grid cell and the corresponding priority for additional sites.

Mean Aggregated Representedness (AR)	Priority for additional sites
−6.00 to −4.00	Very high
−3.99 to −2.00	High
−1.99 to −0.01	Medium
0.00 to 3.00	Low
3.01 to 6.00	Very low

The representativity analysis was performed for all Sites Cat 1 and 2. For illustration purposes Sites Cat 3 in areas of high and very high priority were visualised. *Gaps* of the eLTER RI were then defined geographically as areas where hexagon cells of very high priority clustered. Hexagons of high priority adjacent to these clusters were also regarded as part of a gap. Due to their spatial distributions, *gaps* were geographically described by country borders.

Clusters of high priority hexagons nonadjacent to *gaps* were regarded as additional “focus zones for targeted network development”. From here on, we refer to these regions simply as *focus zones*. Notably, single hexagons of very high priority emerging on the edge of the RA or covering small islands were not regarded as a gap. In these cases, few underlying cells determined the priority, therefore due to these edge effects determined priorities were less robust.

2.2.3. Gap analysis

The next step was to investigate which RPs were causal and decisive for the underrepresentation found. This was done by backtracking to the original categories of RPs that dominate within the *gaps*. On this account, using the function “freq” (Hijmans, 2023a) a frequency table of all cells lying in regions of high or very high priority within *gaps* was produced. For greater clarity, only RP categories covering at least 15 % of the area of a gap were illustrated as a bar plot. Consequently, this way of presenting the results allowed the distillation of the dominant categories of each RP contributing to the high or very high priority of a gap, thus reducing redundant information.

2.2.4. Cluster analysis

To summarise the categories of all RPs manifesting within *gaps*, a multiple correspondence analysis (MCA) was performed. An MCA should be understood as a principal component analysis for categorical instead of numerical variables (Abdi and Williams, 2010). Therefore, using “extract” (Hijmans, 2023a) all categories of all RPs within *gaps* were obtained. To investigate the potential to close *gaps* with Sites Cat 3, all cells covered by Sites Cat 3 located in areas of high and very high priority were additionally extracted. Furthermore, the same analysis was performed for the *focus zones*. The MCA was performed using the packages “FactoMineR” (Lé et al., 2008) and “factoextra” (Kassambara and Mundt, 2020).

The output of the MCA is an n-dimensional data space. New dimensions are formed until all variance in the dataset is explained, determining the number of dimensions. Consequently, every raster cell was depicted by a numerical value in each dimension. The same position of different cells in all dimensions of the MCA means that the category manifestations of all RPs were the same for these cells. Therefore, the MCA allowed us to examine potential clustering of cells within the identified *gaps* in dependence of all six RP manifestations.

3. Results

3.1. Survey Participation and Site categories

In total, 289 sites responded to the survey, of which 204 (70.6 %) defined themselves as future Sites Cat 1 or 2, forming the site network of the emerging eLTER RI. These sites were spread over the entire RA (Fig. 1), with highest site density observed in the Alps and Central Europe. For this study, 85 sites were defined as future Cat 3. Of all sites bearing potential to upgrade to a higher category, for 83.5 % an upgrade was anticipated by the SPCs (Fig. 2).

3.2. Habitat coverage

The eLTER RI covers all eLTER habitat categories (Fig. 3). Compared with the mapped EUNIS habitat distribution for Europe, within the eLTER RI, a marked overrepresentation was found for wetlands, inland waters and coastal waters, and a marked underrepresentation for grasslands, forests and vegetated man-made habitats. The habitat categories “sparsely vegetated habitats” as well as “heathlands, shrub and tundra” appeared well represented.

3.3. The geospatial gaps of the eLTER research infrastructure

The representativity analysis allowed the identification of *gaps* in the geographic coverage of the existing network of sites and the identification of priority regions for network densification. It revealed areas of very low priority in the alpine region, and areas of low and medium priority mainly in the UK, Southern France, Southern Scandinavia, Italy, BeNeLux and Germany (Fig. 4). The outputs of the underlying x^2 tests of homogeneity can be found in the supplement (Table S1). Three distinct geospatial *gaps* were identified: (i) the Eastern Gap, which forms one cluster entailing Poland, Lithuania and East Germany and a second cluster entailing Romania, Bulgaria and Serbia, (ii) the Iberian Gap represented by Spain and Portugal, and (iii) the Nordic Gap which is most pronounced in Finland but extends into Norway and Sweden. Moreover, we identified small clusters of hexagons of high priority in Central and Northern France, Greece and Hungary as further *focus zones*.

Part of the gap analysis was the identification of RP categories that contribute in a substantial way to the underrepresentation (Fig. 5). The Eastern Gap is dominated by the anthrome “residential rainfed croplands”, cool temperate dry and xeric bioclimates, an economic density of 0.1–1 Mio US$/km^2, flat plains and land cover of cropland and herbaceous cover and lied mostly in the Continental biogeoregion. Within the Iberian Gap the anthrome “residential rainfed croplands”, the “cool temperature and xeric” bioclimate, the economic density “0.1–1 Mio US $/km^2”, and herbaceous cover recurred as dominant. Additionally, warm temperate mesic and xeric bioclimate and shrubland dominated. In contrast to the Eastern Gap, the dominant landforms were hills and high mountains and the biogeoregion was exclusively Mediterranean. For the Nordic Gap, the only dominant categories recurring in other *gaps* were the landforms, which were either plains or high mountains. The Nordic Gap manifested as Boreal and alpine needle-leaved mesic woodlands. According to the dominant anthromes they were remote or wild, i.e. with little human impact, and for Europe an extremely low economic density of 0.01–0.1 Mio US$/km^2 manifested.

Importantly, even though these RP categories were also present within *gaps*, the anthromes “rainfed villages”, the bioclimate “cold and mesic”, the alpine biogeoregion, the land cover of needle-leaved evergreen trees, the economic density “1–10 Mio US$ per km^2” as we well as the landform “high hills” were overrepresented and the bioclimate “warm temperate and mesic” was rather well represented on the European scale (Figs. S1–S6). Thus, these categories did not contribute to the formation of the *gaps*.

The MCA revealed a distinct overlap of RP category combinations within the *gaps* (Fig. 6a). Within the Eastern Gap, generally the two geographical clusters identified before were also evident regarding the environmental and socio-ecological gradients that they cover, with a stronger overlap of the southern cluster of Romania, Serbia and Bulgaria. Poland showed the strongest overlap to that southern cluster and Lithuania the most pronounced difference. For the Iberian gap, all RP category combinations evident for Portugal within the Iberian Gap were also found in Spain, but not vice versa. Regarding the Nordic Gap, the countries revealed notable overlaps, but all countries also showed distinct RP category combinations.

Between the Eastern and Nordic *Gaps*, a very limited overlap of RP category combinations was observed, which was most pronounced for Lithuania in the Eastern and Finland and Sweden in the Nordic Gap. Also, some overlap between the Eastern and Iberian *Gaps* was observed, which was only evident for the South Eastern cluster. The overlap was more pronounced to Spain than to Portugal. No overlap was observed between the Iberian and Nordic *Gaps*.

The RP manifestations for the *focus zones* overlapped in their entirety with RP manifestations observed either in the Eastern or the Iberian Gap (Fig. 6b). Sites Cat 3 in areas of high and very high priority for network densification were located mainly within the *focus zones* and in the Mediterranean (Fig. 4b). Accordingly, these Sites Cat 3 revealed similar RP manifestations as in the Eastern and Iberian *Gaps*, with only one site covering one cell with RP manifestations typical for the Nordic Gap (Fig. 6c).

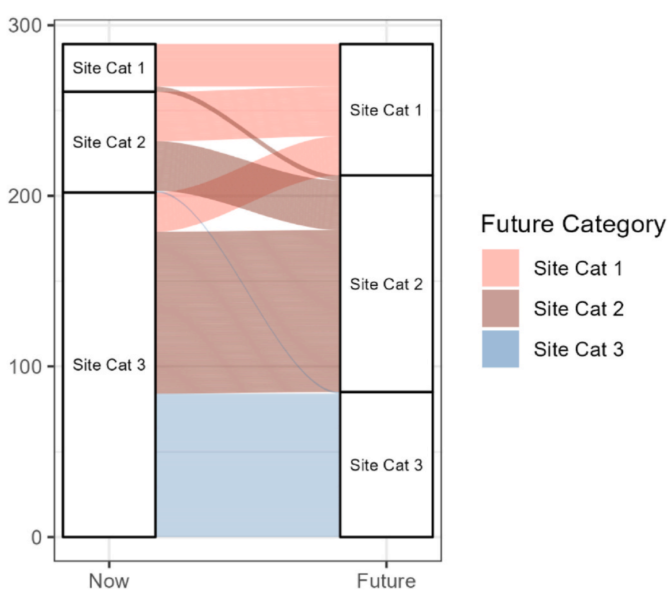

Fig. 2. Projected development of site assignment to categories from present to the future reported by the eLTER National Coordinators in the 2023 survey shown in different colours based on the anticipated future category. Sites Cat 1 and 2 are formally part of the eLTER RI. Sites Cat 3 represent the potential for future network densification. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

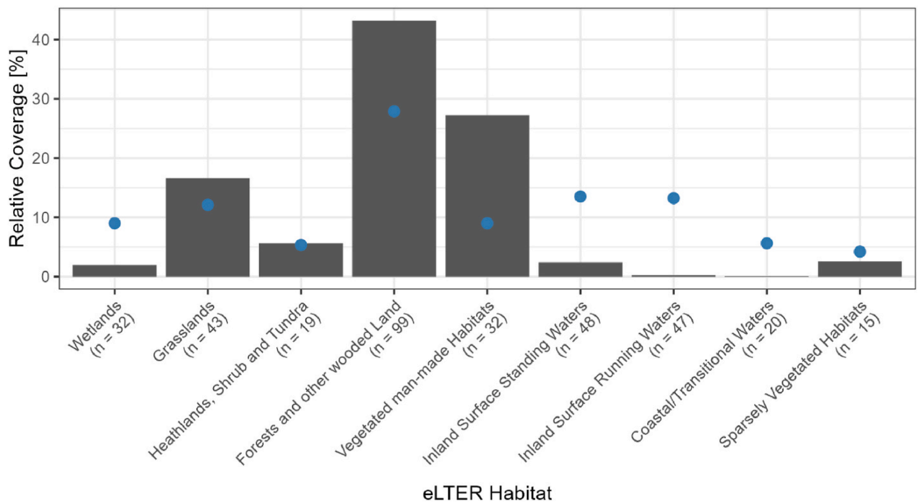

Fig. 3. Relative coverage of eLTER habitat classes in the RA (bars) and as indicated by the SPCs for Sites Cat 1 and 2 (points). Numbers in brackets indicate the number of sites covering a habitat. Multiple mentions in the survey were possible.

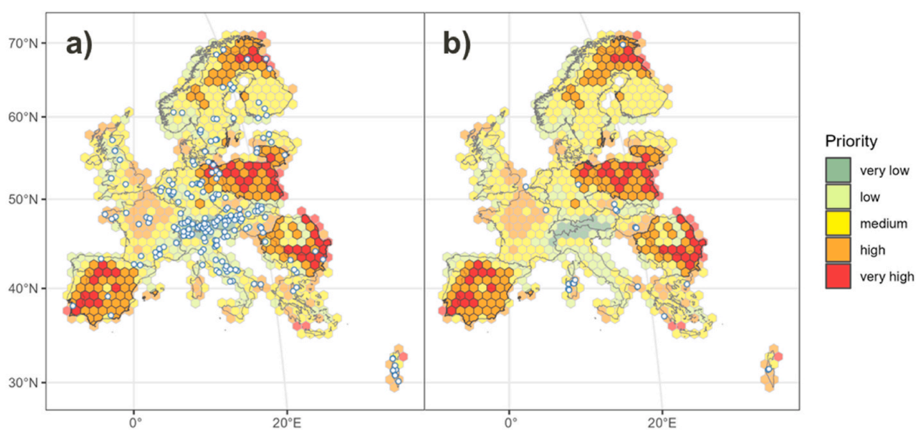

Fig. 4. Priority Regions derived for the RA consisting of the 26 LTER countries. Colours of the hexagons depict the priority for additional sites. Black lines indicate country borders. In a) sites contributing to the eLTER RI are illustrated as white dots, while in b) Sites Cat 3 within regions of high or very high priority are illustrated. In both maps the identified gaps are highlighted. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4. Discussion

4.1. Gaps in eLTER RI coverage

Applying a first set of mandatory criteria for eLTER Sites, 204 compliant sites were reported in 23 countries. This emerging physical network of eLTER RI matches the target size of >200 in-situ facilities envisaged by the fundamental RI planning. Nonetheless, three major *gaps* were identified: the Eastern Gap, the Iberian Gap, and the Nordic Gap (Fig. 4). These are the regions where biases in the six-dimensional thematic space underlying the representativity analysis manifested most dramatically as underrepresentation in space. The Eastern and Iberian gap regions were typically dominated by agricultural lands, while remote areas with little direct human impact are common in the Nordic Gap (Fig. 5). Underrepresentation of areas with little human impact in spatially distributed research infrastructure were observed before on the global scale for the ILTER network (Wohner et al., 2021) and was suggested to be a common phenomenon in global ecological research (Martin et al., 2012). Martin et al. (2012) also found a tendency to study "natural" sites within densely populated and agriculturally-dominated areas. This appears to be the case for the eLTER RI, too, with a clear underrepresentation of managed, agricultural areas.

Another striking underrepresentation generally observed was that of the Boreal, Mediterranean and Continental biogeoregions. However, in particular for the Boreal region the revealed underrepresentation was largely driven by low economic density in the sparsely populated areas. Therefore, underrepresented areas here revealed high remoteness and low accessibility. These patterns, which can be related to logistical challenges and funding availability, were observed before for the global scale (Martin et al., 2012; Wohner et al., 2021). Moreover, the Eastern Gap, which contributed strongly to the underrepresentation of the Continental biogeoregion, mirrors patterns of lowest GDP per Capita in Europe (Solís-Baltodano et al., 2022). In accordance, the GDP per Capita of Portugal as well as Central and Southern Spain were below European average (Solís-Baltodano et al., 2022). This, in turn, may have effects in terms of limited funding for eLTER sites and led to the lower density of sites in these areas, leading to a general underrepresentation of the Mediterranean biogeoregion. The research institutions that operate long-term research sites are often located in regions with higher economic power, a recurring pattern also in other scientific disciplines (e.g. Hefler et al., 1999). Therefore, the generally observed underrepresentation of dry, mesic and xeric areas of Europe can be a direct consequence of lower availability of research resources in these regions, but

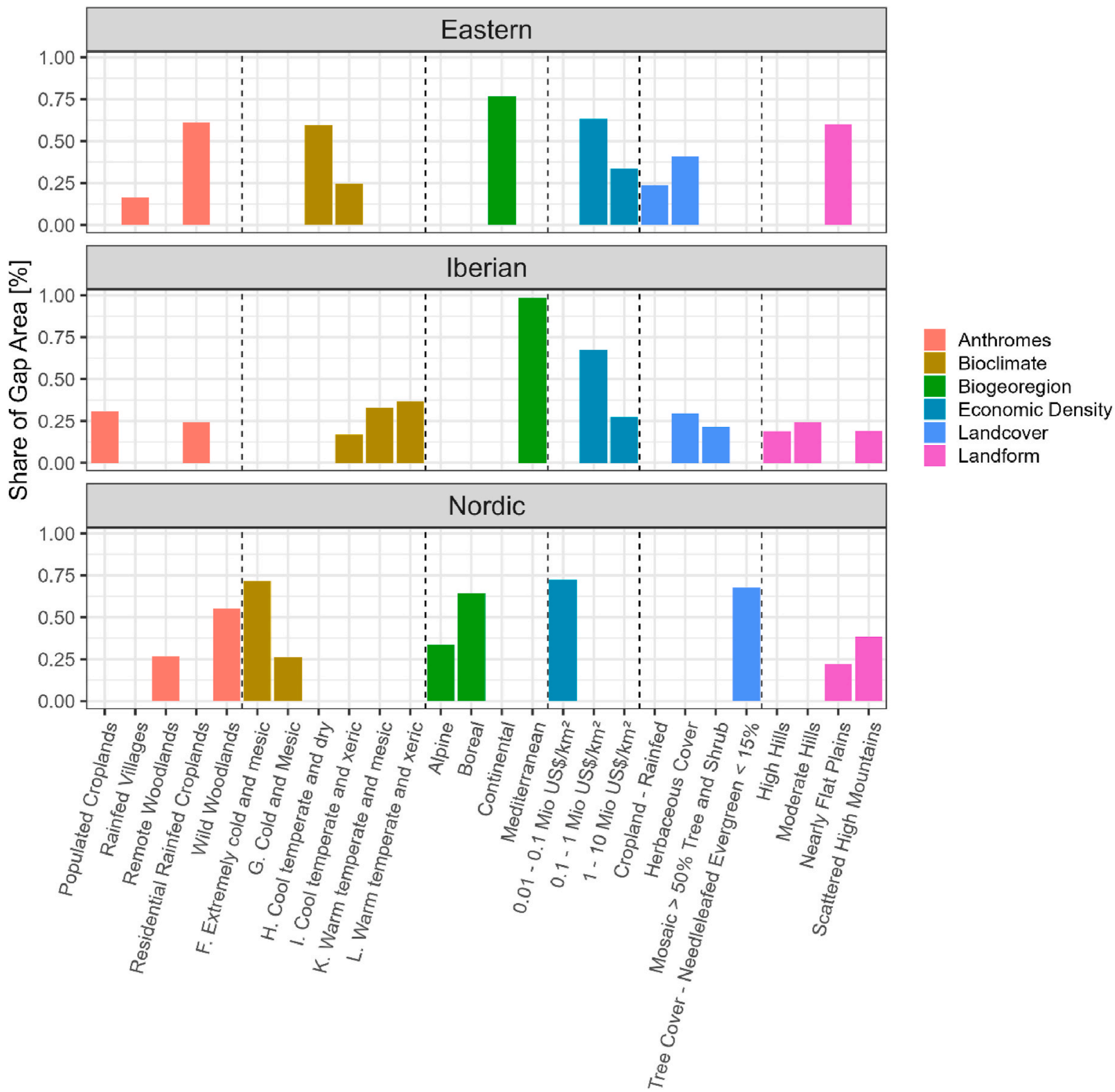

Fig. 5. Categories that cover at least 15 % of the area of any gap for any RP illustrated with their share of the gap area as bar plot. Colours depict the RPs, facets the different gaps. Labels on the x-axis depict the names of the categories of the respective RPs. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

also reflected the pragmatic need to establish long-term operated sites in proximity to the site operating institutions.

The RPs land cover and landforms were more difficult to interpret regarding their influence on site distribution (Wohner et al., 2021). For Europe, where pristine areas hardly occur, the dominant land cover largely mirrored land use history. Within the Iberian and Eastern *Gaps*, the dominant land cover manifestations can be interpreted as arable land. In the Nordic Gap, the dominant land cover mirrored the Boreal and alpine biogeoregions with its manifestation as coniferous forest. Landforms within *gaps*, however, ranged from flat plains to high mountains without a clear pattern. The underrepresentation of flat plains within the eLTER RI was again connected with the lack of agricultural sites in eLTER RI, since these locations are preferable for agricultural practice. In general, it can be stated, while aspects such as population density and existing economic power influence the choice of research locations, the specific landform plays a minor role. A good example was the strong overrepresentation of the Alps. High mountains are generally characterised by difficult accessibility, however, in the Alps the naturally low accessibility was overcome by high economic power and the relevance of ecosystem services such as recreation catalysing touristic infrastructure. Historically, the Alps and other central European regions also contain many sites that were established during the period of European forest dieback caused by air pollutants. Therefore, constraints in research funding, operational logistics and historical regional research foci determined the establishment of long-term ecological research sites. Consequently, these constraints are also visible in the geography of *gaps* in the eLTER RI.

4.2. Habitat representation

As an additional level of ecological representation, the geographical coverage of habitats was examined. Marked over- and underrepresentation of some eLTER habitat categories were observed (Fig. 3). Overrepresentation of inland waters can partly be attributed to the spatial scale of the EUNIS habitat raster. In particular, small streams, rivers and lakes cannot be accurately represented by a cell size of 100 × 100 m. Thus, the area of these habitats might generally be underrepresented in the EUNIS dataset. Nonetheless, a research focus on inland water

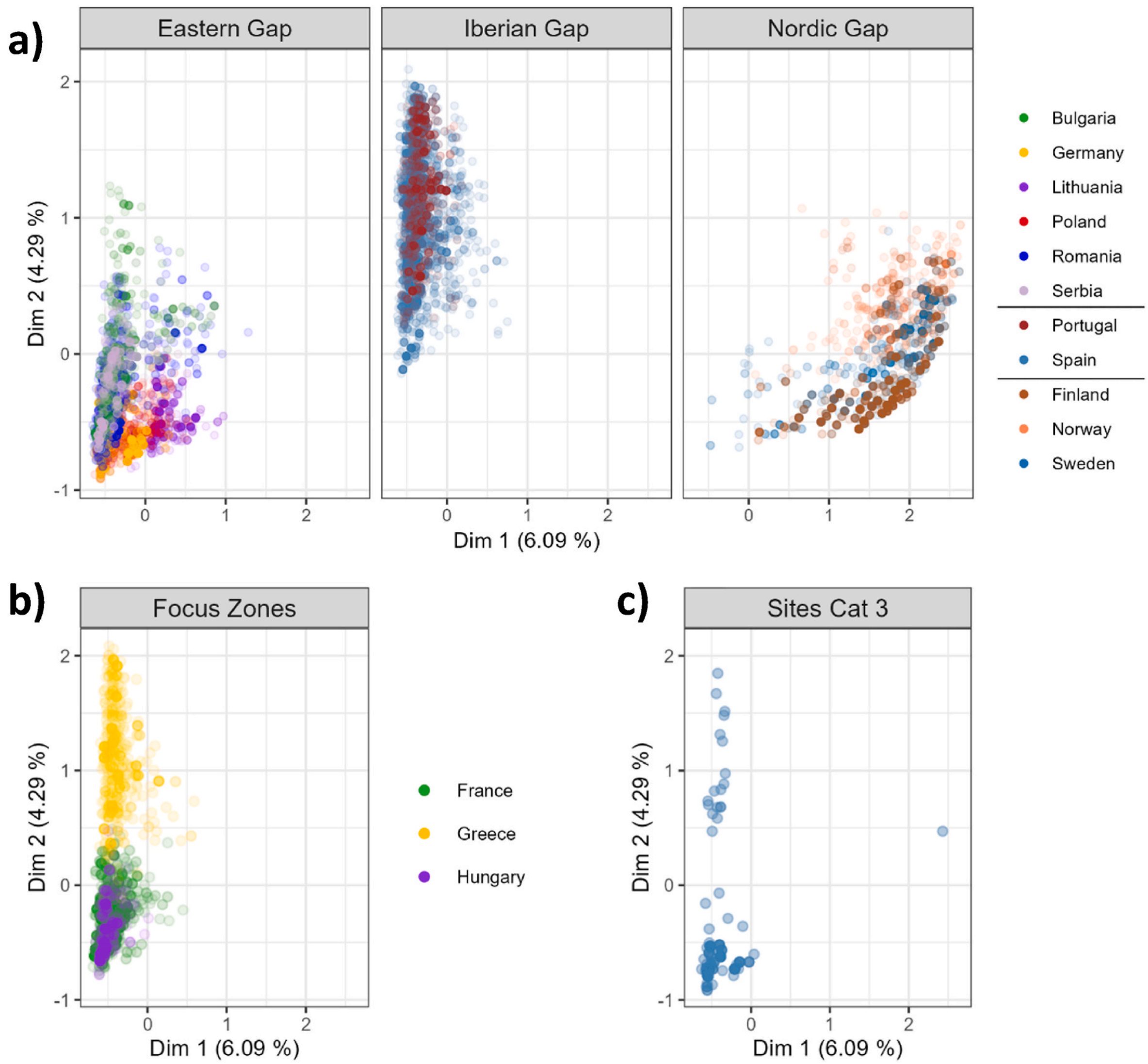

Fig. 6. Illustration of the first two dimensions of a multiple correspondence analysis on the x and y axes. The percentage indicated on the axes depicts the amount of variance explained by each dimension. Each dot reflects a raster cell with its manifestations of the six RPs. Dots in the exact same location have the same manifestations of all six RPs, the greater the distance between the dots the bigger the difference in their manifestations. a) The panels illustrate the different gaps, and the colours indicate the different countries within the gaps. Horizontal black lines in the legend are used as optical divisions between the countries of each gap, b) illustrates the focus zones with colours depicting different countries, c) illustrates the Sites Cat 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

habitats is widespread, certainly contributing to the identified overrepresentation. This was similarly true for the overrepresented wetlands.

Also, coastal waters were overrepresented. However, coastal ecosystems can hardly be accurately depicted in terrestrial geospatial datasets. It was attempted before to address this challenge by implementation of a three nautical mile buffer zone representing coastal ecosystems (Mollenhauer et al., 2018; Wohner et al., 2021). Consequently, the overrepresentation of coastal ecosystems on eLTER RI sites observed here should be regarded as an artefact of the difficult question of correct depiction of coastal ecosystems in such analyses.

Underrepresentation was observed for forests, grasslands and vegetated man-made habitats. The EUNIS habitat classification appears to overestimate the share of forests slightly compared to other data for Europe (EEA, 2022b). Nonetheless, although forested eLTER sites have the largest share in the analysed dataset, on the European scale the eLTER RI underrepresents forests. This is mainly due to the underrepresentation of the Boreal biogeoregion, where most forested land of Europe is located (EEA, 2022b). Due to the substantial number of forested sites in the eLTER RI, the underrepresentation of forests on European scale is only a concern in the Boreal biogeoregion. The clearest underrepresentation regarding habitats was found for vegetated man-made ecosystems. This is related to a general underrepresentation of agricultural (Fig. 5) and urban areas within the eLTER RI. A similar effect but of smaller magnitude was observed for grasslands.

4.3. Recommendations for network development

As observed in the case of other research infrastructures (Wohner et al., 2021), the distribution of eLTER RI in-situ facilities is currently notably biased. Therefore, the eLTER RI site network should be further developed to reduce this bias while considering the feasibility and cost-efficiency of network densification.

The principal recommendations to improve coverage of environmental and socio-ecological gradients are the following.

(A) Closing the three major *gaps* is of primary concern. Several other *focus zones* were identified, showing strong similarities to either the Iberian or Eastern Gap (Fig. 6b). Therefore, placing sites within the Iberian and Eastern *Gaps* will improve the representation of environmental and socio-ecological gradients within the *focus zones* as well.

(B) Target generally underrepresented features. The reoccurrence of certain RP categories in the Eastern and Iberian *Gaps* (Fig. 5) suggests potential to mitigate both *gaps* simultaneously by placement of additional sites in agricultural areas of low economic density. Therefore, addition of new sites outside of *gaps* can contribute to improved representation of certain European environmental and socio-ecological gradients.

(C) Target *gaps* individually. Hardly any individual cells with the exact same manifestation of all RPs across all three *gaps* were observed (Fig. 6a). Therefore, overlaps between *gaps* occurred only in limited areas, e.g. a site in Lithuania could counteract underrepresentation in Finland or Sweden. With all three *gaps* showing some distinct environmental and socio-ecological gradients, additional sites need to be located in each gap to conclusively counteract them.

Densification of the eLTER RI in accordance with these recommendations can be facilitated cost-efficiently either by (i) integrating Sites Cat 3 into the eLTER RI or (ii) through strategic collaborations with other research infrastructure.

(i) Based on the survey, 85 Sites Cat 3 could potentially be upgraded to contribute to the eLTER RI, bearing potential to close *gaps*. However, only two of these sites were located exactly within the identified *gaps*, one in Finland and one in East Germany (Fig. 4b). More sites were located in the *focus zones* and in other regions of high priority in Eastern Europe and the Central and East Mediterranean. These sites cover environmental and socio-ecological gradients that bear potential to substantially mitigate the Eastern Gap, but bear little potential regarding mitigation of the Iberian and the Nordic Gap (Fig. 6c). Additionally to the Sites Cat 3, there are about double as many sites registered in the DEIMS-SDR, the eLTER Site Registry. Further analysis will explore the potential of these sites for network densification and result in country-specific recommendations.

(ii) Beyond that, already existing observation and research facilities of other research infrastructures should be explored concerning their potential to densify the eLTER RI according to the principal recommendations. This bears potential, for example, to counteract the lack of agricultural sites within the eLTER RI, since agricultural research facilities are widespread. This will be important to comprehensively understand ecosystem responses with shifting agricultural systems due to e.g. the Farm to Fork Strategy as part of the European Green Deal (European Commission, 2020). While these sites may not be designed for a holistic approach as warranted by eLTER RI, they could be upgraded more easily than building eLTER RI sites from scratch, thereby leveraging co-location benefits for the entirety of ecosystem research and monitoring in Europe (Futter et al., 2023).

The logical next step, therefore, is to compile a comprehensive dataset of qualified European research and monitoring sites as a basis for analysing co-location options and identifying additional sites best suited to reduce the observed spatial bias. Furthermore, the multiple correspondence analysis allows investigating statistical distances between all cells of a gap to facilitate a statement on the heterogeneity or homogeneity of categories within a gap. This, in turn, would allow to clarify the number of sites required to counteract specific *gaps*, since more heterogeneous *gaps* will require a higher number of sites. Consequently, this would connect the concepts of representativity (Schmill et al., 2014; Wohner et al., 2021) and transferability (Václavík et al., 2016).

Therefore, the current work uncovered notable biases of the eLTER RI regarding the coverage of environmental and socio-ecological gradients and allowed clear recommendations on reducing these biases. Thus, data-driven analyses of representativity or transferability are powerful tools allowing developing research infrastructures towards a representative coverage of their target regions, allowing to conduct scalable holistic ecological research.

5. Conclusions

The emerging eLTER RI comprises over 200 sites across Europe. At these sites research is conducted on all relevant terrestrial, freshwater and transitional water habitats, which cover most facets of European environmental and socio-ecological gradients. Nonetheless, we identified biases regarding the distribution of sites and determined regions, where these thematic biases cluster spatially.

These biases must be mitigated or omitted to provide European ecosystem, critical zone and socio-ecological research with well-equipped in-situ facilities that represent major socio-ecological characteristics. Collecting continental-scale standardised data on these sites with little or no bias will make the eLTER RI a key research infrastructure in large-scale modelling, quantifying global change impacts as well as supporting and evaluating continental-scale environmental policies like the European Farm to Fork Strategy, the EU Biodiversity Strategy 2030 or the EU Soil Strategy 2030.

Overcoming the identified biases would also be possible by using an unbiased subset of in-situ facilities from the current network. However, this comes at the expense of reducing data points underlying data syntheses. Consequently, adding in-situ facilities to reduce the observed biases will simultaneously provide more valuable ecosystem information. Therefore, this is the prime solution for bias mitigation.

To achieve this goal, a comprehensive dataset of qualified European research sites needs to be acquired in order to derive site- and country-specific recommendations on bias mitigation. Research infrastructures as well as meta-studies should regularly conduct data-driven analyses of representativity or transferability to comprehensively uncover potential thematic biases manifesting in space. Until they are overcome, further studies will have to critically engage with the biases identified in this study when synthesising data.

CRediT authorship contribution statement

Thomas Ohnemus: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Steffen Zacharias:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization. **Thomas Dirnböck:** Writing – review & editing. **Jaana Bäck:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Werner Brack:** Conceptualization. **Martin Forsius:** Writing – review & editing, Conceptualization. **Ulf Mallast:** Writing – review & editing, Conceptualization. **Nikolaos P. Nikolaidis:** Writing – review & editing, Project administration, Conceptualization. **Johannes Peterseil:** Software, Data curation, Conceptualization. **Christophe Piscart:** Writing – review & editing, Conceptualization. **Francisco Pando:** Writing – review & editing, Conceptualization. **Christian Poppe Terán:** Writing – review & editing, Conceptualization. **Michael Mirtl:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

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.

Data availability

Data and Software are available online: 10.5281/zenodo.10203904

Acknowledgement

This work would not have been possible without the collaborative effort of eLTER National Coordinators in >20 countries and the involved Sites and Platform Coordinators (SPCs). We gratefully capitalised on the first operational eLTER RI service, the eLTER Site Registry DEIMS-SDR. This research has been supported by the European Commission, Horizon 2020 (H2020 Project eLTER PPP, grant no. 871126 and eLTER PLUS, grant no. 871128).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indic.2024.100456.

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