Spatial Network Design of the eLTER Research Infrastructure

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Contents

List of Figures

List of Tables

List of Abbreviations

ACTRIS	Aerosol, Clouds and Trace Gases Research Infrastructure
AR	Aggregated Representedness
BT	Biotemperature
CERN	Chinese Ecosystem Research Network
DEIMS-SDR	Dynamic Ecological Information Management System – Site and Data Registry
CORDEX	Coordinated Regional Downscaling Experiment
eLTER RI	Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure
GCM	Global Circulation Model
GDP	Gross Domestic Product
GERI	Global Ecosystem Research Infrastructure
HLZ	Holdridge Life Zone
ICOS	Integrated Carbon Observation System
ICP Forests	International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests
ICP IM	International Cooperative Programme on integrated monitoring of air pollution effects on ecosystems
ICP Waters	International Cooperative Programme on assessment and monitoring of the effects of air pollution on rivers and lakes
ILTER	International Long Term Ecological Research Network
LTAR	Long-term Agricultural Research
LTER	Long-term Ecological Research
LUC	Land Use Change
LUH	Land Use Harmonization
MCA	Multiple Correspondence Analysis
MM	Model Mean
NEON	National Ecological Observatory Network
P	Precipitation
PET	Potential Evapotranspiration
PFT	Plant-functional Type

RCM	Regional Circulation Model
RCP	Representative Concentration Pathway
RI	Research Infrastructure
SAEON	South African Environmental Observation Network
S/N ratio	Signal to Noise Ratio
SPEI	Standardized Precipitation Evaporation Index
SSP	Shared Socioeconomic Pathway
TERN	Terrestrial Ecosystem Research Network
WAILS	Whole-system Approach for In-situ research on Life supporting Systems

List of Publications and submitted Manuscripts

Manuscript 1 — **Ohnemus, T**., Zacharias, S., Dirnböck, T., Bäck, J., Brack, W., Forsius, M., Mallast, U., Nikolaidis, N.P., Peterseil, J., Piscart, C., Pando, F., Poppe Terán, C., Mirtl, M., 2024. The eLTER research infrastructure: Current design and coverage of environmental and socio-ecological gradients. Environmental and Sustainability Indicators 23, 100456.

Manuscript 2 — **Ohnemus, T**., Dirnböck, T., Bäck, J., Gaube, V., Kühn, I., Mirtl, M., Mollenhauer, H., Vereecken, H., Zacharias, S., 2025. Fitness for future: eLTER RI's representation of climate and land use change. Ecological Indicators 171, 113159.

Manuscript 3 — **Ohnemus, T**., Zacharias, S., Bäck, J., Mirtl, M., Dirnböck, T., submitted to Ecological Indicators: The potential of co-location to mitigate sampling bias in research infrastructures

Declaration of own Contributions to collaborative Publications

Manuscript 1 was based on an eLTER RI network design workshop in Chania, Greece, in 2023. I was present as data analyst to feed discussions with analyses. Therefore, all analysis, data generation and coding were done by me, interpretation, discussions and scientific ideas were collaborative efforts. This workshop extended the scope of Manuscript 1, I took the lead to create a paper story, polish and extend analyses for publication and I led through the peer-review process.

In Manuscript 2, the general concept to aim for a future perspective and to use the Holdridge Life Zone system was derived in collaboration. All further analyses were suggested by me and discussed with other experts. All analyses, coding and data generation were done by me. While I took the lead, different experts were consulted to help with data interpretation and paper writing.

In Manuscript 3, the general concept and approach was derived by me and discussed with colleagues. All analyses, coding and data generation were done by me. I took the lead in interpreting data and paper writing, with little contribution by others.

Thus, the following own contributions are applicable:

Nr.	**Scientific ideas by the candidate (%)**	**Data generation and/or programming by the candidate (%)**	**Analysis or Interpretation by the candidate (%)**	**Paper writing done by the candidate (%)**
1	75	100	75	75
2	85	100	85	75
3	90	100	90	90

Abstract

Research Infrastructures (RIs) are key to face the grand environmental challenges humanity encounters by providing standardized, accessible, large-scale data. Yet, observation locations in RIs tend to be biased. These biases cannot simply be judged by spatial distance. Rather, meaningful RI-specific indicators describing a status quo and future conditions should be the basis to uncover biases and inform an RI's spatial network design. This thesis studies the spatial network design of the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure (eLTER RI).

Therefore, eLTER RI's target region was defined and a survey was conducted to describe eLTER RI's network of in-situ facilities. As relevant indicators, six indicators collectively describing current ecosystem functioning were chosen and four indicators describing Global Change Pressure on ecosystems were developed. Based on these indicators, using a representativity analysis sampling bias was identified. Lastly, it was investigated whether in-situ facilities of other RIs can resolve sampling bias within eLTER RI.

eLTER RI currently consists of 204 in-situ facilities, which underrepresent agricultural lands, dry bioclimates, areas with low economic density, areas projected to experience a strong increase and a strong decrease in precipitation, little change in biotemperature, both strong and hardly any land use change, and areas where water availability during a year becomes more uniform. Spatially, these conditions and therefore underrepresented regions cluster in the Iberian Peninsula, Fennoscandia and Eastern Europe. Facilities of other RIs can convincingly counteract bias in Eastern Europe, but not in the other regions.

As long as biases within an RI persist, they must be addressed in data analyses, e.g. by removing data or explicitly mention biases uncovered. Only an unbiased in-situ facility network would allow confident upscaling of all data. The procedure to design the spatial network of an RI outlined in this thesis can function as a blueprint for continental or global scale RI development towards minimizing sampling bias.

Zusammenfassung

Forschungsinfrastrukturen (RIs) sind entscheidend, um die großen Umweltherausforderungen der Menschheit zu bewältigen, indem sie standardisierte, zugängliche und umfangreiche Daten bereitstellen. Allerdings zeigen RI-Beobachtungsstandorte oft einen Bias. Dieser Bias lässt sich nicht einfach anhand räumlicher Entfernung beurteilen. Vielmehr sollte Bias aufgrund relevanter, RI-spezifischer Indikatoren untersucht werden und die räumliche RI-Netzwerkgestaltung beeinflussen. Diese Arbeit untersucht die räumlichen Netzwerkgestaltung von eLTER RI (the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure).

Dazu wurde eLTER RIs Zielregion definiert und basierend auf einer Umfrage das in-situ-Netzwerk von eLTER RI beschrieben. Als relevant wurden sechs Indikatoren ausgewählt, die aktuelle Ökosystem-Funktionen und vier Indikatoren entwickelt, die den globalen Wandel mit seinen ökosystemaren Auswirkungen beschreiben. Die Identifikation von Sampling Bias erfolgte mit einer Repräsentativitätsanalyse. Schließlich wurde untersucht, ob eLTER RI Sampling Bias mit in-situ-Einrichtungen anderer RIs behoben werden kann.

eLTER RIs 204 in-situ-Einrichtungen unterrepräsentieren landwirtschaftliche Flächen, trockene Bioklimate, Gebiete mit geringer wirtschaftlicher Dichte, mit projiziertem starkem Niederschlagsanstieg und -rückgang, geringen Biotemperaturveränderungen, starkem und geringem Landnutzungswandel und gleichmäßiger werdender saisonaler Wasserverfügbarkeit. Diese Bedingungen finden sich auf der iberischen Halbinsel, in Fennoskandien und Osteuropa. Einrichtungen anderer RIs können Bias in Osteuropa überzeugend mitigieren, nicht jedoch in den anderen Regionen.

Solange ein Bias innerhalb einer RI besteht, muss er bei der Datenanalyse berücksichtigt werden, etwa durch das Entfernen von Daten. Nur ein In-situ-Netzwerk ohne Bias ermöglicht eine zuverlässige Skalierung aller Daten. Das in dieser Arbeit skizzierte Verfahren zur räumlichen Netzwerkgestaltung einer RI kann als Blaupause für die Entwicklung einer RI auf kontinentaler oder globaler Ebene dienen, um Sampling Bias zu minimieren.

1 Introduction

1.1 The Role of Research Infrastructures in the Research Landscape

Humanity faces grand environmental challenges (Rounsevell et al., 2006; Reid et al., 2010; Kulmala, 2018), affecting the earth system on various temporal and spatial scales. While each single observation gathers knowledge about the earth system (Lovett et al., 2007), these multi-scale challenges cannot be comprehensively quantified by in-situ observations of a single facility (Futter et al., 2023). Thus, compiling in-situ data gathered at several in-situ facilities can uncover processes and large-scale patterns in the earth system beyond what a single in-situ facility is capable of (e.g. Hautier et al., 2014; El Yaacoubi et al., 2016). To synthesize data from different facilities and, in effect, scale these data to regional, continental or global scales, meta-studies are widely used (e.g. Forster, 2014; Li et al., 2017; Wolf et al., 2022). Yet, compiling data from different in-situ facilities can be challenging due to observational protocols varying between in-situ facilities, reducing comparability, which can lead to the determination of differing or potentially even contrasting effects (Forster, 2014; Gould et al., 2025). Hence, developing and implementing standardized observational protocols and coordinating single in-situ facilities is crucial to collect and collate environmental knowledge. This role is fulfilled by research infrastructures (RIs) like the National Ecological Observatory Network (NEON, Kampe, 2010) in the United States, the Integrated Carbon Observation System (ICOS, Storm et al., 2023) in Europe, FLUXNET (Baldocchi et al., 2001) operating globally, the Aerosol, Clouds and Trace Gases Research Infrastructure (ACTRIS, Laj et al., 2024) in Europe, the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure (eLTER RI, Mollenhauer et al., 2018) in Europe, the International Long Term Ecological Research Network (ILTER, Mirtl et al., 2018) operating globally, the Chinese Ecosystem Research Network (CERN, Huang and Niu, 2005), the South African Environmental Observation Network (SAEON, van Jaarsveld et al., 2007) or the Terrestrial Ecosystem Research Network (TERN, Cleverly et al., 2019) in Australia as well as the currently emerging Global

Ecosystem Research Infrastructure (GERI, Loescher et al., 2022), harnessing the networks established by several regional to continental scale RIs. These RIs organize in-situ facilities operating in the long-term, creating comprehensive, standardized and more accessible data (Futter et al., 2023) for the different compartments and geographies of the earth system they observe. Consequently, RIs are key in investigating and facing these grand environmental challenges.

1.2 Investigating Sampling Bias in Research Infrastructures

These RIs, serving as overarching entities coordinating in-situ facilities and observations, aim to represent different spatial scales and target regions, from regional (e.g. CERN, SAEON, NEON) through continental (e.g. TERN, ICOS, ACTRIS, eLTER RI) to global (e.g. ILTER, FLUXNET, GERI). Therefore, besides the standardization of observations within and among their in-situ facilities, also the geographic arrangement of their in-situ facilities must be considered. In an ideal scenario, the conditions of the Earth system encompassed by the in-situ facilities of the RI would be a precise reflection of their respective target regions. This would result in the in-situ facilities being, in essence, a geospatial replica or “geospatial twin” of the conditions present in the target region. Following the definition of the term representativeness by Sulkava et al. (2011), a geospatial twin should reproduce the characteristics of processes and quantities of the target region. Importantly, no ecosystem at a given place is completely similar to another, hence there is an infinite number of unique ecosystems that would ideally be observed, which is practically impossible with the finite number of facilities RIs can operate. While, therefore, each and every single ecosystem observation is valuable, the spatial network design must be crafted carefully so the finite number of RI in-situ facilities approximates a geospatial twin of the target region of an RI. Contrary to the ideal of a geospatial twin, a bias regarding the location of observations was identified before, as a general pattern in ecological research (Martin et al., 2012) as well as for research projects or RIs (Václavík et al., 2016; Villarreal et al., 2018; Ohnemus et al., 2021; Wohner et al., 2021; Kumar et al., 2023).

This bias can be described as sampling bias, since the conditions represented by observation locations represent a sample from the population of conditions in the target region.

Besides the definition of a target region an RI wants to represent, uncovering sampling bias requires two prerequisites: the definition of reliable indicators an RI wants to represent and a methodological framework to investigate sampling bias. Defining suitable, meaningful RI-specific indicators is tedious, must be done carefully, and depends on the observational design and aims of an RI. In previous studies, the coverage of target region conditions was evaluated compared to soil, vegetation, or climatic parameters (e.g. Hargrove et al., 2003; Sulkava et al., 2011) or to the distribution of a single target variable like gross primary production or evapotranspiration (e.g. Villarreal et al., 2019). The downside of using a single variable is that it is difficult to approximate a regional or continental scale value distribution of any variable. Usually, these upscaled value distributions depend on the outputs of models, which in turn are fed with and rely on in-situ data. Since underlying networks of in-situ observations are regularly biased, the input data of these models is likely biased, and therefore the determined value distributions themselves might inherit bias. Consequently, the approach of using continental scale value distributions can be deemed insufficient as indicator to judge the bias of an in-situ facility network. Additionally, a functional description beyond regarding simple parameters or variables is important for a thorough ecosystem understanding (Reichstein et al., 2014), and thus for RIs with a more holistic design a more functional description is warranted. Therefore, other authors used ecosystem functional types as indicators (Villarreal et al., 2018; Villarreal et al., 2019). NEON stratified ecological domains they aimed to represent based on a variety of numerical eco-climatological indicators, where human influence is no explicit factor (Hargrove and Hoffman, 2006). Yet, in the anthropocene (Waters et al., 2016; Ellis et al., 2021) the large human impact on ecosystems should additionally be considered. Therefore, Wohner et al. (2021) combined four indicators describing rather natural conditions – bioclimate, biomes, landforms and land use – with two indicators explicitly depicting the human dimension – economic density and anthromes - to investigate sampling bias within ILTER. This approach is conceptually similar to using ecosystem functional types, as it approximates a functional description of ecosystems. Yet, it additionally emphasizes the human impact. Indicator sets like these are promising, as they integrate natural and anthropogenic factors influencing ecosystems.

Not only are ecosystems already altered by humans, they will in the future be further altered by Global Change, manifesting inter alia as land use change (LUC) and climate change (Steffen et al., 2005). In the past, especially over the course of the 20th century, land use was dramatically changed and intensified due to increasing industrialisation and associated development processes, thus amplifying humanity's impact on the Earth (Kummu et al., 2010; Krausmann et al., 2013; Steffen et al., 2015; IPCC, 2019). This development determined the evolution of land systems in recent decades, exhibiting the pressure exerted by LUC on ecosystems and their processes (Erb et al., 2018; Shukla et al., 2019). LUC even drives global patterns of biodiversity loss and disturbs global biogeochemical cycles (Pereira et al., 2012; Newbold et al., 2015; IPBES, 2019). Many aspects of societal development govern LUC, which includes patterns and developments of urbanisation, migration, demography, production, consumption, and economic relations. Especially political developments as well as emerging and fading policies, therefore, drive LUC. Consequently, the present land use and its past and future changes summarize humanity's direct impacts on ecosystems.

Likewise, notable impacts on ecosystems and ecological consequences are associated with climate change. Dominant vegetation types are already and will in the future be further altered by changing climate. This leads to shifts in so-called plant-functional types (PFTs, Harrison et al., 2010; Poulter et al., 2011; Wullschleger et al., 2014), which classify plant species based on their similar functions within ecosystems. All trophic levels of ecosystems are affected by these shifts in PFTs. Consequently, climate change is, among other detrimental effects, another major culprit in global biodiversity loss (Habibullah et al., 2022). The ecosystems prevailing in specific climatic regimes are usually classified in bioclimatic classification systems (e.g. Holdridge, 1947; Walter and Breckle, 1991; Rivas-Martínez et al., 2002; Metzger et al., 2013; Camara Artigas et al., 2020). However, with climatic conditions and PFTs further changing, existing bioclimatic classifications will become decreasingly valid (e.g. Davis and Shaw, 2001; Devictor et al., 2012; Wallingford et al., 2020). Summarising, climate change and LUC are key controls for ecosystem functioning, processes and emergence. Therefore, indicators describing an ecosystem status quo will not represent future conditions adequately. This is especially important for RIs designing their in-situ facility networks for long-term operation, since they should be fit for the grand challenge of Earth System Science to observe global and regional environmental change (Reid et al., 2010). Therefore, Villarreal et al. (2019) suggested future conditions should be considered in the classification of ecosystems. Consequently, in addition to indicators describing the status quo or current conditions, additional indicators that reflect future conditions or anticipated changes of current conditions must be regarded in a comprehensive investigation of sampling bias.

As methodological frameworks to investigate sampling bias, two general concepts emerged: concepts of representativity and concepts of transferability (Diogo et al., 2023). With both concepts the distribution of observation locations, i.e. RI in-situ facilities, compared to the spatial distribution of single or numerous indicators is investigated. Representativity approaches (e.g. Schmill et al., 2014; Malek and Verburg, 2017; Meyfroidt et al., 2018; Villarreal et al., 2018; Wohner et al., 2021) compare value distributions covered by in-situ facilities with value distributions of the entire target region, while transferability approaches (e.g. Hargrove et al., 2003; Sulkava et al., 2011; Václavík et al., 2016; Villarreal et al., 2019; Piemontese et al., 2020; Villarreal and Vargas, 2021) investigate the similarity of conditions covered by in-situ facilities with those of the entire target region. Thus, both concepts extend beyond simple spatial distance analyses.

1.3 Research Infrastructure Co-Location and its Benefits

While numerous studies have exposed sampling biases based on different methodological concepts and different indicator sets, few developed clear pathways to rectify or mitigate such biases. Villarreal et al. (2018) showed that pooling in-situ facilities from AmeriFlux and NEON improves coverage for the conterminous United States compared to facilities of each network alone. Likewise in the United States, Kumar et al. (2023) revealed notable benefits pooling facilities from LTAR (long-term agricultural research) and NEON. This concept of associating a single in-situ facility with several RIs or pooling in-situ facilities from different RIs is referred to as "co-location". Futter et al. (2023) investigated co-location conceptually regarding carbon cycling research. Beyond the potential to address sampling bias uncovered in an RI's spatial network design, co-location has several advantages, for i) ecosystem understanding since it provides information of a wider array of earth system variables, ii) site managers and researchers to engage in different RIs, and iii) RIs as a cost-efficient approach to densify their networks of in-situ facilities. Besides the two aforementioned studies the author is not aware of publications regarding the potential of co-location, i.e. there appear to be no studies investigating this concept outside the United States and no studies investigating the potential of several RIs to be co-located. However, this concept of co-location seems to be especially promising for the European research landscape where a range of continental scale long-term RIs are operative.

1.4 The eLTER Research Infrastructure

One such pan-European RI operating long-term observatories is eLTER RI. eLTER RI initially developed in a voluntary community-driven bottom-up manner within national LTER networks (Mirtl et al., 2018). Many of the eLTER RI facilities were founded in locations where research activities have been ongoing in the past, with some over 100 years. The spatial organization and continental coverage of eLTER RI, therefore, reflect aspects of local and independent research planning. These planning processes, in turn, generally disregarded the aspect of continental coverage and representativity.

Therefore, on continental scale a sampling bias can be expected for eLTER RI. Contrary, top-down developed RIs are usually planned with a strategy to represent their target region, e.g. NEON stratified 20 domains in the United States with one core site per domain (Keller et al., 2008; Schimel and Keller, 2015). Only later, this rather loose network was consolidated as an RI with a common observational design and common scientific goals (Mirtl et al., 2018; Zacharias et al., 2025). Thus, the consolidated 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 eLTER RI and will benefit from a harmonised design and instrumentation. While the facilities will still be managed by national networks, their operations and research will be supported by central services, achieving the interoperability typical for a top-down approach (Vargas et al., 2017). Therefore eLTER RI unites strengths of the bottom-up and top-down approaches (Holzer et al., 2018).

In the Site and Data Registry DEIMS-SDR (Wohner et al., 2019), which aims to register all LTER facilities, in August 2025 over 600 operational facilities within the national LTER networks were listed. However, these LTER facilities do not necessarily commit to eLTER RI or comply with its requirements. One of the distinguishing characteristics of all eLTER RI in-situ facilities is the design alignment with the "Whole-system Approach for In-situ research on Life supporting Systems" (WAILS, Mirtl et al., 2021). WAILS implies a holistic approach for observations and research at compliant in-situ facilities covering characteristics of (i) ecosystem structures (abiotic characteristics and biotic heterogeneity), (ii) ecosystem functions (balance of energy, water, and matter) and (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, and biosphere. The composition of these Standard Observations is customised for the respective habitat (Zacharias et al., 2021; Zacharias et al., 2025). An extensive overview of the standard observations required for the different ecosystem spheres of different habitats can be found in Zacharias et al. (2025). Thus, eLTER RI implements a whole-systems approach at an unprecedented scale (Zacharias et al., 2024). Therefore, the eLTER RI observational design will allow measurements of all ecosystem spheres in a standardised manner, providing a sound basis for scientists, policy and decision-makers.

Due to the implementation of these strict criteria, it is unclear how many and which facilities will comply and become part of the consolidated eLTER RI. It can be expected that the eLTER RI in-situ facility network will differ substantially from the European LTER facilities analysed before for their geospatial representativity (Mollenhauer et al., 2018). Based on the initial bottom-up approach, a sampling bias of the eLTER RI facilities is expected. Thus, eLTER RI and other bottom-up developed RIs could especially benefit from sound analyses of sampling bias and the establishment of pathways to bias reduction, i.e. a thorough investigation of the spatial network design of the RI.

2 Objectives

This thesis concerns the spatial network design of eLTER RI. To evaluate eLTER RI’s representation of its target region and potential sampling bias, the 1st objective of this thesis is to

i) Choose a methodological framework to investigate sampling bias (manuscripts 1, 2, 3)

Due to the consolidation process, no comprehensive database of the in-situ facilities that form eLTER RI exists. Therefore, the 2nd objective is to

ii) Describe eLTER RI’s in-situ facility network and the target region it aims to represent (manuscript 1)

For eLTER RI, following the holistic WAILS approach, it is pertinent to define indicators allowing for a functional ecosystem understanding. It is indispensable that these indicators entail current conditions as well as anticipated future changes. Based on these indicators, sampling bias shall be investigated, thus the following detailed objectives emerge:

iii) Defining indicators describing currently prevailing ecosystems in eLTER RI's target region (manuscript 1)
iv) Describing eLTER RI’s sampling bias for these current conditions (manuscript 1)
v) Defining ecologically meaningful indicators epitomising Global Change features (manuscript 2)
vi) Describing biases for these Global Change features (manuscript 2)

Lastly, the potential to mitigate biases is investigated. Three objectives are associated with this step:

vii) Mapping the bias reduction potential based on the chosen indicators
viii) Synthesizing a dataset of candidate facilities to mitigate sampling bias in eLTER RI from other pan-European RIs (manuscript 3)
ix) Identifying candidate facilities that would be most suitable to reduce sampling bias within eLTER RI (manuscript 3)

3 Material and Methods

This section gives only a brief overview of the materials and methods used for the different studies compiled in this thesis. For detailed and reproducible methodology please refer to the different publications in the appendix.

3.1 Representativity Analysis (Manuscripts 1, 2, 3)

To analyse sampling bias, as basic analytical framework recurring in every study undertaken in this thesis, the representativity analysis was chosen. The representativity analysis was developed by Wohner et al. (2021), extending an analysis first published by Schmill et al. (2014). This analysis compares the value distribution of a categorical indicator in the target region with the value distribution covered by in-situ facilities. This comparison is based on a x^2-test of homogeneity, leading to a parameter Schmill et al. (2014) coined "representedness" which is calculated based on the *p*-value of the test statistic and results in a continuous value range of +1 (overrepresentation of a category on in-situ facilities compared to the target region) to -1 (underrepresentation), with values around 0 indicating a category is well represented on RI in-situ facilities (Table 1).

Table 1: Conditions, value calculations, meaning and the value range of the different possible states of "representedness". Table produced after Wohner et al. (2021). obs stands for the observed count, exp for the expected count in the x^2-test of homogeneity.

Condition	Representedness		
	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

A multitude of indicators should be used to approximate a functional description of ecosystems. To accommodate this, within the representativity analysis the "representedness" values of the single indicators investigated are summarized, leading to a parameter termed "aggregated representedness" (AR, Wohner et al., 2021). For six indicators, this parameter can consequently have a value range of +6 (overrepresented for all indicators) to -6 (underrepresented for all indicators). Importantly, the meaning of a value of 0 is less clear, since it could be six well represented indicators or three over- and three underrepresented ones. However, this thesis focusses on areas underrepresented for the majority of indicators, i.e. AR values of -4 or lower, for which this analysis is well suited. To associate AR values with a priority for the establishment of new in-situ facilities, Wohner et al. (2021) aggregated AR values into so-called priority regions (Table 2).

Table 2: Threshold values for the reclassification of the mean aggregated representedness (Mean AR) into priority regions as introduced by Wohner et al. (2021)

Mean AR	Priority for network extension
-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

Running on the comparison of value distributions, the representativity analysis is especially well suited to investigate bias. Importantly, newly incorporated in-situ facilities can also lead to worse representation of conditions in other regions. It is indispensable for an analysis of bias, that the methodology is able to produce such a result. Furthermore, this analysis allows to generally trace back features of underrepresentation to single categories of each indicator. Therefore, this framework is ideal for this thesis. Yet, the relevant features to run this analysis, i.e. the target region and relevant indicators eLTER RI strives to represent as well as its network of in-situ facilities must be defined.

3.2 The Target Region and the in-situ Facility Network of eLTER RI (Manuscript 1)

As target region for eLTER RI the 26 countries contributing to the LTER network were chosen. With eLTER RI transitioning from the initial bottom-up development to a consolidated RI, the in-situ facilities that will comply with the eLTER RI observational design requirements had to be defined. While DEIMS-SDR (Wohner et al., 2019) is a comprehensive database for the European LTER facilities, it was insufficient to judge which facilities fulfil the eLTER RI requirements. Thus, a survey was conducted and distributed to the facility coordinators. The survey asked to provide geographic data, either an identifier associated with geodata stored in DEIMS-SDR or geographic coordinates, and to assign a facility to a “site category”. There were three site categories available, with categories 1 and 2 complying with eLTER RI’s WAILS approach and the standard observations required (Mirtl et al., 2021; Zacharias et al., 2025). Consequently, from these responses, whether an in-situ facility will comply with eLTER RI or not was classified. If geodata were provided as coordinates in the survey, they were buffered to represent a circular 1 ha polygon, the area and shape of a typical site in the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests, Ferretti, 2013). This can be seen as a realistic extent for an intense environmental research in-situ facility. To investigate sampling bias in eLTER RI, next, indicators depicting a functional description of ecosystems must be defined.

3.3 Current Sampling Bias (Manuscript 1)

To describe current ecosystems, indicators were largely taken from Wohner et al. (2021). These indicators were (i) anthromes describing anthropogenic biomes (Ellis et al., 2020), (ii) bioclimatic zones (Metzger et al., 2013), (iii) economic density calculated based on the datasets GDP per capita (Kummu et al., 2018) and population density (CIESIN, 2017), (iv) land cover (ESA, 2017) and (v) landforms (Karagulle et al., 2017). For the last indicator, following Ohnemus et al. (2021) global biomes were replaced with (vi) the biogeographical regions of Europe (EEA, 2016), here referred to as biogeoregions. Thus, collectively, these indicators depict environmental and socio-ecological gradients that are key to describe ecosystem functioning.

The geodata of the in-situ facilities along with the six indicators describing current conditions were then used as input data for the representativity analysis to investigate sampling bias within eLTER RI. In this work, areas where the underrepresentation of indicators accumulated in space were defined as *clusters*. In effect, a cluster depicts the spatial accumulation of cells with very high priority for network densification. Further, which categories of indicators were causal and decisive tor the underrepresentation found was analysed. Lastly, to understand whether the causal categories were unique to respective clusters a multiple correspondence analysis (MCA) was performed. A MCA should be understood as the equivalent to a principle component analysis for categorical instead of numerical variables (Abdi and Williams, 2010). The MCA output is an n-dimensional data space, with new dimensions formed until all variance is explained. Every input raster cell was then depicted with a numerical value in each dimension, i.e. with its coordinate for this dimension. The same position of two different cells in all dimensions means that the category manifestations of all indicators were the same. Thus, the MCA allowed to identify aggregation of cells regarding prevailing ecosystem conditions within the identified clusters. Additionally, the conditions in areas where cells of high but not very high priority for network densification aggregated were analysed, these areas are referred to as *focus zones*.

3.4 The Fitness for Future of eLTER RI (Manuscript 2)

While the first study investigated sampling bias in dependence of current conditions, it fails to incorporate projected alterations through Global Change, manifesting inter alia as LUC and climate change (Steffen et al., 2005). Yet, especially for an RI designed to operate long-term observatories, anticipated future conditions must be considered. Due to a lack of suitable indicators describing future conditions, ecologically meaningful indicators were developed.

Climate Change Pressure

To depict pressure exerted by climate change on ecosystems, we used the Holdridge Life Zone concept (HLZ, Holdridge, 1947). HLZs define conditions of ecosystem functioning (Lugo et al., 1999) in relation to annual precipitation (P) and annual biotemperature (BT) (Kummu et al., 2021; Tekin et al., 2021).

Thus, the HLZ concept allows to link changes in annual P and BT to ecological effects. To derive indicators called P and BT Pressure, bias-adjusted near-surface P and air temperature data were taken from the European domain (WRCP CORDEX, 2015) of the Coordinated Regional Downscaling Experiment (CORDEX, Giorgi et al., 2009; Jacob et al., 2014; Gutowski Jr. et al., 2016) for two representative concentration pathways (RCP): 4.5 and 8.5. Based on an ensemble chosen by Holmberg et al. (2018) nine simulation runs extending from 2021-2098 were used. From the annual P and BT values for the individual runs, the Model Mean (MM) was calculated, since MMs frequently outperform individual simulations (Pierce et al., 2009; Feng and Fu, 2013; Huang et al., 2016; Carrão et al., 2018). P and BT Pressure depict a change between the future and the baseline period 1971-2000. Thus, the mean MM BT and P was calculated for the baseline. Per cell, based on the projected MM BT and P data an estimate for the year 2098 was produced. To investigate changes within the HLZ data space, the binary logarithm of the baseline was subtracted from the binary logarithm of the estimate for 2098, resulting in the indicators P and BT Pressure. A P or BT Pressure of 0 indicates “no change” in P or BT, a value of +1 suggests a shift of one HLZ towards wetter or warmer conditions, a value of -1 a shift towards dryer or colder conditions. As a measure of robustness the signal to noise ratio (S/N-ratio, Christensen et al., 2019) was calculated, with the absolute MM as the signal and the noise as the standard deviation of the nine simulation runs. In summary, P and BT Pressure relate change in P and BT to baseline conditions within an ecologically meaningful framework, providing a metric of pressure exerted on ecosystems.

However, seasonality is not depicted with P and BT Pressure and not recognized in the HLZ (Szelepcsényi et al., 2014). Therefore, the SPEI Pressure, based on the standardised precipitation evaporation index (SPEI, Vicente-Serrano et al., 2010), was introduced. SPEI subtracts monthly potential evapotranspiration (PET) from monthly P, providing an adequate water balance metric on timescales affected by global warming (Pohl et al., 2023a). PET was calculated from the BT data based on Thornthwaite, as implemented in the SPEI package (Beguería and Vicente-Serrano, 2023). SPEI was aggregated over three months, which is believed to reflect the soil water reservoir (Pohl et al., 2023b). As baseline, for each calendar month the mean SPEI from 1971-2000 was calculated. Then, the range between the wettest and driest month was calculated, i.e. the baseline range, reflecting interannual soil water variability. Then, for each month separately a local linear model was used to calculate monthly SPEI values for 2098, from which the projection range was extracted. Finally, the baseline range was subtracted from the projection range, resulting in the SPEI Pressure. A positive SPEI Pressure means that interannual soil water availability becomes increasingly variable. Since interannual soil water availability patterns are an important control of ecosystems, the SPEI Pressure is another ecologically meaningful quantification of climate change. Thus, SPEI, P and BT Pressure combined are suitable indicators to inform ecological impacts from climate change.

Land Use Change Pressure

In addition to climate change, LUC is a major culprit in Global Change. To assess the pressure LUC is projected to exert on ecosystems, the LUC Pressure was introduced. Therefore, the land use harmonization 2 (LUH2) dataset was chosen (Hurtt et al., 2020), which already follows shared socioeconomic pathways (SSPs, O'Neill et al., 2017; Popp et al., 2017). As equivalent to RCP4.5 and RCP8.5, respectively, SSP2 and SSP5 with their marker models MESSAGE-GLOBIUM and REMIND-MAgPIE (LUH2, 2017a, 2017b; Riahi et al., 2017) were used. The assumed socio-economic development is used as input for SSPs (Riahi et al., 2017), thus the land use projections in the LUH2 dataset are driven by these assumed developments.

The mean share of each of its twelve recognised land use states was calculated per cell for the period 2091-2100 and, based on a historical dataset (LUH2, 2016), for the baseline 1971-2000. Taking a multi-year future period was necessary to distinguish crop rotation from LUC. Then, the difference between the baseline and future periods of the individual land use states can be used to determine LUC Pressure. To calculate the share of LUC per cell the resulting change was divided by the sum of all twelve states in the baseline period. Thus, LUC Pressure depicts the share of each raster cell affected by a LUC.

Representation of Global Change Aspects by eLTER RI

The ecologically meaningful indicators P Pressure, BT Pressure, SPEI Pressure, and LUC Pressure were then used as input for the representativity analysis to elucidate eLTER RI's sampling bias for future conditions. On this account, the indicators were cropped (Hijmans, 2024) to the target region and LUC was resampled (Hijmans, 2024) to the same cell size as the Climate Change Pressure. Since the representativity analysis runs on categorical data, the indicators were reclassified (Hijmans, 2024) into ten categories based on equal-interval quantiles. Where negative pressure occurred (i.e. SPEI and P Pressure) the closest quantile threshold was set to zero for clear distinction between negative and positive changes. Lastly, with LUC Pressure summarizing a multitude of aspects, it was weighted trifold to enter the sampling bias analysis with the same weight as the three indicators for Climate Change Pressure. Consequently, based on these data, sampling bias for future conditions was analysed.

3.5 Mapping the Bias Mitigation Potential

The comprehensive suite of indicators and the associated sampling bias uncovered within eLTER RI allows to map the potential for each cell over Europe to contribute to bias mitigation, if an in-situ facility would be established there. This is of particular interest, since the conditions aggregating in the clusters eLTER RI underrepresents can occur in other locations of Europe, too. Therefore, also areas with already a dense in-situ facility network should display potential to mitigate sampling bias.

On this account, the representedness values of underrepresented categories of all indicators, i.e. six depicting current conditions and four for each RCP4.5 and RCP8.5, were summed up for each cell. To ensure that only the underrepresented cells were counted, a deliberately lavish threshold of -0.3

was set, i.e. only representedness values of -0.3 or lower were classified as underrepresented. The absolute values were then summed up. Thus, this measure counts the underrepresented indicators on a continuous value range from 0 to 14. The higher the value, the more categories occur that are underrepresented on European scale, and therefore the higher the potential of this cell to mitigate sampling bias if an in-situ facility would be established there. While this is a simple metric to indicate the potential to mitigate bias, it disregards the availability of potentially suitable in-situ facilities. Consequently, the mapped potential cannot necessarily be exhausted.

3.6 The Potential of Co-Location to mitigate Sampling Bias within eLTER RI (Manuscript 3)

Therefore, contrasting with the simple analysis of the potential of each cell, one can analyse the potential of existing in-situ facilities in the European research landscape to mitigate sampling bias within eLTER RI. Consequently, this potential of co-location was investigated.

Candidate Facilities

For the investigation of potential candidate facilities that could be co-located with eLTER RI, geodata depicting in-situ facility locations from seven spatially distributed pan-European environmental RIs was obtained: ICOS, FLUXNET, ACTRIS, INTERACT, the International Cooperative Programme on assessment and monitoring of the effects of air pollution on rivers and lakes (ICP Waters, Kvaeven et al., 2001), ICP Forests and the International Cooperative Programme on integrated monitoring of air pollution effects on ecosystems (ICP Integrated Monitoring, here abbreviated as ICP IM, Vuorenmaa et al., 2018).

To ensure that facilities are suitable as candidates, they were further subset. For ICOS only facilities labelled as ecosystem stations and for ICP Forests only facilities providing data in 2022 or more recently were regarded as candidates. For ICP IM and INTERACT only facilities respectively labelled active or open were regarded. Additionally, already existing co-location must be considered to avoid regarding the same facility multiple times as a candidate. Using metadata stored in DEIMS-SDR and geographic subsets, facilities that were already co-located with eLTER RI were removed as candidate and facilities that were co-located between two other RIs were reduced to only one occurrence within the candidate facility dataset.

Network Optimization

To elucidate the bias reduction potential relative to current and anticipated future conditions an iterative network optimization procedure was established. At the start of each iteration from all candidates with an AR of -4 or lower, one candidate was sampled and added to eLTER RI. Since the candidate facilities are spatially biased (see section 4.4), a weight was assigned to the sampling procedure. As weight, the candidate facility density was calculated as the mean Euclidean distance to the 10 nearest candidate facilities, with lower density increasing the sampling probability. After addition of a candidate to eLTER RI, the representativity analysis was run again and the next iteration was performed, until 50 candidates were added. Sampling was required, since several candidates displayed the same AR and therefore there was no “perfect” solution of this optimization problem. To account for the randomness introduced due to the sampling procedure, this iterative process was repeated 500 times for each current conditions as well as RCP4.5 and RCP8.5.

These 500 runs are not equally successful in counteracting bias. Therefore, to elucidate which runs performed best, areas were classified as biased when they exhibited an AR value of -4 or lower, i.e. when all or all but one thematic dimension were underrepresented on a cell. The results were subset to the 25 runs with the strongest bias reduction after addition of 50 facilities and the areas classified as biased in these runs were mapped. Therefore, the 25 single best runs were overlain and the probability that a cell is classified as biased was calculated, e.g. if a cell is classified as biased in 5 of 25 runs, its probability is 20 %. This metric is referred to as "bias probability".

Candidate Facility Recommendations

Similarly to the bias probability, for each candidate the probability to be added to eLTER RI was calculated. Therefore, the probability of a facility to be added within the 25 best runs for each individual facet, current conditions, RCP4.5 or RCP8.5 was determined, e.g. if a facility was added in 5 of 25 runs of the current conditions facet, its probability to be added is 20 %. Furthermore, to regard the probability of a candidate to be added independent of the facet, the mean of all facets was calculated. Thus, if the same candidate had a probability of 70 % for RCP4.5 and of 0 % for RCP8.5, its overall probability to be added to eLTER RI would be (20+70+0)/3 = 30 %. The higher this probability, the higher the potential of a candidate to reduce bias within eLTER RI.

Transferability Analysis

The representativity analysis, while ideally suited to investigate sampling bias, does not address the dissimilarity between conditions on in-situ facilities and in the target region. To elucidate this dissimilarity a transferability analysis, based on an MCA, was performed. This procedure was again implemented iteratively, i.e. the MCA was performed, a candidate of the 1 % with the greatest distance in MCA data space was sampled and added to eLTER RI, and the MCA was rerun until 50 candidates were added. This was repeated 1,500 times to account for the randomness introduced. The 25 runs with the smallest distance between remaining candidates and eLTER RI facilities were chosen as best runs. The candidates chosen by the representativity analysis were then subset with those chosen in the best runs of the transferability analysis. This elucidates which facilities simultaneously mitigate bias and gather data in ecosystems most dissimilar to those already instrumented by eLTER RI in-situ facilities.

4 Results and Discussion

4.1 The in-situ Facility Network of eLTER RI and current Sampling Bias (Manuscript 1)

Of 289 survey responses, 204 (70.6 %) facilities fulfil the requirements of eLTER RI and can, therefore, be considered as the current eLTER RI in-situ facility network (Figure 1). While these facilities are generally spread over eLTER RI's target region, the highest facility density was observed in the Alps and Central Europe. Contrary, facility density was especially low in parts of Eastern Europe, the Iberian Peninsula and the southern Mediterranean as well as parts of Fennoscandia.

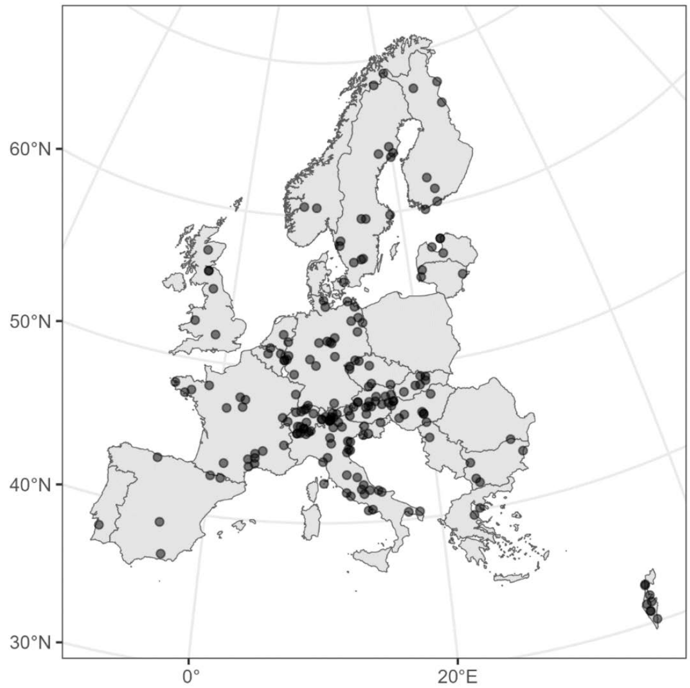

Figure 1: The in-situ facility network of eLTER RI. The target region eLTER RI strives to represent is illustrated as grey polygons, borders do not necessarily depict accepted national boundaries. Dots depict the centroid of the eLTER RI in-situ facilities based on the survey responses by the in-situ facility coordinators.

The representativity analysis revealed a clustering of underrepresented areas and, therefore, the manifestation of sampling bias. In space, these biases form an Eastern Cluster, consisting of Poland and Lithuania, an Iberian Cluster in the Iberian Peninsula and a Nordic Cluster encompassing parts of

Fennoscandia (Figure 2). Consequently, in these areas network densification is required. These clusters lie mainly in the areas where low facility density was observed, but reach into some regions with a higher facility density, e.g. Eastern Germany. Importantly, the manifestation of the biases in space is driven by the representation of the underlying indicators. In the Eastern

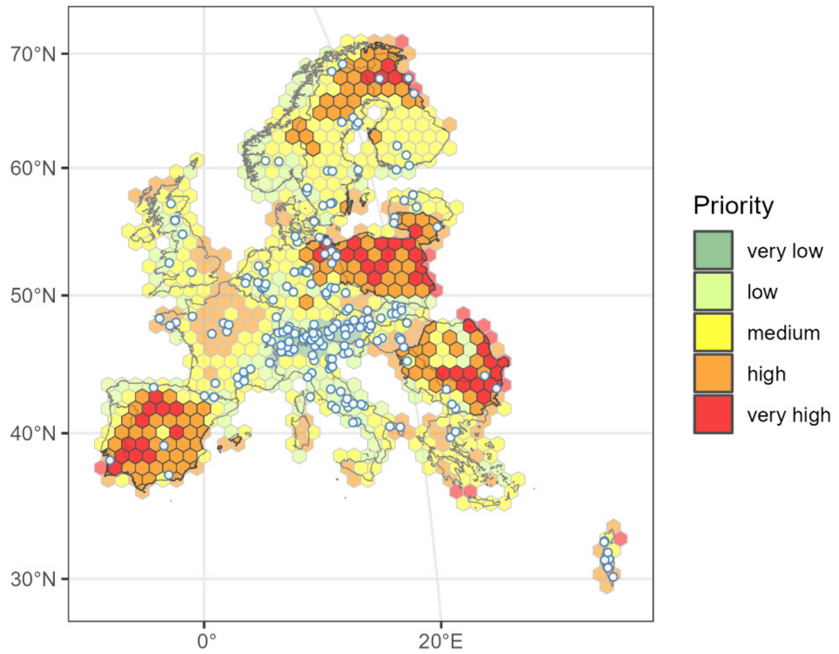

Figure 2: Priority Regions derived for the target region. Colours of the hexagons depict the priority for the addition of in-situ facilities. Black lines indicate country borders, which do not necessarily depict accepted boundaries. In-situ facilities of the eLTER RI are depicted as white dots. The identified gaps are highlighted.

Cluster, these were mainly areas of low economic density, with dry bioclimates and agricultural lands. Likewise, the Iberian Cluster manifested due to underrepresentation of dry bioclimates, agricultural lands and areas of low economic density. The marked differences between these clusters were the biogeoregion and the landform underrepresented. The Nordic Cluster, however, showed widely different conditions, with areas exhibiting very low economic densities and generally little human impact. Consequently, a small overlap in conditions that could be targeted simultaneously was observed for the Iberian and Eastern Clusters, while such an overlap was not observed for the Nordic Cluster (Figure 3a). Interestingly, areas where regions of high priority accumulated – i.e. in France, Greece and Hungary – show notably similar conditions to the Eastern and Iberian Clusters (Figure 3b). Therefore, the addition of new facilities in these regions would also counteract the identified biases. Also, the 85 facilities which – according to the survey – do not comply with eLTER RI's requirements lie mainly in areas with conditions similar to these within the Iberian and Eastern Clusters (Figure 3c), therefore bearing some potential to mitigate sampling bias.

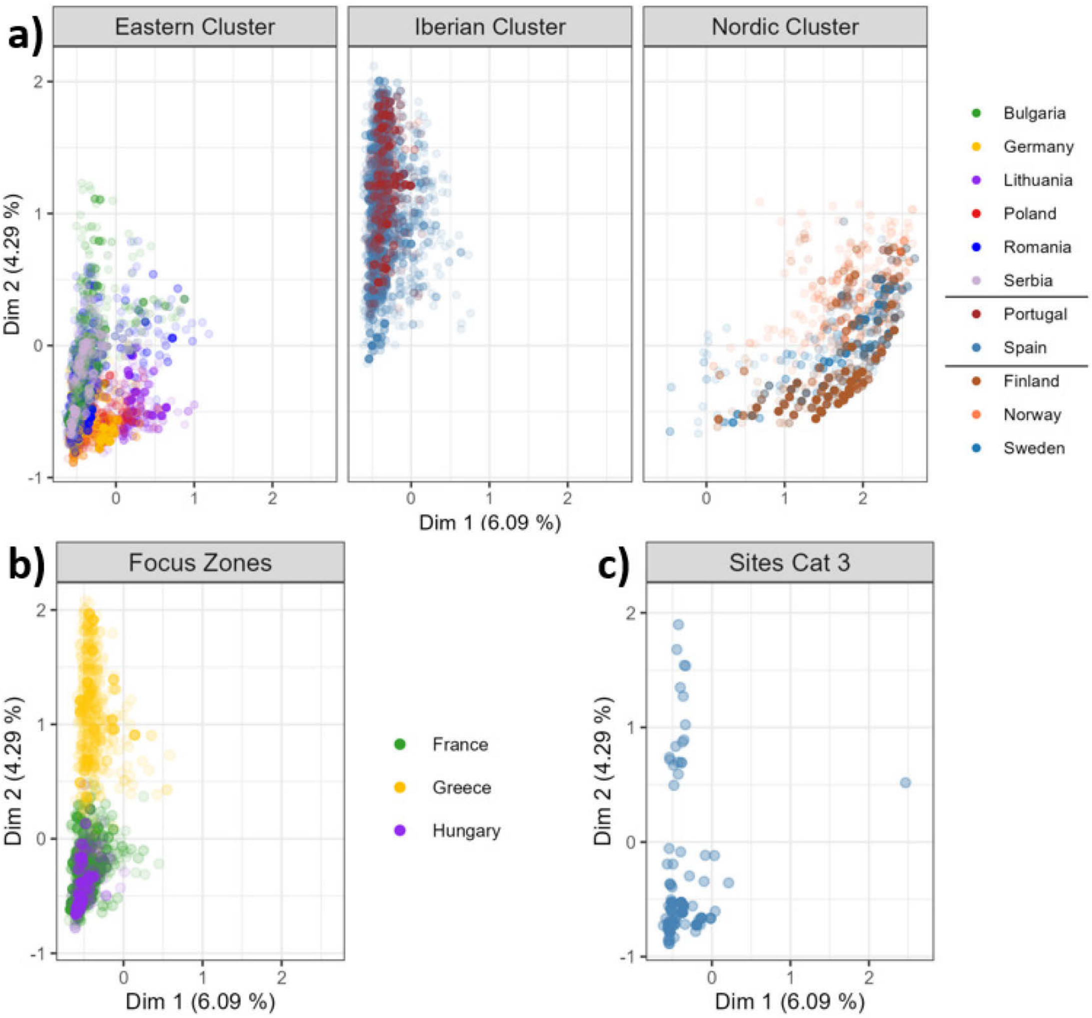

Figure 3: The first two dimensions of a multiple correspondence analysis on the x and y axes. The percentage indicated on the axes depicts the share of variance explained by each dimension. Each dot reflects a raster cell with its manifestations of the six indicators. Dots in the exact same location have the same manifestations of all six indicators, the greater the distance between the dots the bigger the difference in their manifestations. a) The panels illustrate the different clusters, the colours indicate the different countries within clusters. Horizontal black lines in the legend are used as optical division between the countries of each cluster, b) illustrates the focus zones with colours depicting different countries, c) illustrates the Sites Category 3 which are not part of eLTER RI.

Underrepresentation of areas with little human impact were observed before in other RIs, e.g. for ILTER (Wohner et al., 2021). This feature was also suggested to be a general pattern in global ecological research (Martin et al., 2012). Contrary, in densely populated and agriculturally-dominated areas a tendency to study more natural sites is evident (Martin et al., 2012). This is reflected in eLTER RI, too, with the generally observed underrepresentation of agricultural lands and a tendency towards the study of forest ecosystems, which might be seen as more pristine. The Nordic Cluster manifests as areas of high remoteness and low accessibility. These conditions pose challenges for the establishment of research facilities, which is particularly prominent on the global scale (Martin et al., 2012; Li et al., 2017; Wohner et al., 2021; Wolf et al., 2022). Furthermore, the spatial extent of the Eastern Cluster mirrors patterns of lowest GDP per capita in Europe (Solís-Baltodano et al., 2021). Also, in other scientific disciplines the pattern of locating research institutions in areas with higher economic power is evident (e.g. Hefler et al., 1999). Nonetheless, local, regional or global research agendas overcome simple resource constraints in in-situ environmental research. This is especially notable for research facilities in the Arctic and Antarctic where special research foci lead to the deployment of funding. However, underrepresented features on continental scale can also be counteracted in different regions – e.g. the overlap between the conditions observed in the Iberian Cluster and other parts of the Mediterranean (Figure 3) suggests that in-situ facilities elsewhere in the Mediterranean can mitigate the observed sampling bias in the Iberian Cluster.

Herewith, the first four objectives of this study are met: i) choosing a methodological framework, ii) describing the eLTER RI in-situ facility network, iii) defining indicators describing currently prevailing ecosystems in Europe, and iv) describing sampling bias for ecosystems currently prevailing in Europe.

4.2 The Fitness for Future of eLTER RI (Manuscript 2)

The next objectives deal with the representation of Global Change features and, therefore, with the development of suitable Global Change indicators. The indicators depicting the pressure exerted on ecosystems by biotemperature change (BT Pressure) and by precipitation change (P Pressure) each showed a high correlation between RCP4.5 and RCP8.5 (respectively $R^2 = 0.93$ and 0.87), leading to similar spatial patterns independent of the scenario (Figure 4a, b). All of Europe exhibits a positive BT Pressure, as expected with consistent projections of increasing future temperature (IPCC, 2023). Yet, the BT Pressure experienced under RCP8.5 is almost double that under RCP4.5. Expressing warming as BT Pressure suggests most notable ecological consequences in high mountains, followed by the Mediterranean, Northern, Western and Easternmost Europe. Other studies suggested strongest warming in the Mediterranean (Lionello and Scarascia, 2018) and in winter in northern Europe (Dosio and Fischer, 2018; Kjellström et al., 2018; Schaller et al., 2018; Teichmann et al., 2021), with increasing heatwaves in these areas (Forzieri et al., 2016; Abaurrea et al., 2018; Rohat et al., 2019). While the BT Pressure did not explicitly consider heat waves, their effects do influence the determined BT Pressure values. Importantly, Lionello and Scarascia (2018) suggested strong increases in temperature in Eastern Europe, which contrasts with this study, where BT Pressure was lowest in Eastern Europe, the only region where noise dominated. However, they regarded the period from 1901 to 2100, attributing a large part of the observed signal to historical observations. On multi-decadal timescales, manifestations of climatic parameters can change dramatically (Legates and Willmott, 1990; Hulme and New, 1997; Visser et al., 2000), therefore, the chosen baseline can influence conclusions derived from climatic data (Baker et al., 2016). In the present thesis, the baseline 1971-2000 was chosen due to the availability of consistent CORDEX data, yet it misses recent global temperature rise and spatio-temporal precipitation and temperature shifts (Ma et al., 2021; Daramola and Xu, 2022; Yuan et al., 2023).

For P Pressure a strong meridional gradient was observed, with negative P Pressure (i.e. decreased rainfall) in the Mediterranean and Southern Europe, P Pressure close to 0 (i.e. no change in rainfall) in a distinct stretch from Western France via the Alps and Black Sea to Russia, and positive P Pressure (i.e. increased rainfall) north of that strip (Figure 4c, d). This meridional gradient

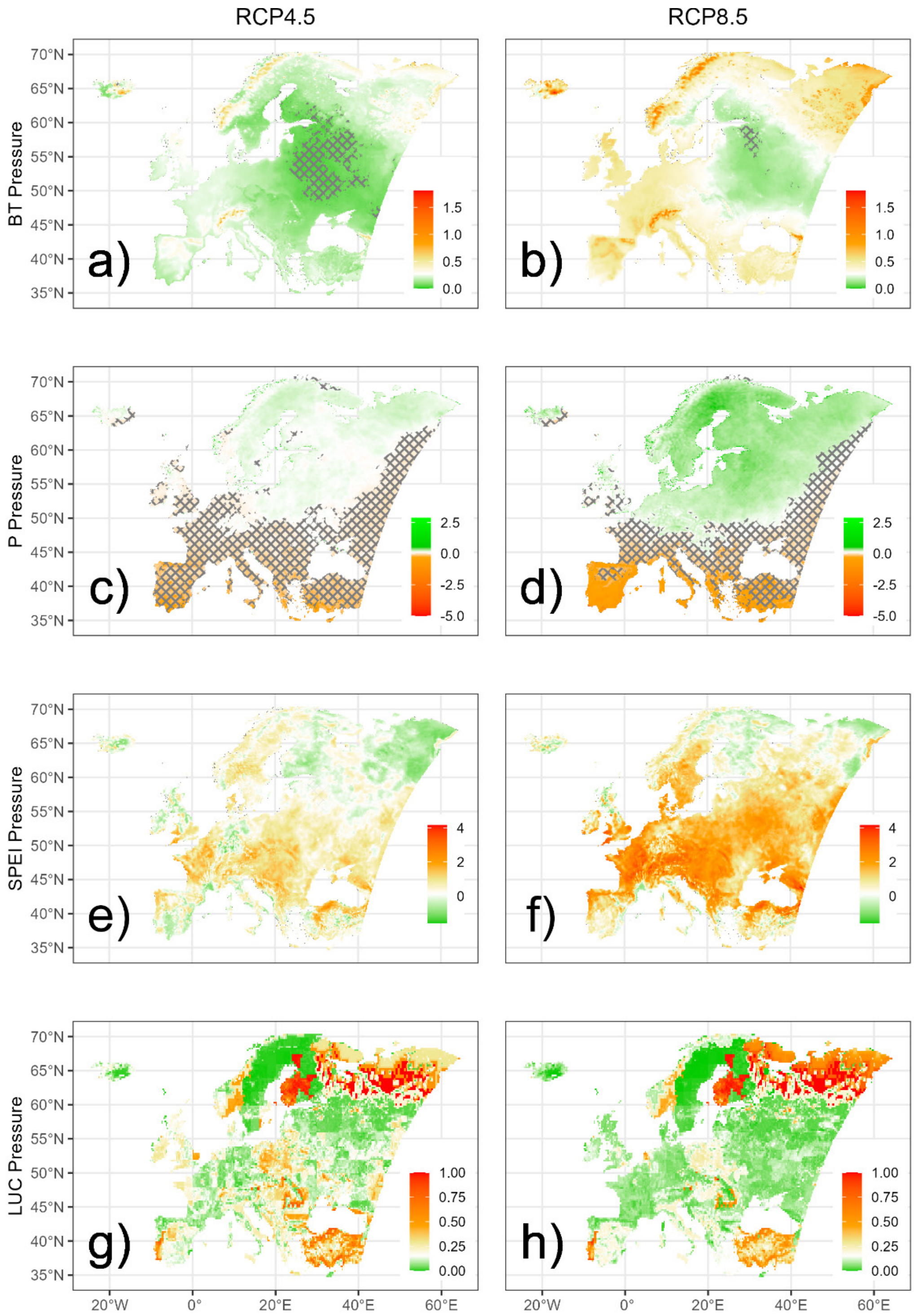

Figure 4: The developed indicators depicting Global Change Pressure. The left column illustrates the pressure under an RCP4.5, the right column under an RCP8.5 scenario. a) and b) illustrate the biotemperature (BT) Pressure with the colour scale diverging around 0.2, c) and d) illustrate precipitation (P) Pressure with the colour scale diverging around 0. For BT and P Pressure hatching depicts areas where the noise was stronger than the signal. e) and f) illustrate SPEI Pressure with the colour scale diverging around 0, g) and h) LUC Pressure with a diversion around 0.2.

is well known (IPCC, 2023) with drying in southern Europe consistently predicted by different models (Russo et al., 2013; Hertig and Tramblay, 2017; Guerreiro et al., 2018; Raymond et al., 2019). Nonetheless, P projections deviate more strongly between single models (Faggian, 2021; Adib et al., 2022) leading to the more widespread noise dominance observed. These deviations are particularly strong in Western, Central and Eastern Europe (Partasenok et al., 2015; Kattsov et al., 2017; Vogel et al., 2018). Under RCP8.5 75.59 % of cells experience a higher P Pressure, and 94.49 % a greater absolute P Pressure suggesting more extreme values than for RCP4.5. Thus, the direction of pressure (positive or negative) is mainly independent of the scenario, but the magnitude will be stronger under RCP8.5.

P changes over Europe are subjected to pronounced seasonality (IPCC, 2023), therefore, the SPEI Pressure was introduced. Regarding seasonality is indispensable, since for the same P and BT Pressure determined SPEI Pressure varied strongly (Figure 5). Most cells experienced positive SPEI Pressure, i.e. soil water availability throughout the year becomes increasingly variable, and spatial patterns were again consistent between scenarios (R^2 = 0.65, Figure 4e, f). Notably, 88.53 % of cells revealed a higher SPEI Pressure under RCP8.5. Highest SPEI Pressure was observed in Western, Central and Eastern Europe. For these regions, an increase in winter P is projected, with Western and Central Europe additionally anticipated to see decreasing water availability in summer and within Eastern Europe summer water availability projections are inconclusive (Jacob et al., 2018; Lionello and Scarascia, 2018; IPCC, 2023). Thus, here, interannual water availability is projected to become more variable. Negative SPEI Pressure was mainly observed in Northern Europe. Here, water availability is projected to increase in the driest months (Spinoni et al., 2018) without a clear trend for the rest of the year (IPCC, 2023). In Southern Europe, SPEI Pressure was close to 0 or slightly negative. Here, no change in winter water availability is projected, but a decrease in summer P (Jacob et al., 2018; Lionello and Scarascia, 2018). Since summer P is already low in the Mediterranean, the impact on the SPEI Pressure indicator is low.

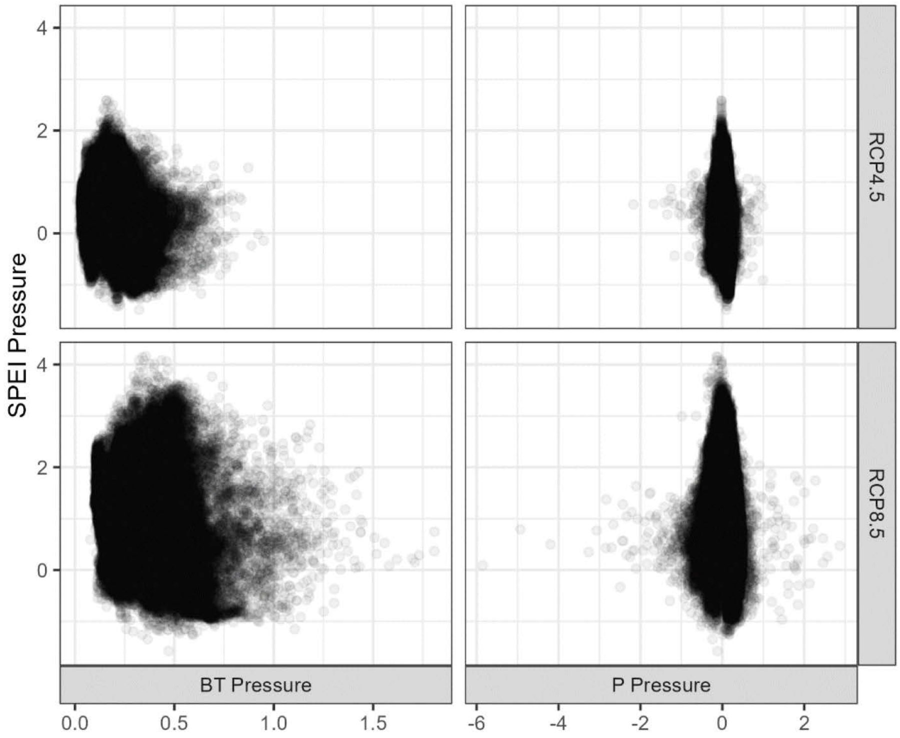

Figure 5: The relationship between precipitation, biotemperature and SPEI Pressure. Points illustrate the respective precipitation (P), biotemperature (BT) and SPEI Pressure of each cell for the RCP4.5 and RCP8.5 scenarios.

Also patterns of LUC Pressure were consistent between scenarios ($R^2 = 0.82$, Figure 4g, h). Large parts in Fennoscandia and Iceland exhibit no or little LUC Pressure, while in parts of Finland and Russia up to 100 % of a cell is expected to undergo LUC. For most cells, LUC Pressure is higher under RCP4.5. Generally, most LUC can be attributed to agricultural land (Rounsevell et al., 2006), yet under RCP8.5 a shift from extensive to intensive management is projected without an increase in agricultural land area (Popp et al., 2017). Contrary, under RCP4.5 agricultural land area can expand, thus without considering land use intensity LUC is more severe under RCP4.5. The sharp boundaries observed in LUC Pressure can be attributed to assumptions for diverging land-use futures (O’Neill et al., 2016; Riahi et al., 2017) as well as regional regulations and global governance (O’Neill et al., 2017). Importantly, SSPs are based on qualitative narratives, which would benefit from extended assumptions for more spatially precise LUC analyses (van Ruijven et al., 2014). Summarizing, the indicators P, BT and SPEI Pressure are suitable to epitomize projected pressure climate change exerts on ecosystems, LUC Pressure alone encapsulates direct human pressure on ecosystems. RCP4.5 and RCP8.5 are based on widely differing assumptions (Hausfather, 2019), yet the correlation between scenarios was high, especially for Pressure derived on annual timescales. Therefore, spatial patterns can be expected to be stable for future pathways not analysed, e.g. RCP6.0 or RCP7.0, yet the magnitude of Pressure can be expected to differ.

These indicators depicting Global Change are due to their ecological meaning a sound basis to analyse sampling bias within eLTER RI. While eLTER RI facilities are located in all categories of the Global Change indicators developed, notable biases were observed. Generally, eLTER RI underrepresents lowest BT Pressure, lowest and highest P Pressure, lowest SPEI Pressure, and lowest and highest LUC Pressure (Figure 4). Aggregating the single indicators leads to a high priority for network densification in a Nordic Cluster in Fennoscandia, an Eastern Cluster covering parts of Eastern Europe and an Iberian Cluster in the South of the Iberian Peninsula (Figure 6). These Cluster areas vastly overlap between scenarios and with the Clusters of underrepresentation derived for current conditions (Figure 2). Thus, by densifying the network in areas projected to be subjected to strong ecological pressure due to changes in P, LUC and interannual water availability eLTER RI can simultaneously reduce the sampling bias for current conditions. Additionally, even though eLTER RI does not explicitly investigate climate extremes, long-term observations in these areas expected to develop towards more extreme conditions would generate invaluable knowledge. RIs that explicitly investigate extreme conditions should additionally incorporate size distribution characteristics of extreme events as indicator (Mahecha et al., 2017), yet this is not necessary to meet eLTER RI's observational goals. For the purpose of this thesis the objectives five and six were fulfilled, v) definition of indicators describing Global Change features relevant for ecosystem development and vi) Describing biases for these Global Change features.

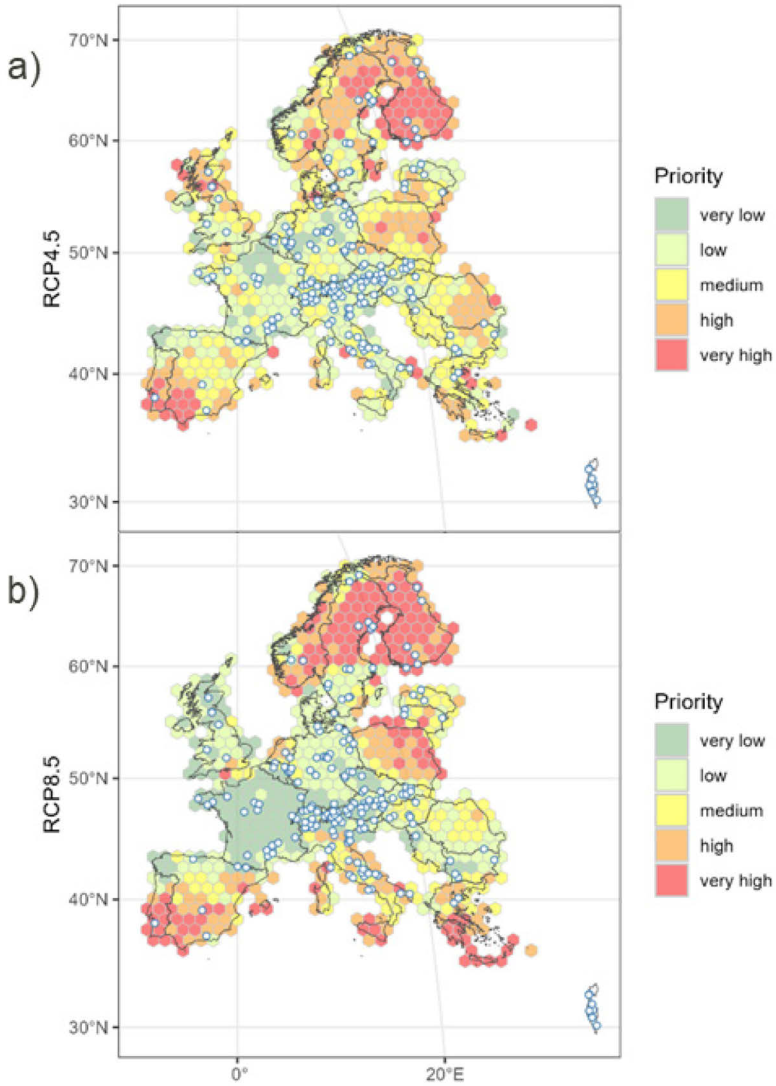

Figure 6: Priority for the establishment of new facilities within eLTER RI regarding Climate and Land Use Change Pressure. a) illustrates the RCP4.5 scenario and b) the RCP8.5 scenario. Hexagon colours depict the priority, white dots the eLTER RI in-situ facilities analysed. As background the target region is illustrated. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

4.3 Mapping the Bias Mitigation Potential

After investigating sampling bias within eLTER RI in relation to ecologically meaningful indicators for current conditions and anticipated Global Change, the bias mitigation potential was analysed (Figure 7). This potential is, as expected, highest in the areas before identified as clusters (Figure 2, Figure 6), i.e. parts of Fennoscandia, Eastern Europe and the Iberian Peninsula (Figure 7a). Contrary, especially the alpine region bears no potential to

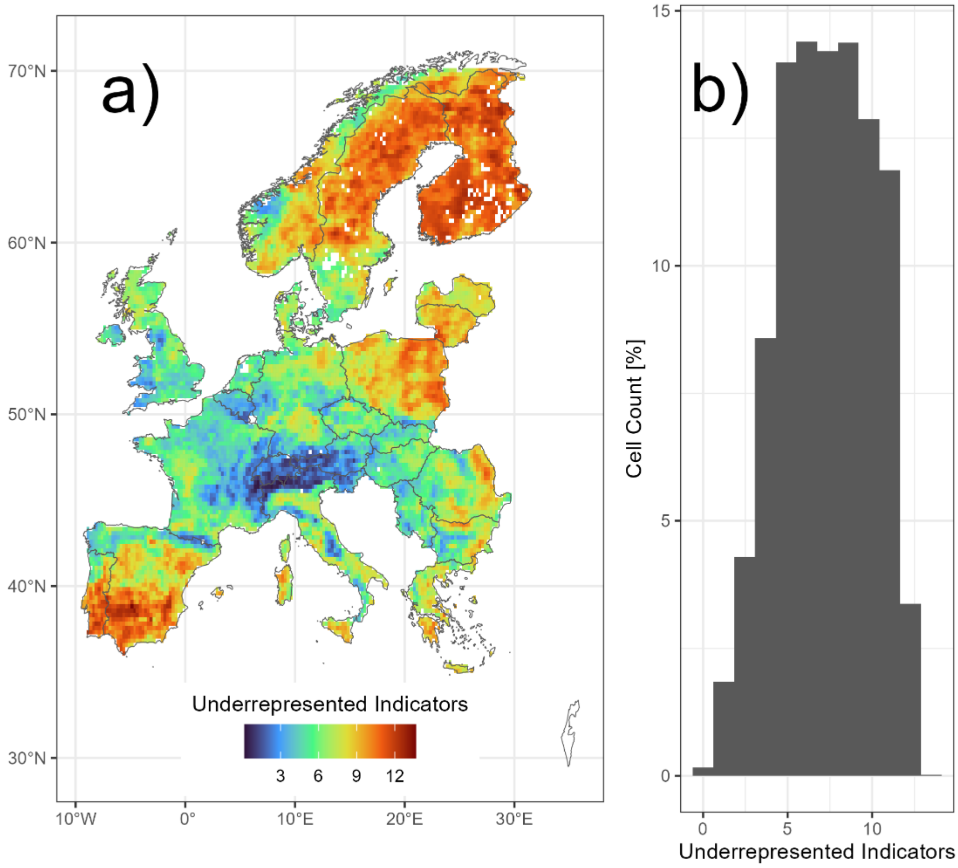

Figure 7: The underrepresented indicators within eLTER RI. The higher the number the greater the potential of an in-situ facility established to mitigated sampling bias within eLTER RI. a) depicts the underrepresented indicators on a colour scale, with blueish colours depicting little, yellow-orange colours medium and reddish colours great potential. Blank cells display water bodies, for which some indicators did not provide data, b) depicts the distribution of these values as histogram, with binwidhts of one category.

mitigate sampling bias. With many conditions prevalent in the alps mirrored in other high-mountain ranges and a few facilities present in the Pyrenees and the Apennine, new in-situ facilities in these mountain ranges would also not mitigate but rather exacerbate sampling bias. Yet, other regions with medium to high eLTER RI facility densities (Figure 1) that were not previously identified as clusters mirror conditions observed as underrepresented. Some of these regions were previously identified as focus zones (Figure 3), e.g. Greece, parts of France. Furthermore, establishing in-situ facilities in parts of Italy, Germany, Czechia, Denmark and the UK can mitigate sampling bias on European scale. Indeed, a substantial area of the target region displays seven to nine underrepresented indicators (Figure 7b), i.e. just more than half of the indicators were found to be underrepresented here. Thus, for most national eLTER RI networks it should be advised, if they plan to establish additional eLTER RI in-situ facilities, to place them strategically to mitigate continental scale sampling bias. This analysis fulfilled objective vii) mapping the bias reduction potential based on the chosen indicators.

Importantly, while this bias mitigation potential map can advise strategic network development, it is not necessarily realistic to establish facilities in areas of high potential. A contrasting approach, therefore, is to regard the location of suitable candidate facilities and to investigate their potential to mitigate eLTER RI sampling bias. Co-location could be a pathway to cost-efficiently mitigate sampling bias observed within RIs.

4.4 The Potential of Co-Location to mitigate Sampling Bias within eLTER RI (Manuscript 3)

Spread over Europe, 832 facilities from the seven pan-European RIs investigated were defined as candidates (Figure 8). Most candidates cluster between Northern Italy in the South, Southern Sweden in the North, Poland in the East and Eastern France in the West. Thus, it has to be noted that the candidate facility dataset itself is tremendously spatially biased. Of these facilities, 27 were already co-located between two RIs.

Importantly, a study like this would benefit from geodata from different RIs following a universal standard on reporting coordinates, complex geometries and using a common database, like DEIMS-SDR (Wohner et al., 2019). With the current standard of meta- and geodata reporting, a subsetting procedure that rather removed valid candidate facilities than keeping invalid ones was chosen. This was successful, since for most candidates the distance to the next candidate far exceeded the spatial extent that can be expected for such a facility. Importantly, RIs based on long-term operation that, in principle, measure similar variables as eLTER RI were investigated. Nonetheless, integrating facilities within eLTER RI will require adaptation of the measurement design to meet eLTER RI's standard observations (Zacharias et al., 2025). The effort to facilitate co-location will differ from facility to facility and from RI to RI. For example, an aquatic ICP Waters facility would have to adapt a terrestrial catchment approach to comply with the observational design of eLTER RI. Also, there might be other suitable RIs that were not regarded in this study.

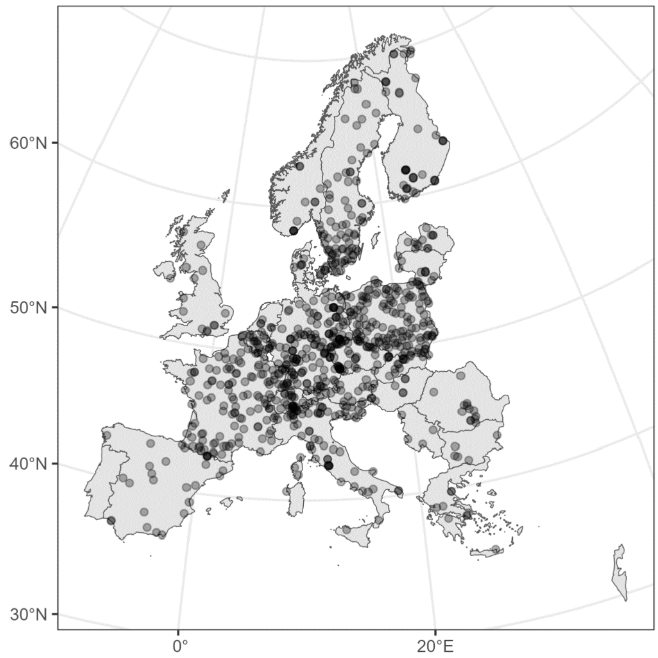

Figure 8: The colocation candidate facilities. Dots illustrate the location of the facilities and they are depicted with slight transparency to illustrate facility density. Grey polygons illustrate the target region and do not necessarily depict accepted national boundaries.

With the present set of candidate facilities it was possible to mitigate biases within eLTER RI (Figure 9). After addition of 50 candidates, the best 25 runs reduced biases on average by 20 %, 40 % and 30 % respectively for current conditions, RCP4.5 and RCP8.5. For current conditions, all areas initially classified as biased still exhibited a bias, at least in some of the best runs. Yet, in most runs the biases in Eastern Europe and Fennoscandia were counteracted, while co-location alone was not able to remove biases in the Mediterranean, France and South-Eastern Europe (Figure 9b). For RCP4.5 and RCP8.5 vast initial biases were completely removed, especially in Eastern Europe. For RCP4.5, also biases in the Iberian Peninsula were conclusively targeted. Nonetheless, two main regions where the co-location approach alone was insufficient to completely counteract biases were identified: the Iberian Peninsula (for current conditions and RCP8.5) and Fennoscandia (for all facets).

This analysis suggested 282 candidate facilities that could contribute to bias reduction, with higher probabilities indicating greater importance for eLTER RI bias reduction (Figure 10). However, only 199 of these were suggested by both analyses of representativity and transferability, indicating that these would contribute in reducing bias while observing ecosystems with low similarity to those already observed by eLTER RI facilities (Figure 10a). Most candidate facilities recommended by both analyses, especially those with high probabilities, lie in the areas with initial low facility density in the eLTER RI. The 50 candidate facilities with the highest potential to counteract bias were found in Poland (n = 13), Finland (n = 12), Sweden (n = 10), Spain (n = 5), Norway (n = 4), Italy (n = 3), Denmark (n = 1), Bulgaria (n = 1) and France, specifically Corsica (n = 1). Nonetheless, the facilities suggested with a high probability in Italy, Denmark, Bulgaria and Corsica lie outside those previously identified Clusters – yet were identified as regions with medium to high potential to counteract sampling bias (Figure 7a) – and would still be tremendously important in counteracting these sampling bias. Candidates not suggested by the transferability analysis were mainly located in Central Europe, but also in Poland and Finland. This suggests, that even here ecosystems exist that have very close conditions to those observed on eLTER RI facilities.

These facilities are recommended, since they would best develop the spatial network design of eLTER RI, based on the chosen indicators and the identified underrepresentation of agricultural lands, dry bioclimates, areas with low economic density, areas projected to experience strong changes in P, both strong and hardly any LUC, hardly any change in BT, and areas where water availability during a year becomes more uniform. Also, specific facilities recommended in Greece, Italy, Germany, Switzerland, the UK and the Netherlands show that the development in national LTER networks has the potential to follow a strategic targeting of continental scale sampling bias.

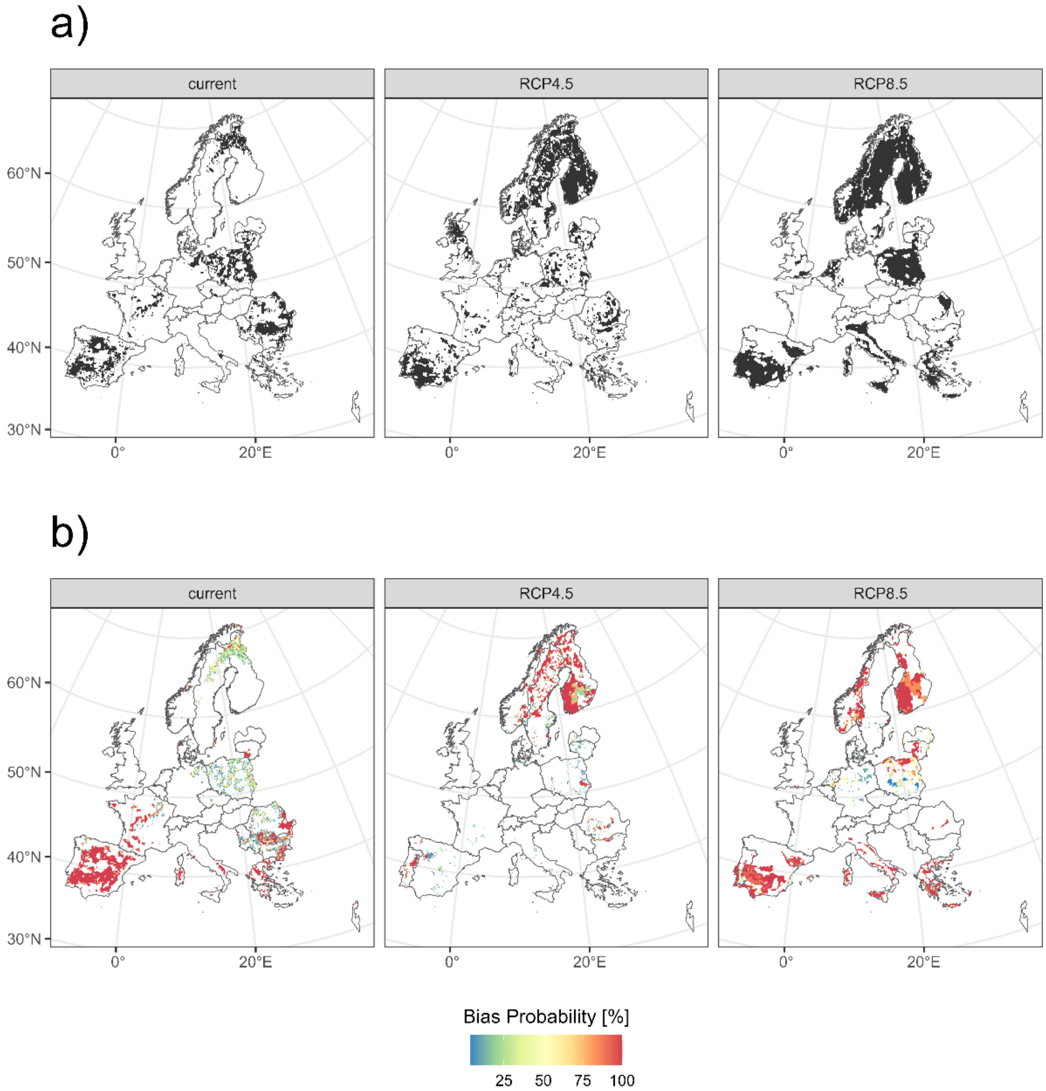

Figure 9: The spatial distribution of the sampling bias. a) Areas classified as biased before the addition of candidate facilities illustrated in black. b) Areas coloured in their bias probability after the addition of 50 candidate facilities. The bias probability depicts in which percentage of best quality runs (n = 25) a cell was classified as biased. Facets depict current conditions, RCP4.5 and RCP8.5. Boundaries depict the study region and not necessarily accepted geographic boundaries.

This thesis also showed that choosing indicators that depict both current conditions as well as Global Change aspects or future conditions is necessary to thoroughly design the spatial network of an RI. The greatest limitation to mitigating sampling bias by co-location is the low number of candidate facilities covering conditions that prevail and are projected in the Mediterranean, which cluster most prominently in the Iberian Peninsula, and conditions as they prevail in parts of Fennoscandia. While there would be some suitable candidates for conditions in the Iberian Peninsula as part of LTER, they already indicated they will not fulfil the requirements of eLTER RI (Figure 3c). Further facilities in these areas could be part of RIs that were not investigated, or they would have to be newly established, e.g. ICOS plans three more facilities in Spain and two more in Greece (Storm et al., 2023).

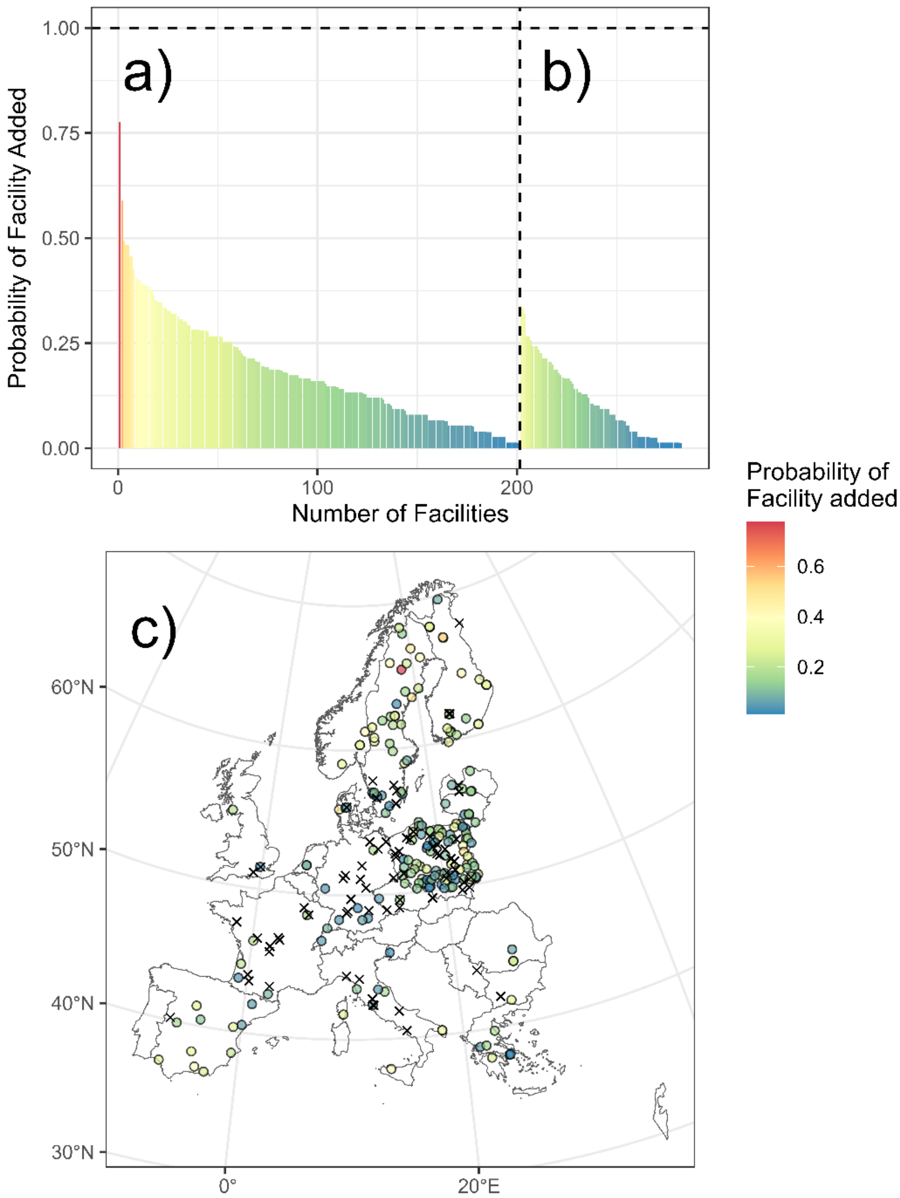

Figure 10: Probability that a facility is added in one of the best performing runs (n = 25) illustrated in colour. The probability is the mean of the current, the RCP4.5 or the RCP8.5 facet's probabilities. The dashed horizontal line depicts the maximally possible probability of 1. a) includes all facilities that are suggested by the representativity and the transferability analysis in order of probability, b) includes facilities only suggested by the representativity analysis, c) coloured points illustrate candidate facilities listed in a) with their probability of addition to eLTER RI, black crosses illustrate the location of facilities listed in b). Boundaries depict the study region and not necessarily accepted geographic boundaries.

Nonetheless, even if further suitable candidates were found, it is unlikely that eLTER RI would be able to incorporate more than 50 further facilities. Therefore, the prioritization of the 282 identified candidates down to country and RI-level allows to inform the eLTER RI community as well as policy and decision makers, based on the calculated probabilities. It is advisable to repeat this analysis after incorporation of an additional facility in eLTER RI and whenever new suitable candidates emerge to derive a new candidate facility prioritization. Completely removing sampling bias from eLTER RI will be tedious due to the historically high facility density in the Alps. This density leads, in turn, to continental-scale underrepresentation of conditions not occurring in the Alps. For high facility density RIs it will be more difficult to counteract bias. To this effect, Villarreal and Vargas (2021) showed that 60 flux towers optimally distributed over Latin America reach a similar representativeness as 200 towers. However, the high variability in alpine ecosystems due to steep gradients and rough relief may warrant a dense facility network in the European Alps. This might not be the case for an RI only interested in observing a single parameter (Sulkava et al., 2011). Importantly, bottom-up developed RIs can reproduce parameter variability better than top-down approaches, if in top-down approaches facilities are placed close to cluster centres (Sulkava et al., 2011). Thus, herewith the last two objectives of this thesis were fulfilled, viii) synthesizing suitable candidates from other RIs to investigate the co-location potential and ix) identifying candidate facilities that eLTER RI would most benefit from in terms of bias reduction.

However, with eLTER RI in-situ data already informing the development of large-scale models (e.g. Baatz et al., 2018; Forsius et al., 2023), sampling bias should not only be tackled in the in-situ network design. On this account, a less biased or even unbiased subset should be chosen when undertaking comprehensive meta-analyses or developing models. Removing bias in data would be concomitant with the loss of valuable data that could also contribute to ecosystem understanding and macrosystems ecology (Heffernan et al., 2014). However, addressing these biases is important, e.g. Sulkava et al. (2011) showed that upscaling from the persistent European flux tower network would lead to a mean overestimation of gross primary production of 8 % and of > 20 % in certain regions. To avoid loss of data, Schmill et al. (2014) suggested to assign greater weight to data from underrepresented regions. Practically, one could multiply single data points, artificially creating data to reduce sampling bias. However, since ecosystems are unique, while removing one kind of bias this approach will rather introduce others. Therefore, as long as sampling bias within an RI persists, the scalability of its in-situ data is limited. Consequently, only mirror imaging the target region in a “geospatial twin” would allow to create unbiased data without the loss of single data points, i.e. harnessing the complete data pool of eLTER RI.

5 Conclusions

The procedure to design the spatial network of an RI outlined in this thesis can function as a blueprint for RI development towards minimizing sampling bias. The steps that must be fulfilled are i) the sound definition of the in-situ facilities of a RI, in number, design as well as geographic extent, ii) the sound definition of meaningful indicators, for a socio-ecological RI like eLTER RI these indicators must describe both the status quo of ecosystem conditions as well as anticipated Global Change or future conditions, iii) uncovering sampling bias based on these meaningful indicators, and iv) revealing ways towards bias mitigation.

For eLTER RI, this procedure permitted to uncover conditions that are substantially underrepresented. To reduce sampling bias in the in-situ facility network, agricultural lands, dry bioclimates, areas with low economic density, areas projected to experience a strong increase and a strong decrease in precipitation, little change in biotemperature, both strong and hardly any LUC and areas where water availability during a year becomes more uniform must be targeted. Using co-location, facilities could be identified that cover these conditions, therefore sampling bias can generally be addressed, but not removed from eLTER RI. It is advisable for other RIs to adopt similar investigations of sampling bias. The observed lack of in-situ facilities covering conditions as they occur in the Mediterranean in all pan-European RIs suggests that sampling bias might persist for these RIs, too. Therefore, pooling efforts and resources of several RIs to establish additional facilities in these areas can be advised. This is another function, co-location could fulfil, besides allowing to measure a wider range of earth system parameters in a single facility, pushing RIs further towards a whole-systems approach. Until RIs removed sampling bias within their in-situ facility network, biases should be addressed in data analyses to avoid developing flawed models and coming to deficient conclusions.

Tackling sampling bias becomes especially important when aiming to develop a global scale earth observatory (Kulmala, 2018), as e.g. GERI tries to achieve

(Loescher et al., 2022). GERI unites efforts of six regional to continental-scale RIs on five continents, with no RI covering Central and South America. Standardizing the data of these different RIs is a substantial on-going effort (Deshpande et al., 2025) and indispensable for such an effort. Thus, while GERI will be a first of its kind RI collecting data on an unprecedented scale, sampling bias will be substantial (Ohnemus and Mirtl, 2025). Therefore, also global efforts like GERI will benefit from an analysis as presented here, to uncover, mitigate and be able to address biases in data analyses and ultimately push environmental sciences to an improved, more representative understanding of the Earth System.

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Appendix

Manuscript 1

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

Environmental and Sustainability Indicators 23 (2024), 100456

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Abstract

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; Da 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., 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

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.

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.

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., 2021), 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.

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 (Figure 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 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

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 x 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.

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 x 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.

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

A hexagonal grid with a cell area of 10,000 km² 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 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.

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.

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 (Figure 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 (Figure 2).

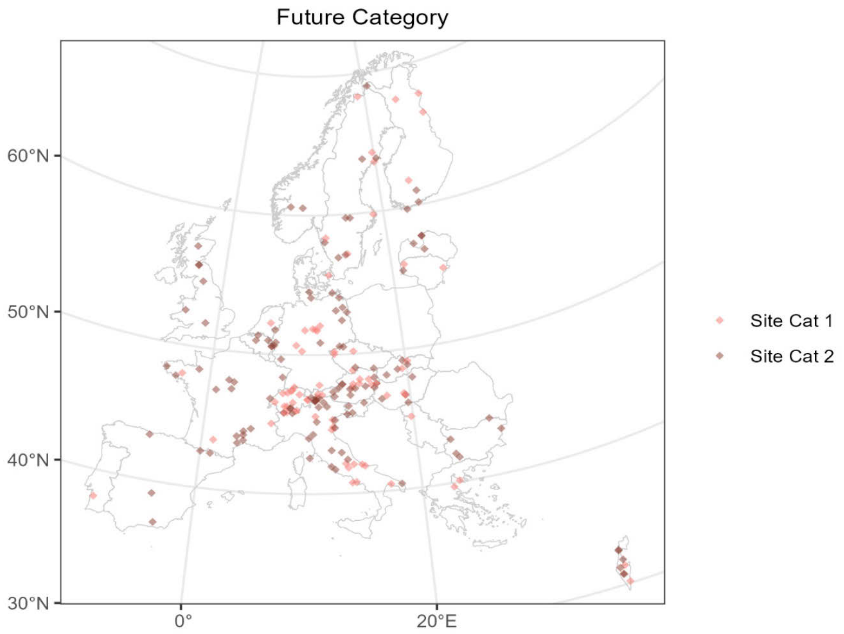

Figure 1: Spatial distribution of the sites contributing to the eLTER Research Infrastructure with their anticipated future category as indicated by the eLTER National Coordinators in the 2023 survey, illustrated as dots with the respective colour. Grey country boundaries depict the RA.

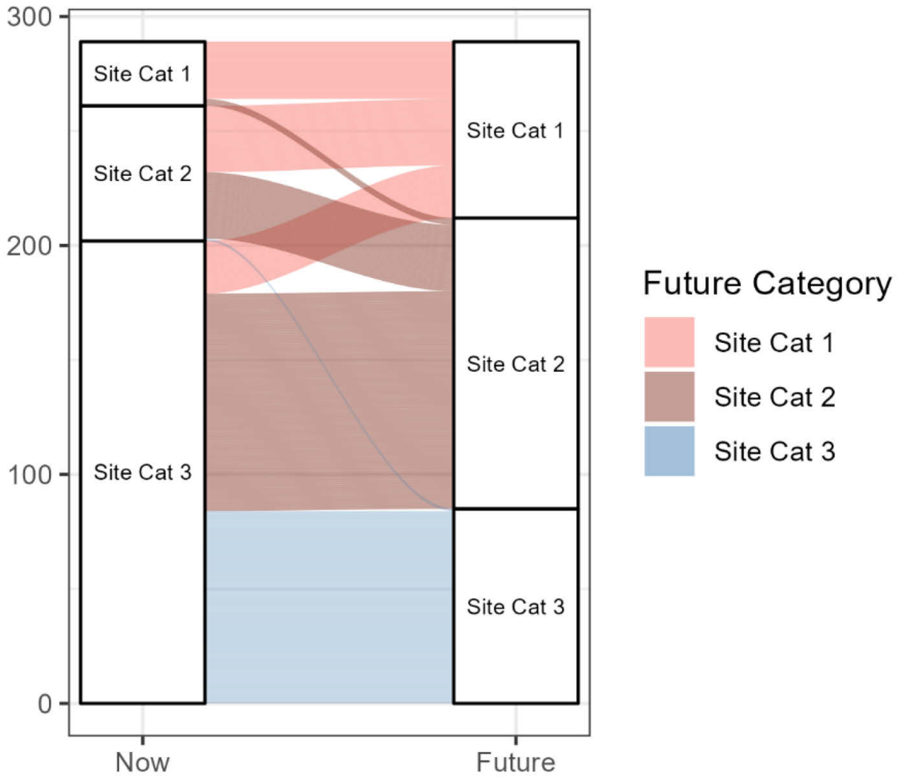

Figure 2: Projected development of site assignment to categories from present to the future reported by the eLTER National Coordinators in the 2023 survey shown in different colours based on the anticipated future category. Sites Cat 1 and 2 are formally part of the eLTER RI. Sites Cat 3 represent the potential for future network densification.

3.2 Habitat Coverage

The eLTER RI covers all eLTER habitat categories (Figure 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 (Figure 4). The outputs of the underlying x² tests of homogeneity can be found in the supplement (Table S 1). 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*.

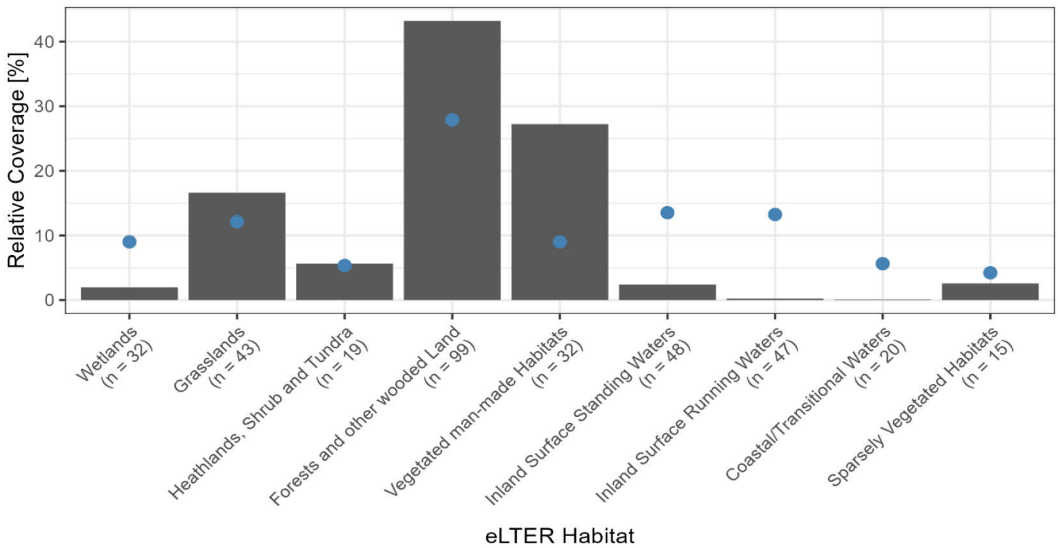

Figure 3: Relative coverage of eLTER habitat classes in the RA (bars) and as indicated by the SPCs for Sites Cat 1 and 2 (points). Numbers in brackets indicate the number of sites covering a habitat. Multiple mentions in the survey were possible.

Part of the gap analysis was the identification of RP categories that contribute in a substantial way to the underrepresentation (Figure 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$/km², flat plains and land cover of cropland and herbaceous cover and lied mostly in the Continental biogeoregion. Within the Iberian Gap the anthrome “residential rainfed croplands”, the “cool temperature and xeric” bioclimate, the economic density “0.1 - 1 Mio US$/km²”, 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$/km² manifested.

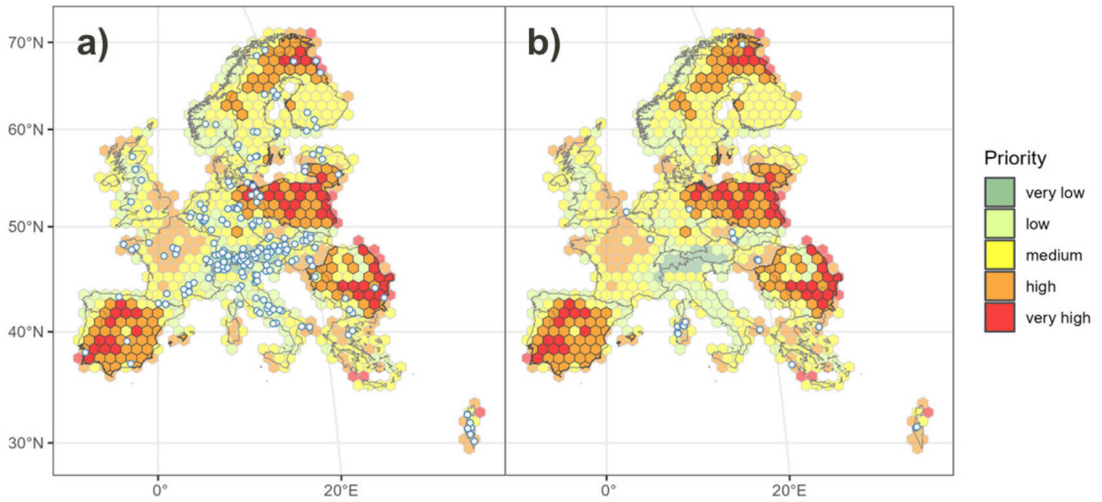

Figure 4: Priority Regions derived for the RA consisting of the 26 LTER countries. Colours of the hexagons depict the priority for additional sites. Black lines indicate country borders. In a) sites contributing to the eLTER RI are illustrated as white dots, while in b) Sites Cat 3 within regions of high or very high priority are illustrated. In both maps the identified gaps are highlighted.

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 km²” 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 (Figure S 1 to Figure S 6). Thus, these categories did not contribute to the formation of the *gaps*.

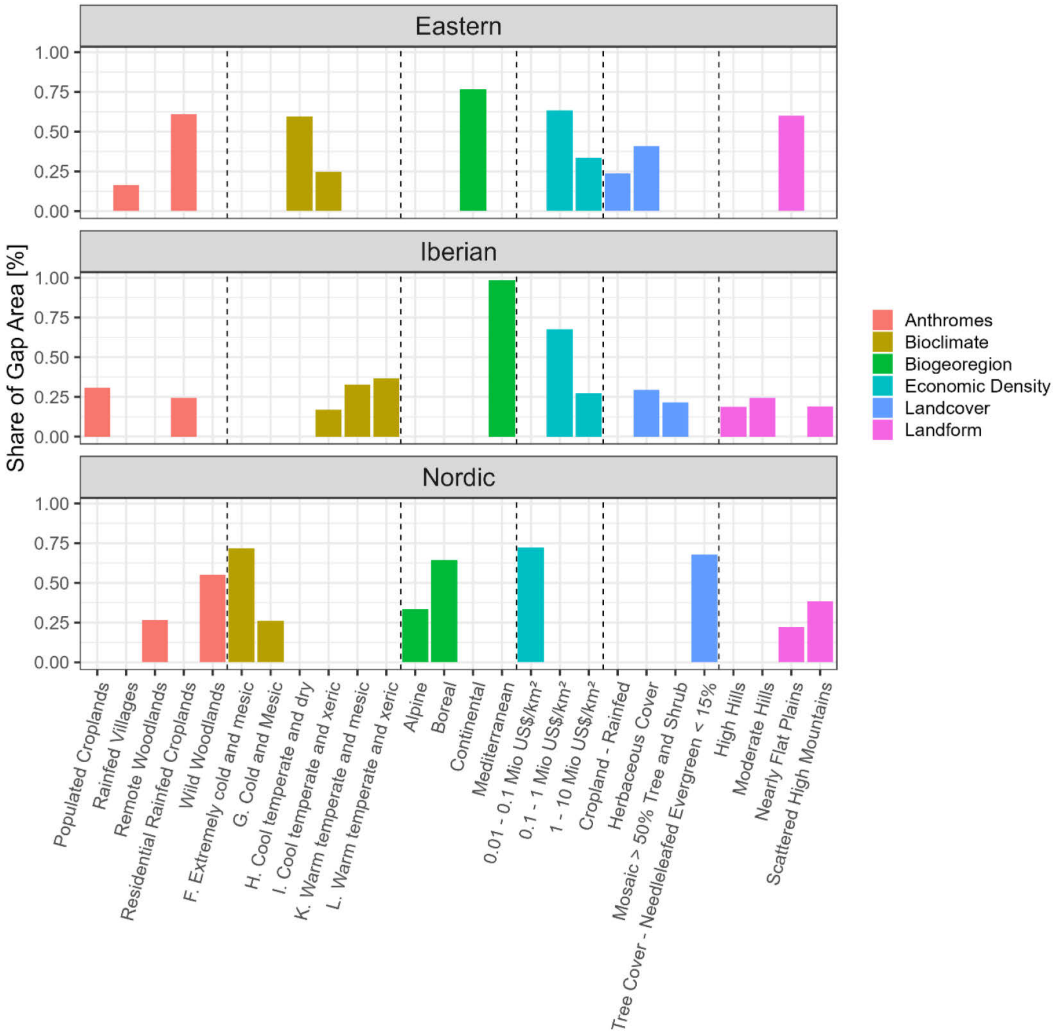

Figure 5: Categories that cover at least 15 % of the area of any gap for any RP illustrated with their share of the gap area as bar plot. Colours depict the RPs, facets the different gaps. Labels on the x-axis depict the names of the categories of the respective RPs.

The MCA revealed a distinct overlap of RP category combinations within the *gaps* (Figure 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 (Figure 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 (Figure 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 (Figure 6c).

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 (Figure 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 (Figure 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.

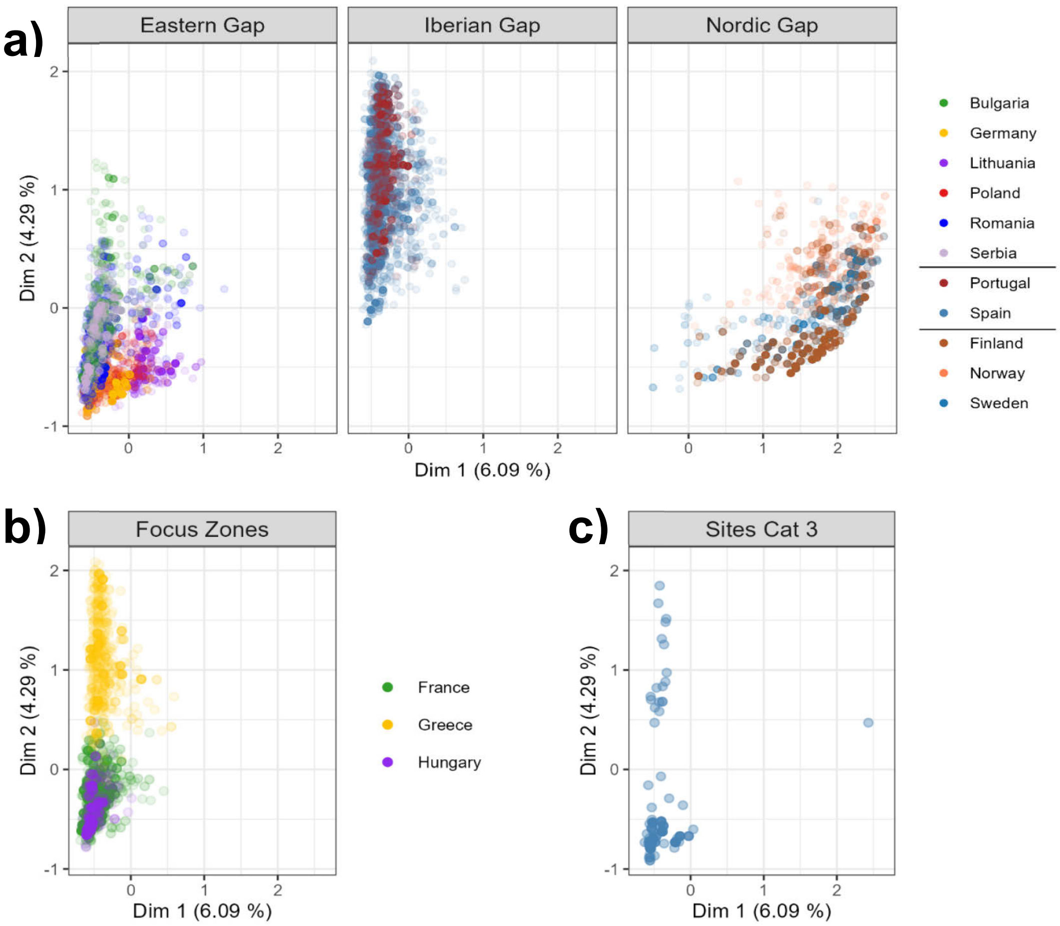

Figure 6: Illustration of the first two dimensions of a multiple correspondence analysis on the x and y axes. The percentage indicated on the axes depicts the amount of variance explained by each dimension. Each dot reflects a raster cell with its manifestations of the six RPs. Dots in the exact same 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.

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 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 (Figure 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 x 100 m. Thus, the area of these habitats might generally be underrepresented in the EUNIS dataset. Nonetheless, a research focus on inland water 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 (Figure 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 (Figure 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* (Figure 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 (Figure 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 (Figure 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 (Figure 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.

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Supplement

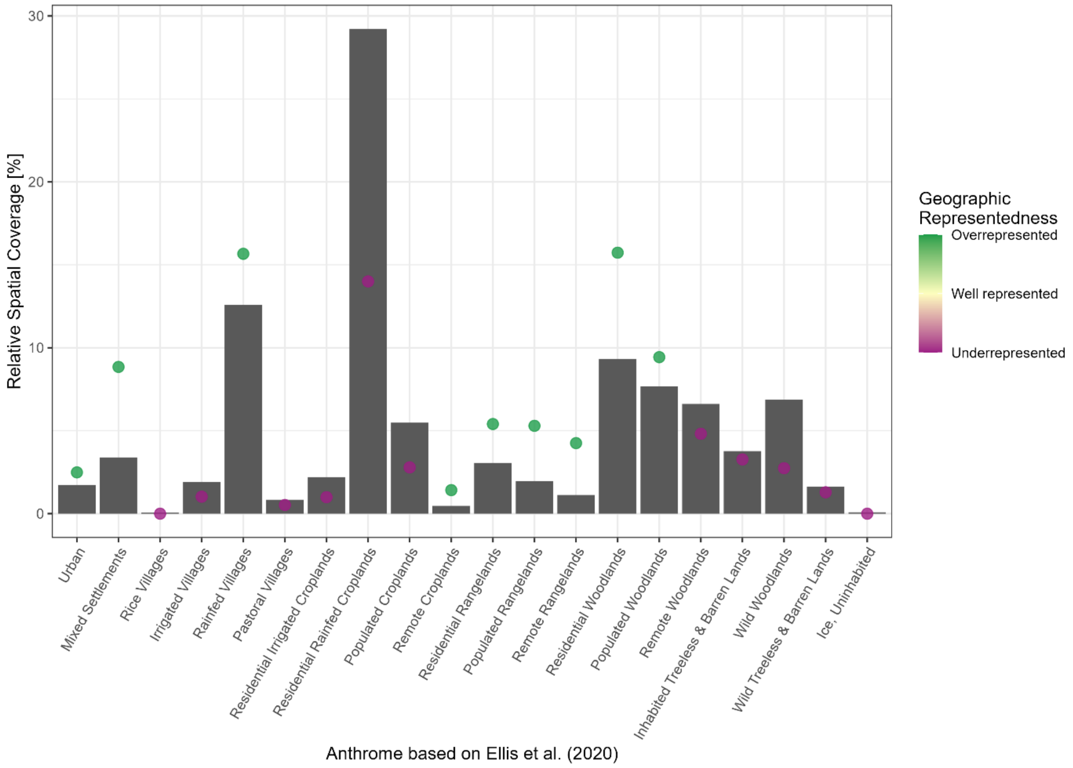

Figure S 1: Relative spatial coverage for each RP category within the RA (bars) and within the sites contributing to the eLTER RI (points) for the Anthrome dataset. Additionally, Geographic Representedness (GR) per Anthrome RP category is presented with a colour scale.

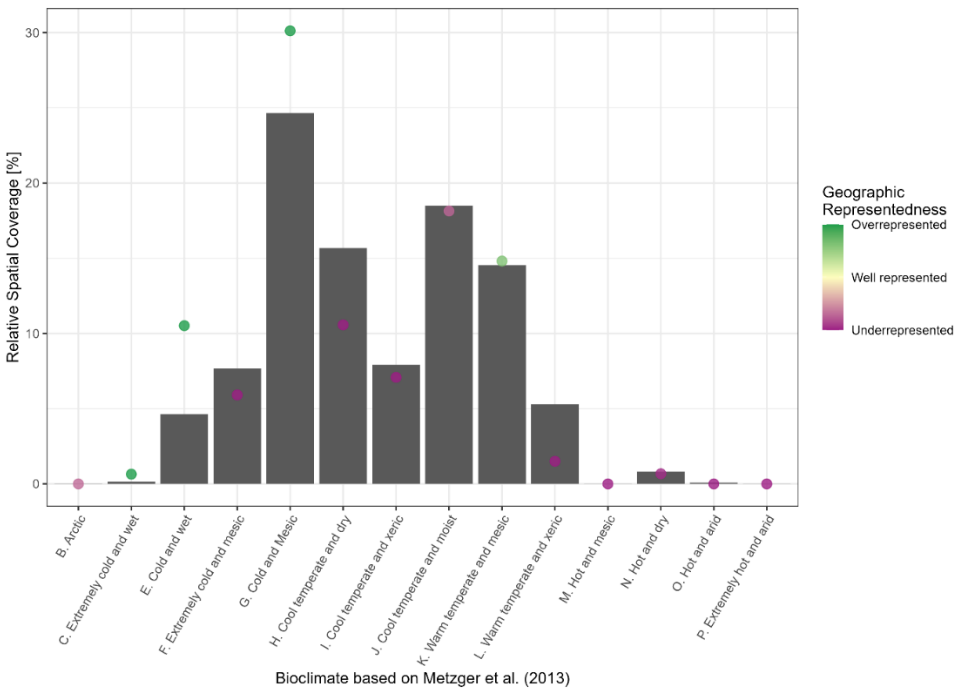

Figure S 2: Relative spatial coverage for each RP category within the RA (bars) and within the sites contributing to the eLTER RI (points) for the bioclimate dataset. Additionally, Geographic Representedness (GR) per bioclimate RP category is presented with a colour scale.

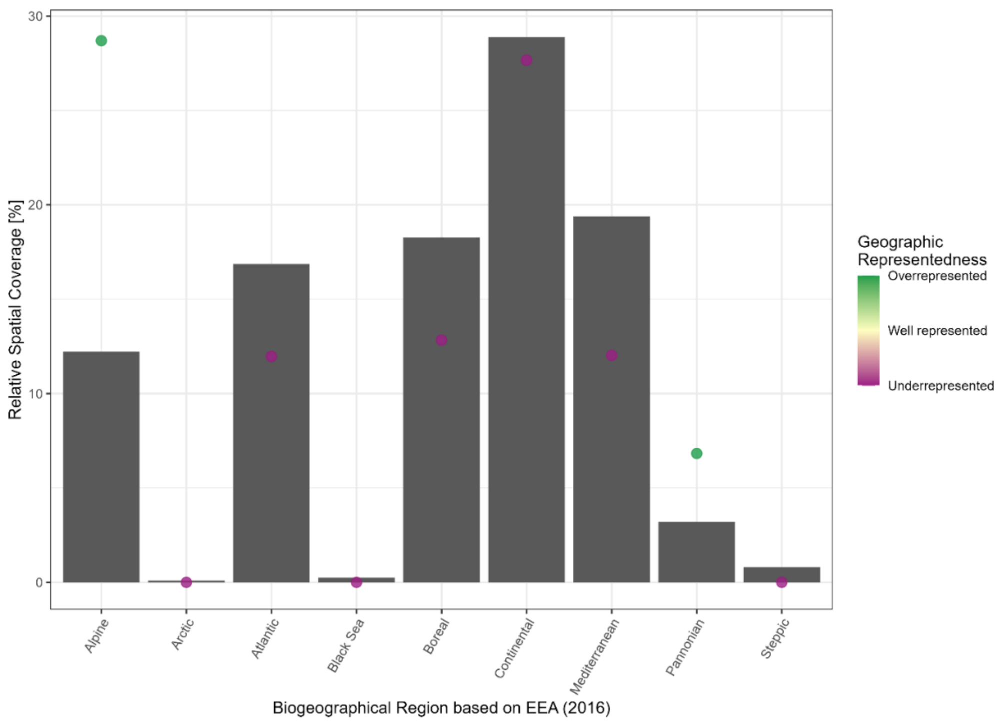

Figure S 3: Relative spatial coverage for each RP category within the RA (bars) and within the sites contributing to the eLTER RI (points) for the biogeoregionn dataset. Additionally, Geographic Representedness (GR) per biogeoregion is presented with a colour scale.

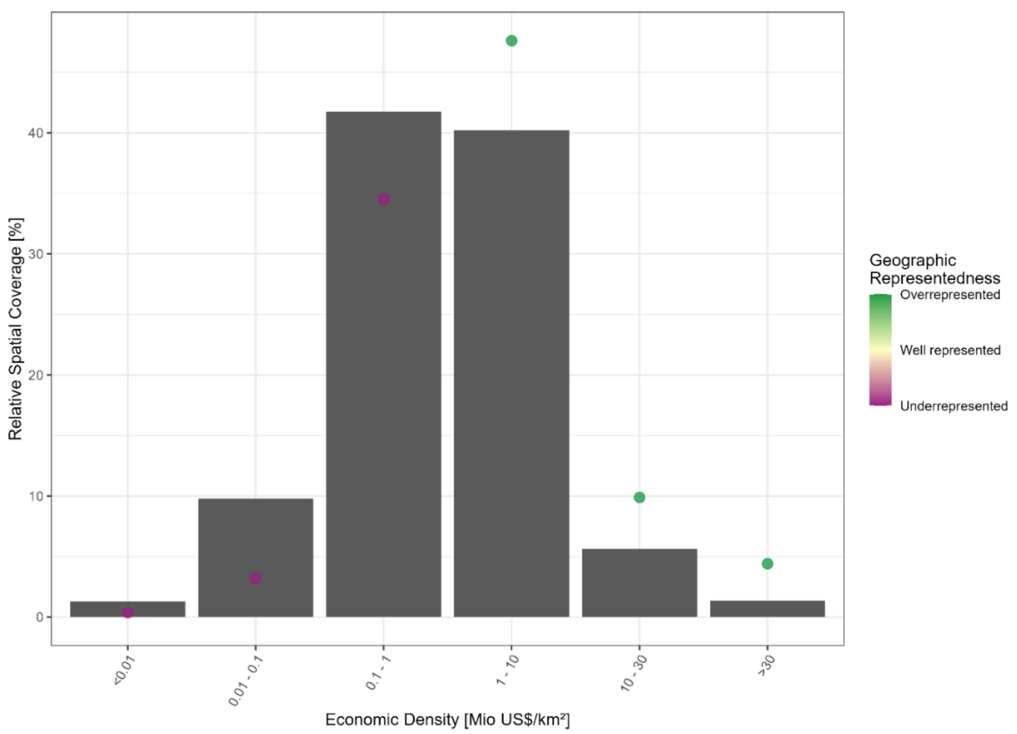

Figure S 4: Relative spatial coverage for each RP category within the RA (bars) and within the sites contributing to the eLTER RI (points) for the economic density dataset. Additionally, Geographic Representedness (GR) per economic density RP category is presented with a colour scale.

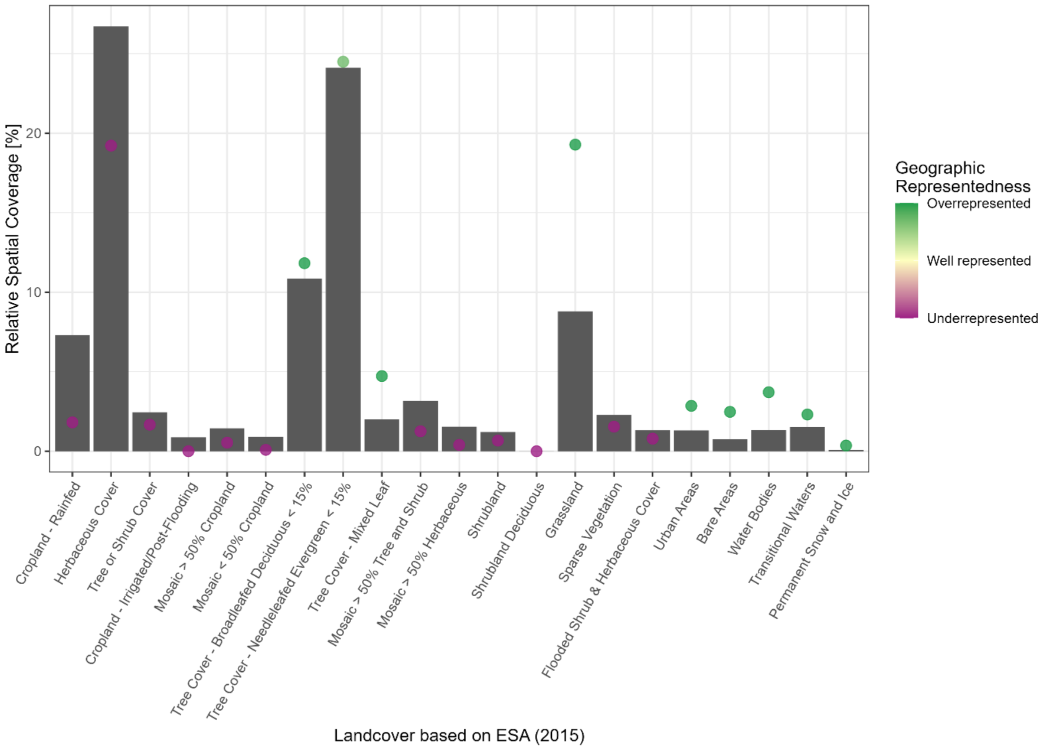

Figure S 5: Relative spatial coverage for each RP category within the RA (bars) and within the sites contributing to the eLTER RI (points) for the landcover dataset. Additionally, Geographic Representedness (GR) per landcover RP category is presented with a colour scale.

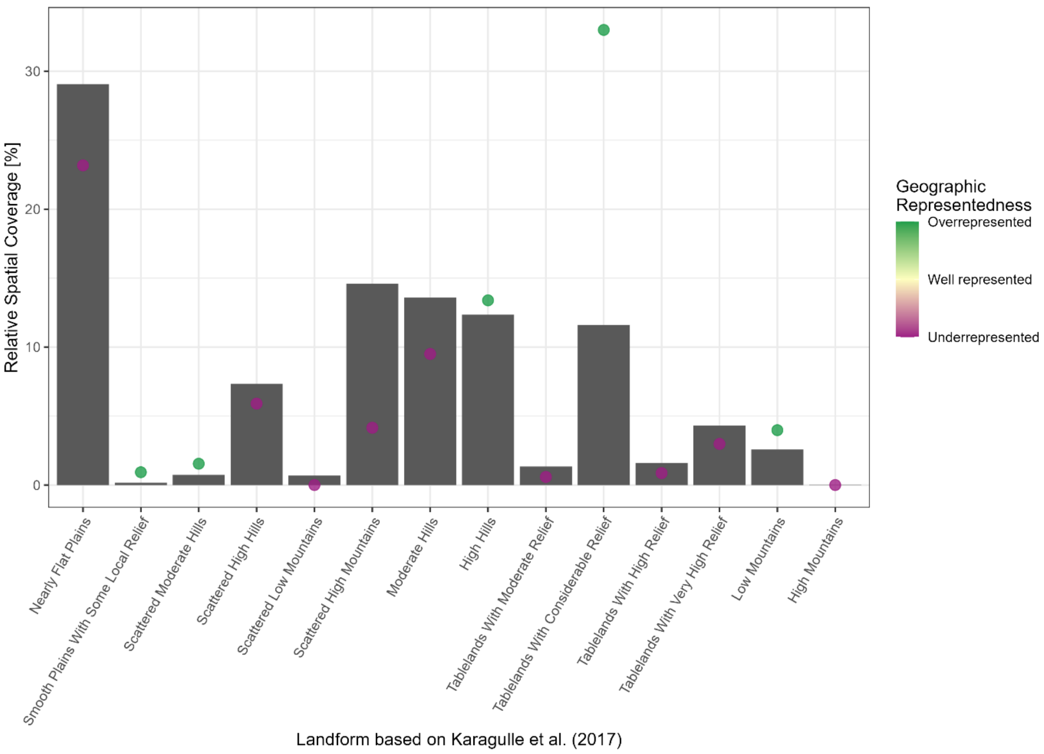

Figure S 6: Relative spatial coverage for each RP category within the RA (bars) and within the sites contributing to the eLTER RI (points) for the landform dataset. Additionally, Geographic Representedness (GR) per landform RP category is presented with a colour scale.

Table S 1: Test statistics of the x² test of homogeneity for each reference parameter and their respective individual categories. The derived p value of the individual categories was used to calculated the geographic representedness of each category.

Reference Parameter Category	X² value	p value
Anthromes	*14152*	*0*
Urban	41.36	0
Mixed Settlements	788.26	0
Rice Villages	17.99	0.0000222
Irrigated Villages	83.58	0
Rainfed Villages	118.48	0
Pastoral Villages	21.33	0.0000039
Residential Irrigated Croplands	140.36	0
Residential Rainfed Croplands	2083.89	0
Populated Croplands	279.51	0
Remote Croplands	145.59	0
Residential Rangelands	206.80	0
Populated Rangelands	483.43	0
Remote Rangelands	565.23	0
Residential Woodlands	571.02	0
Populated Woodlands	59.88	0
Remote Woodlands	91.46	0
Inhabited Treeless & Barren Lands	11.17	0.0008316
Wild Woodlands	567.53	0
Wild Treeless & Barren Lands	11.20	0.0008162
Ice. Uninhabited	23.11	0.0000015
Bioclimate	*4693.8*	*0*
B. Arctic	1.27	0.259946
C. Extremely cold and wet	94.41	0
E. Cold and wet	750.87	0
F. Extremely cold and mesic	74.27	0
G. Cold and Mesic	228.85	0
H. Cool temperate and dry	348.61	0
I. Cool temperature and xeric	15.40	0.0000868
J. Cool temperate and moist	1.25	0.263318
K. Warm temperate and mesic	0.84	0.359807
L. Warm temperate and xeric	670.31	0
M. Hot and mesic	0.72	0.397398
N. Hot and dry	4.40	0.0359697
O. Hot and arid	24.23	0.0000009
P. Extremely hot and arid	0.72	0.397398
Biogeographical Region	*10190*	*0*
Alpine	2544.55	0
Arctic	26.60	0.000003
Atlantic	296.82	0
Black Sea	73.48	0
Boreal	345.04	0
Continental	11.33	0.000763
Mediterranean	628.05	0
Pannonian	416.72	0

Steppic	246.26	0
Economic Density [in Mio US$/km²]	*5423.8*	*0*
<0.01	154.90	0
0.01 – 0.1	1092.60	0
0.1 – 1	336.77	0
1 – 10	339.84	0
10 – 30	386.60	0
>30	503.39	0
Landcover	*11908*	*0*
Cropland – Rainfed	1056.87	0
Herbaceous Cover	484.37	0
Tree or Shrub Cover	46.39	0
Cropland – Irrigated/Post-Flooding	268.08	0
Mosaic > 50% Cropland	126.87	0
Mosaic <50% Cropland	206.39	0
Tree Cover – Broadleafed Deciduous < 15%	13.93	0.000189
Tree Cover – Needleleafed Evergreen < 15%	1.17	0.280042
Tree Cover – Mixed Leaf	344.08	0
Mosaic > 50% Tree and Shrub	258.29	0
Mosaic > 50% Herbaceous	206.55	0
Shrubland	47.41	0
Shrubland Deciduous	0.02	0.896081
Grassland	1384.63	0
Sparse Vegetation	44.02	0
Flooded Shrub & Herbaceous Cover	40.60	0
Urban Areas	177.11	0
Bare Areas	280.77	0
Water Bodies	351.33	0
Transitional Waters	48.80	0
Permanent Snow and Ice	53.76	0
Landforms	*16809*	*0*
Nearly Flat Plains	267.76	0
Smooth Plains With Some Local Relief	153.53	0
Scattered Moderate Hills	85.62	0
Scattered High Hills	49.59	0
Scattered Low Mountains	205.33	0
Scattered High Mountains	1920.52	0
Moderate Hills	242.95	0
High Hills	14.32	0.000154
Tablelands With Moderate Relief	88.11	0
Tablelands With Considerable Relief	3926.43	0
Tablelands With High Relief	67.18	0
Tablelands With Very High Relief	74.57	0
Low Mountains	91.31	0
High Mountains	2.77	0.09584

Manuscript 2

Fitness for future: eLTER RI's representation of climate and land use change

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Abstract

Optimisation of the spatial arrangement of distributed in-situ research infrastructures is often based on analyses of the transferability or representativity of its current site network. However, current conditions shift dramatically due to Global Change, posing fundamental challenges for the establishment of research infrastructures. Climate and land use change (LUC) are among the ecologically most relevant Global Change aspects. This study analysed how well the geographical distribution of the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure (eLTER RI) represents these future changes at European scale. Therefore, we (i) derived ecologically meaningful metrics depicting both changes and identified associated hotspots, (ii) estimated eLTER RI’s fitness for these Global Change aspects, and (iii) compared the eLTER RI's coverage of current environmental and socio-ecological gradients with its representation of climate change and LUC.

Climate change and LUC were quantified as Pressures, expressing changes in biotemperature (BT Pressure), precipitation (P Pressures), seasonal water availability (SPEI Pressure) and Land Use (Land Use Change Pressure) relative to a location's baseline conditions. Individual Pressures revealed consistent spatial patterns of different magnitude between the RCP4.5 and RCP8.5 scenarios. The eLTER RI covers a wide variety of Pressures, but is spatially biased. BT and SPEI Pressure Hotspots are overrepresented by the eLTER RI, while P Pressure and Land Use Change Pressure Hotspots are underrepresented. Gaps in eLTER RI coverage manifested in both RCP scenarios in the Southern Iberian Peninsula, Poland, and Fennoscandia. Gap locations are assumed to be consistent under various potential futures and they largely overlap with gaps already identified for current conditions.

Therefore, we recommend primarily targeting overlapping gaps, with an additional focus on underrepresented hotspot areas. Consequently, incorporating future conditions allows sharpening of the network design of RI's in-situ facilities. This is a key step to transfer local measurements into continental-scale policy support.

1 Introduction

Environmental research and monitoring infrastructures are of great importance in collecting and collating environmental knowledge, facilitating understanding of the great challenges humanity faces (Reid et al., 2010; Da Rounsevell et al., 2012; Kulmala, 2018). To scale up local data to regional, continental, or global domains and gain insight into the broader picture of human-environmental interactions, it is essential that spatially distributed research infrastructures (RIs) are well-designed regarding the geographic arrangement of in-situ facilities and their observational design.

However, spatial biases in site selection are widespread (Martin et al., 2012; Schmill et al., 2014; Václavík et al., 2016; Wohner et al., 2021; Ohnemus et al., 2024). Hence, to infer representative statements from site networks, the spatial design must be carefully crafted and biases must be identified and ideally avoided (Schmill et al., 2014; Mahecha et al., 2017; Mollenhauer et al., 2018; Ohnemus et al., 2021; Wohner et al., 2021). Several approaches were already developed and applied to estimate optimal spatial site distribution (Diogo et al., 2023), which can be generalised to approaches following either concepts of transferability (Václavík et al., 2016; Piemontese et al., 2020) or concepts of representativity (Meyfroidt et al., 2014; Schmill et al., 2014; Malek and Verburg, 2017; Mollenhauer et al., 2018; Ohnemus et al., 2021). Transferability approaches rather reveal conditions not covered by an RI, while representativity approaches elucidate unequal representations of study region conditions within an RI.

In the aforementioned studies, transferability and representativity analyses have been successfully used to analyse current conditions. However, when considering one of the 'Grand Challenges for Earth System Science', to 'develop, enhance and integrate observation systems to manage global and regional environmental change' (Reid et al., 2010), it is crucial to also consider the changes in environmental conditions over time. This is of particular importance for spatially distributed RIs designed to operate long-term observations on their in-situ facilities. Consequently, a research infrastructure should be adapted to the *emerging* challenges relevant to the associated field of study.

In the present study, the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research infrastructure (eLTER RI) was investigated regarding its fitness for the future. The emerging eLTER RI is placed on the roadmap of the European Strategy Forum on Research Infrastructures and will integrate >200 in-situ facilities into a pan-European, distributed research infrastructure. eLTER RI in-situ facilities seek to fulfil a systemic observation approach addressing all compartments of the socio-ecological realm (geosphere, hydrosphere, atmosphere, biosphere, sociosphere) (Mirtl et al., 2021) and the overarching eLTER RI strives to represent the main environmental and socio-ecological gradients of the European domain (Ohnemus et al., 2024).

Environmental and socio-ecological conditions will be altered by Global Change, manifesting *inter alia* as land use change (LUC) and climate change (Steffen et al., 2005). Over the course of the 20th century, industrialisation and development processes have greatly increased and gradually intensified humanity's land use and thus its physical impact on the Earth (Kummu et al., 2010; Krausmann et al., 2013; Steffen et al., 2015; IPCC, 2022). These trends have shaped the evolution of land systems in recent decades, and have also shaped the pressures that land use exerts on ecosystems and ecosystem processes (Erb et al., 2018; Shukla et al., 2019), including biodiversity loss and perturbation of biogeochemical cycling (Pereira et al., 2012; Newbold et al., 2015; IPBES, 2019). LUC is driven by many aspects of societal development, including urbanisation, migration, demographic and economic patterns, production and consumption relations and in particular driven by underlying policies and political developments. Thus, land use as well as its changes denote the sum of human activities.

Similarly, climate change brings notable ecological consequences. Bioclimatic classification systems reflect the adaptation of ecosystems to specific climatic regimes (Holdridge, 1947; Walter and Breckle, 1991; Rivas-Martinez et al., 2002; Metzger et al., 2013; Camara Artigas et al., 2020). Frequently used classification systems are based on 'plant functional types' (PFTs, Harrison et al., 2010, Poulter et al., 2011, Wullschleger et al., 2014), which are often used in climate models and classify plant species based on similarities in their ecosystem functions. However, the predominant vegetation types will change with future climate due to changing climatic conditions which can lead to a reduction of validity of existing bioclimatic vegetation systems (Davis and Shaw, 2001; Devictor et al., 2012; Wallingford et al., 2020). A change in the PFT renders numerous subsequent effects on all trophic levels of an ecosystem. Summarising, climate change and LUC are two key controls for ecosystem development.

For distributed research infrastructures such as eLTER RI, which is dedicated to observe the long-term development of ecosystems, changes in climate and land use pose a particular challenge. This study investigates to which extent the spatial design of the eLTER RI covers the projected ranges of climate change and LUC at the European continental scale. The study particularly emphasises areas where the anticipated pressures climate and land use change exert on ecosystems are expected to be most severe, i.e. climate and land use change hotspots. To assess the suitability of the eLTER RI for this challenge, we applied a representativity analysis as detailed in Wohner et al. (2021) with refinements by Ohnemus et al. (2021). The same methodology was already used to assess the current representativity of the eLTER RI regarding the environmental and socio-ecological gradients present in Europe (Ohnemus et al., 2024). Here, we compare the findings of Ohnemus et al. (2024) with the fitness of the eLTER RI for projected climate and land use changes.

Consequently, the analysis must achieve three objectives:

- derive ecologically meaningful metrics to quantify future climate change and LUC and identify associated hotspots,

- estimate the representation of climate change and LUC and the associated hotspots within the eLTER RI, i.e. eLTER RI's fitness for the future, and
- compare the representation of climate change and LUC with the coverage of current environmental and socio-ecological gradients

2 Material and Methods

2.1 Data

The eLTER RI is a distributed pan-European in-situ research infrastructure focusing on long-term ecological research. It seeks to provide researchers across Europe and beyond with access to long-term environmental data, facilities, and expertise. Furthermore, it aims at deriving actionable knowledge to support environmental policy makers at the local, regional and continental scale (Futter et al., 2023). The area eLTER RI strives to represent, i.e. the reference area (Figure 1), was defined in Ohnemus et al. (2024).

eLTER RI comprises a network of in-situ facilities covering a variety of habitats and ecosystems. These sites are equipped with monitoring systems and facilities to support research on all spheres of the socio-ecological system. The present study considers 204 eLTER in-situ facilities as part of the eLTER RI (Figure 1), the information on these sites was compiled by Ohnemus et al. (2024). Many of these facilities have been founded in locations where research activities have been ongoing in the past (some more than 100 years). Therefore, the spatial design and continental coverage is not a result of active planning but rather reflects local research needs.

2.2 Methods

Climate Change Pressures

We derived a metric we refer to as Climate Change Pressures, which depict a climate change compared to climatic conditions of the baseline 1971-2000 (calculation see below). To quantify the effects on ecosystems, the Holdridge Life Zone concept (HLZ, Figure S 1, Holdridge, 1947) was used. HLZs are ecological units defining conditions of ecosystem functioning (Lugo et al., 1999), which are delimited by the climatic variables annual precipitation (P), annual biotemperature (BT) and the occurrence of frost within a year (Kummu et al., 2021; Tekin et al., 2021). This allows transparent reproducibility of the classification results (Lugo et al., 1999). BT refers to the mean annual temperature after setting temperature values below 0 and above 30 °C to zero, approximating the growing season temperature (Holdridge, 1947). However, following Kummu et al. (2021) we did not implement the 30 °C cap. In the HLZ, each ecosystem is defined by a BT and P range on a binary logarithmic scale. Thus, the same change in BT or P exerts a stronger pressure on ecosystems with a low initial BT or P value. Therefore, in the HLZ data space, projected climatic changes on annual time scale can be linked to ecological effects with the BT and P Pressure metrics which are detailed below.

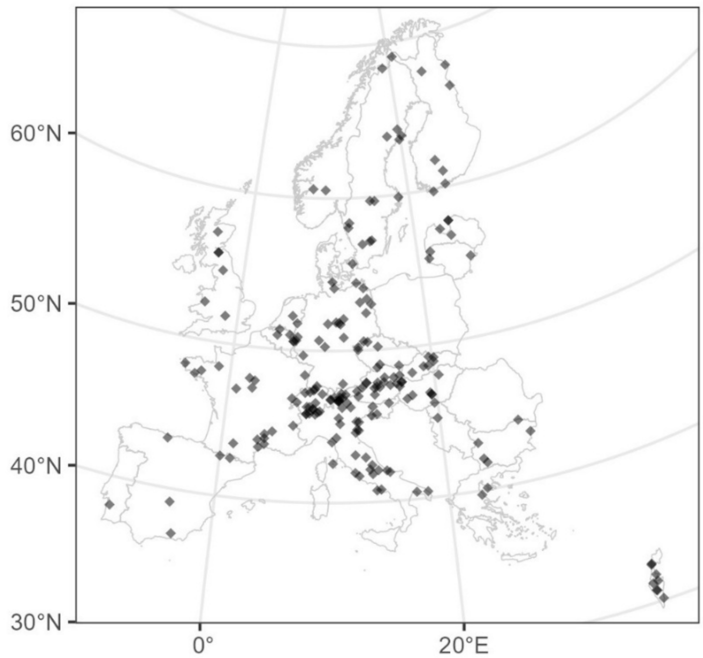

Figure 1: Map showing the geographical distribution of the eLTER RI sites as black dots. Lines delineate the reference area, i.e. the area the eLTER RI strives to represent and do not necessarily depict accepted national boundaries.

Although the HLZ concept has been shown to be a successful scheme for quantifying climate-environment feedbacks, especially on large scales (Post et al., 1982; Emanuel et al., 1985; Szelepcsényi et al., 2014; Jungkunst et al., 2021), it ignores various ecological and climatological aspects. The main criticisms voiced were (i) a supposed focus on tropical regions, (ii) an apparent inconsistency between HLZ classifications and empirical observations, (iii) not considering seasonality, (iv) failure to address transitional ecosystems (Lugo et al., 1999; Szelepcsényi et al., 2014) and, a general criticism that ecosystem classifications introduce arbitrary ecosystem boundaries (Evans, 1956). However, Holdridge (1947) explicitly included non-tropical systems in the concept, and it has been successfully applied to such ecoregions (Tekin et al., 2021) and the global scale (Jungkunst et al., 2021; Kummu et al., 2021). Targeting the second criticism, HLZs should be understood as a framework depicting predominantly occurring PFTs under certain climatic conditions and typical soils for this climate. Different manifestations of ecosystems can occur within single life zones (Lugo et al., 1999; Lin et al., 2015; Fan et al., 2017), e.g. due to unusual edaphic conditions or land management. The third criticism, not considering seasonality, is valid, since seasonal climatic patterns are a major control for emerging ecosystems. Therefore, we introduce the SPEI Pressure which depicts seasonal differences in water availability as expression of seasonal BT and P patterns (details see below). The pressure metrics are also suitable to counteract the reservation regarding transitional ecosystems and arbitrary ecosystem boundaries, since they relate to the data space of the HLZ, not to specific ecosystems. Consequently, using the BT and P Pressures derived in the HLZ framework in combination with the SPEI Pressure introducing seasonality allowed depicting anticipated stressors of ecosystems due to climate change.

Climate Data

To quantify changing BT and P we used CMIP5-projections of Regional Circulation Model (RCM) data in 0.11° spatial and monthly temporal resolution from the European domain (WRCP CORDEX, 2015) of the Coordinated Regional Downscaling Experiment (CORDEX, Giorgi et al., 2009, Gutowski Jr. et al. (2016), Jacob et al., 2014) for two representative concentration pathways (RCP): 4.5 and 8.5. Nine different simulation runs were used, based on an ensemble in Holmberg et al. (2018) (Table 1).

For each individual simulation run, we obtained bias-adjusted near-surface precipitation and bias-adjusted near-surface air temperature to calculate annual P and BT, respectively. Bias-adjusted data was chosen, as they minimise RCM-intrinsic systematic biases (Kotlarski et al., 2014; Holmberg et al., 2018).

Annual P for each year was calculated as the sum of monthly P of each cell. To obtain BT, all negative cell values of each monthly raster were set to 0 °C, and the annual mean of the resulting monthly rasters was calculated. Then, from the individual simulation runs the Model Mean (MM) annual P and BT were calculated, since MMs frequently provided better correlations to observed values than individual simulation runs (Pierce et al., 2009; Feng and Fu, 2013; Huang et al., 2016; Carrão et al., 2018).

Table 1: Simulation runs chosen in this study. Further details on the simulations can be found in Holmberg et al. (2018).

Global Circulation Model (GCM)	Regional Circulation Model (RCM)
CNRM-CERFACS-CRNM-CM5	CCLM4-8-17
CNRM-CERFACS-CRNM-CM5	RCA4
ICHEC-EC-EARTH	RACMO22E
IPSL-IPSL-CM5A-MR	RCA4
MOHC-HadGEM2-ES	CCLM4-8-17
MOHC-HadGEM2-ES	RACMO22E
MOHC-HadGEM2-ES	RCA4
MPI-M-MPI-ESM-LR	CCLM4-8-17
MPI-M-MPI-ESM-LR	RCA4
CNRM-CERFACS-CRNM-CM5	ARPEGE51
IPSL-IPSL-CM5A-MR	WRF331F
MPI-M-MPI-ESM-LR	REMO2009

The baseline climatic conditions were calculated for the years 1971 – 2000 using the same GCM-RCM combinations. Again, MM annual P and BT were calculated and averaged to express mean P and BT of the baseline period (Figure S 2).

Quantification of Climate Change Pressures

To capture Climate Change Pressures on ecosystems, the parameters BT and P Pressure were introduced. Therefore, a local linear model for each Pressure was produced. This linear model uses the baseline value and all values of the simulation period of a specific cell, with the year on the x-axis and the corresponding mean annual BT or mean annual P on the y-axis. The slope of this linear model was then used to calculate an estimate for the year 2098 for each raster cell. To relate the changes between the baseline and the year 2098 to pressures on ecosystems we computed the binary logarithm for both the baseline and the estimates. This effectively transformed these values into the HLZ data space (Kummu et al., 2021; Tekin et al., 2021). Subtracting the logarithmic baseline from the logarithmic estimates resulted in the parameters P Pressure and BT Pressure, respectively. A P or BT Pressure of 0 indicates 'no change' in P or BT. A value of +1 suggests a shift of one HLZ towards wetter or warmer conditions or -1 a shift towards dryer or colder conditions. Consequently, the P and BT Pressures relate changes in P and BT to the baseline conditions, providing a metric of ecosystem pressure.

The HLZ system allows expressing annual water availability based on annual P and BT (Holdridge, 1947; Tekin et al., 2021). However, water availability in ecosystems exerts strong seasonality, which we captured by introducing the SPEI Pressure, based on the standardised precipitation evaporation index (SPEI, Vicente-Serrano et al., 2010). The SPEI is based on a climatic water balance subtracting monthly potential evapotranspiration (PET) from monthly P, providing an adequate measure for interannual variability of water availability on timescales affected by global warming (Pohl et al., 2023a). For mean monthly P, the data described above were used, while for PET, Thornthwaite evapotranspiration was computed from the previously derived monthly BT using the R-package SPEI (Beguería and Vicente-Serrano, 2023).

This is possible, since temperatures of 0 °C and below lead to a PET of zero. Then, by subtracting PET from P a monthly water balance was derived.

For SPEI calculation, the monthly water balance values can be aggregated on different time scales. We applied an aggregation period of three months (SPEI-3) with the standard log-logistic distribution (Vicente-Serrano et al., 2010; Beguería and Vicente-Serrano, 2023). Different aggregation periods have in the past shown to describe different water reservoirs (Pohl et al., 2023b), and SPEI-3 is expected to reflect soil water. Importantly, the baseline period was also used as the calibration period for the SPEI-3.

Similar to the BT and P Pressures, SPEI Pressure indicates a change relative to the baseline 1971 - 2000. Therefore, the mean SPEI-3 value for each month during the baseline period was calculated, and the baseline range was then determined from these twelve monthly values. The baseline range describes the mean interannual variability in soil water availability for the period 1971 – 2000.

As for BT and P Pressure calculation, a local linear model was produced with the slope allowing the estimation of the SPEI-3 for the year 2098. This was performed for each month separately. Then, the range of the SPEI-3 estimates was calculated from the monthly estimates, quantifying the range of SPEI projections. The SPEI projection range measures the interannual variability in soil water availability for the year 2098.

Subsequently, the baseline range was subtracted from the projection range, resulting in the SPEI Pressure. A positive SPEI Pressure means that the range between the lowest and highest monthly SPEI increased from the baseline to the year 2098, i.e. interannual water availability becomes increasingly variable. Since interannual soil water availability patterns are an important control of ecosystems, the SPEI Pressure is another ecologically meaningful quantification of climate change.

After deriving the different Climate Change Pressures, their relationship was investigated. The BT to P Pressure ratio was computed to determine which parameter exerts greater pressure on ecosystems. RCP scenario outcomes were compared using the coefficient of determination (R^2) of a linear model of the common logarithmic BT and P Pressures. Additionally, P and BT Pressures were compared to the SPEI Pressure visually since no statistical relationship between them could be obtained.

We calculated four different measures of robustness for the Climate Change Pressures obtained. As first measure, for the BT and P Pressures the signal to noise ratio (S/N-ratio) was implemented (Christensen et al., 2019). The signal is identified as the absolute MM for RCP4.5 and RCP8.5, respectively. This was divided by the noise defined as the standard deviation of the nine individual simulation runs. Furthermore, a Tukey test on the 0.05 significance level (Mendiburu, 2021) was performed to compare the value distributions in noise- and signal-dominated areas. For this comparison, noise was defined as the noise observed under RCP4.5. While the S/N-ratio indicates whether the signal is reliable, it cannot distinguish whether the dominance of noise occurs due to differences in trends or varying magnitudes between single simulations. Therefore, as second robustness measure, we counted the number of single simulations agreeing with the algebraic sign of the MM for each cell, i.e. the single simulations agreeing with the general tendency of the MM (e.g. wetting or drying, warming or cooling).

A third robustness indicator measures the stability of trends underlying the local linear models of the BT, P and SPEI Pressures. On this account, Mann-Kendall tests indicating the significance of trends were performed (McLeod, 2011) using the data underlying the local linear models described above. For SPEI Pressure, tests were performed for each monthly local linear model.

As a fourth robustness measure, the variation between RCP scenarios for each Pressure was investigated. Therefore, the Pressure values for both scenarios were extracted for each cell. The relationship of the RCP4.5 and RCP8.5 value distributions was investigated using a linear model with R^2 as quality marker.

Land Use Change Pressure

The land use harmonization 2 (LUH2) dataset (Hurtt et al., 2020) was used to assess the pressure of projected LUC on ecosystems. These data were already updated to the CMIP6 (Eyring et al., 2016), following shared socioeconomic pathways (SSPs, O'Neill et al., 2017, Popp et al. 2017). SSP models evaluate the development of energy systems, land use, greenhouse gas emissions, and air pollutant emissions based on demographic and economic drivers (Riahi et al., 2017). Thus, assumed population, education, urbanisation and economic development are inputs for SSPs (Riahi et al., 2017). As equivalent to RCP4.5 and RCP8.5 we used SSP2 with its marker model MESSAGE-GLOBIUM and SSP5 with its marker model REMIND-MAgPIE (LUH2, 2017b, 2017a; Riahi et al., 2017), respectively. Importantly, MESSAGE-GLOBIUM and REMIND-MAgPIE are not completely harmonised, leading to different outcomes even for the same SSP (Popp et al., 2017).

LUH2 classifies twelve different land use states. A historical land use baseline was produced from a historical dataset (LUH2, 2016) for the period 1971 to 2000 by cell-wise calculating the mean of the share of each land use state of the single raster layers available within this period. Likewise, the projected future state was derived by calculating the mean share of each cell for each land use state in the period 2091 to 2100. Compared to using a single year, the effects of crop rotation can thus be neglected. The resulting states were then cropped (Hijmans, 2023a) to the European domain as defined in CORDEX (WRCP CORDEX, 2015).

To quantify Land Use Change Pressure, the difference of the land use share between the future and baseline periods was calculated for each land use state. Changes in one direction for one land use state are equalled by changes in the opposite direction for at least one other land use state (unit sum constraint). Consequently, to quantify the magnitude of Land Use Change Pressure all positive values were summed up. However, the twelve land use states included in LUH2 do not always encompass all land cover manifestations of a cell (e.g. water bodies are not represented). To correct this effect, the result was divided by the sum of the single baseline land use states.

This leads to a metric where higher values depict stronger pressures due to LUC. The relationship between RCP4.5 and RCP8.5 values was investigated similarly as for the Climate Change Pressures.

Hotspots of Climate and Land Use Change Pressure

To identify Climate and Land Use Change Pressure Hotspots, the datasets were masked with the reference area (Figure 1) and z-transformed. z-Transformation expressed each cell value in unit standard deviation from the mean (Tachtsoglou and König, 2017). We classified hotspots as all z-transformed cell values of +1 or more. Using absolute Pressures ensured regarding positive and negative Pressures of same magnitude similarly.

Representation of Global Change aspects by the eLTER Research Infrastructure

The eLTER RI's representation of Global Change aspects, i.e. its "Fitness for the Future", was estimated using the representativity analysis (Wohner et al., 2021), with adaptations by Ohnemus et al. (2021). This analysis compares the distribution of *reference parameter* values in the defined reference area (Figure 1) with the value distribution of these parameters in the areas covered by in-situ facilities of an RI. This analysis enables the identification of regions where reference parameters are underrepresented due to the spatial distribution of in-situ facilities.

The *reference parameters* used in the present study are the Climate and Land Use Change Pressure data (sections Quantification of Climate Change Pressures and Land Use Change Pressure) which underwent geoprocessing before the representativity analysis: First, the datasets were projected (Hijmans, 2023b) to the equal-area Mollweide projection and masked with the reference area. Second, the Land Use Change Pressure dataset was resampled to the same cell size as the Climate Change Pressures using a bilinear interpolation (Hijmans, 2023b). Third, the Climate and Land Use Change Pressure values were reclassified (Hijmans, 2023b) into ten categories based on equal-interval quantiles (Table S 1). Where negative

Pressures occurred (i.e. SPEI and P Pressure), the closest quantile threshold was set to zero for clear distinction between negative and positive values.

The representation of pressures within the eLTER RI facilities was then analysed. Therefore, a chi² test of homogeneity was performed comparing the distribution of values on eLTER RI facilities with the distribution of values within the reference area, providing a p-value for each category. The p-values range from -1 (underrepresented) to +1 (overrepresented) on a continuous scale. Following Wohner et al. (2021) the reference parameters were reclassified. Thus, each reference parameter category was replaced with the respective p-value. Consequently, the value for each raster cell now indicates its representation within the eLTER RI. The reclassified reference parameters are then summarised to the so-called Aggregated Representedness (AR, Wohner et al., 2021). Climate and Land Use Change Pressures are regarded as equally important challenges for the eLTER RI. Therefore, Land Use Change Pressure was multiplied with three to contribute to the AR with the same weight as the Climate Change Pressures which consist of three elements, the P, BT and SPEI Pressures. Thus, the final AR dataset has a continuous value range of -6 to +6, respectively describing under- and overrepresentation for all reference parameters. The AR is then overlain with a hexagon grid (Strimas-Mackey, 2020) of 10,000 km² cell size and the mean AR value of all raster cells within a hexagon grid cell was assigned. Based on this value, so called *priority regions* were identified (Table 2). Priority refers here to the priority for the establishment of additional in-situ facilities within an area. This allows prioritising the establishment of additional sites to optimise the geographical design of the RI.

Software Used for Statistical Analyses and Visualisation

All analyses were conducted in R (R Core Team, 2023, Table S 2), with all illustrations based on the package ggplot2 (Wickham, 2016). All netcdf data were handled with the package ncdf4 (Pierce, 2023). R scripts and data associated with this work are available online (Ohnemus, 2024). Most maps were visualised with QGIS v. 3.26.0 (QGIS.org, 2023).

Table 2: Threshold values for the reclassification of the mean aggregated representedness into priority regions as introduced by Wohner et al. (2021).

Mean Agg. Representedness	Priority for Network Extension
-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

3 Results

3.1 Climate Change Pressures

Biotemperature Pressure

Due to a high correlation between the scenarios (R^2 = 0.93) the spatial patterns between scenarios were similar (Figure 2a). However, all cells experience higher BT Pressures at RCP8.5. On average the BT Pressure experienced is almost double that of RCP4.5 (Figure 2c). Highest BT Pressures were found for parts of Iceland, Northwestern Russia, the Alps, the Pyrenees and the Scandes, lowest BT Pressures in Sweden and a vast region from Southern Finland in the North to the Black Sea in the South and Poland in the West to Russia in the East (Figure 2a). Thus, while the spatial patterns of expected ecological pressure due to BT change are similar in both scenarios, the ecological pressure under RCP8.5 will be more severe.

Noise dominance occurred only in few cells of Eastern Europe where BT Pressures were low (Figure 2, Figure S 3b, d). In these areas some simulations disagreed with the MM trend (Figure S 4, Figure S 5) projecting lower BT than for the baseline period.

Precipitation Pressure

A strong correlation between the RCP scenarios was observed (R^2 = 0.87), leading again to similar spatial patterns between scenarios (Figure 3). A notable meridional gradient of P Pressures was observed, with negative P Pressures (i.e. decreased rainfall) in the Mediterranean and Southern Europe, P Pressures close to 0 (i.e. no change in rainfall) in a distinct stretch from Western France via the Alps and Black Sea to Russia, and positive P Pressures (i.e. increased rainfall) north of that strip. Higher P Pressures were found for 75.59\% of cells under RCP8.5, and 94.49\% revealed a greater absolute P Pressure, suggesting more extreme values than in the RCP4.5 scenario for almost all cells (Figure 3c). Thus, while negative, low or positive P Pressures can be expected in the same regions under different scenarios, the pressures experienced by ecosystems from P changes will be notably stronger under RCP8.5.

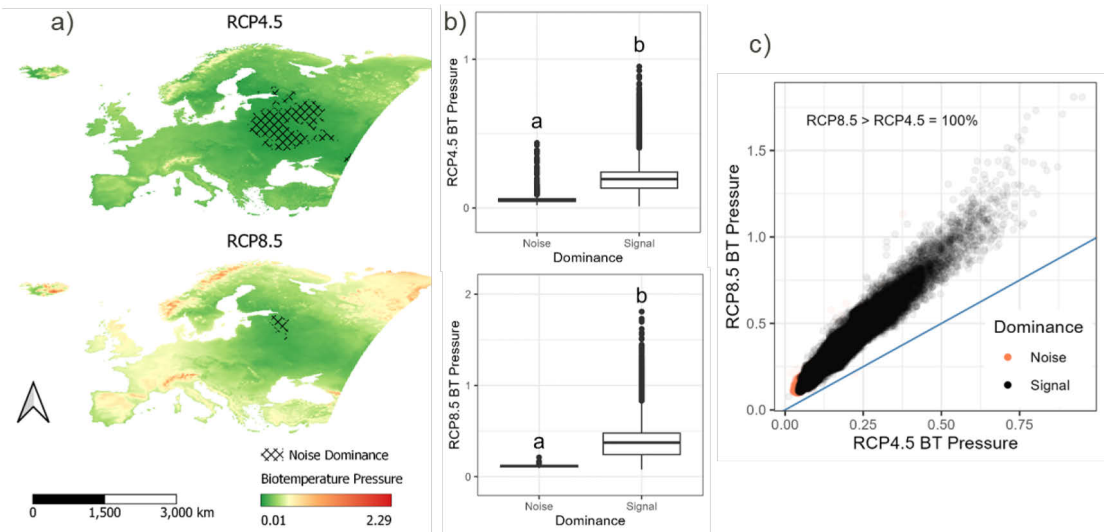

Figure 2: (a) Biotemperature (BT) Pressure for respectively the RCP4.5 and RCP8.5 scenarios. The colour scale diverges around 0.5. Hatching depicts areas where the noise is stronger than the signal. (b) Boxplots indicating the BT Pressure value distribution where the noise is stronger than the signal and vice versa for the RCP4.5 and RCP8.5 scenarios. The bold horizontal line indicates the median, hinges the 25th and 75th percentile, the whiskers extend 1.5 times the interquartile range from the hinges and the bold points are outliers. Different letters reveal significant differences. (c) Scatterplot of the BT Pressure values of each raster cell for the RCP8.5 and RCP4.5 scenarios, the blue line is the 1:1 line. Orange colours depict noise dominance, black colours signal dominance.

For P Pressures noise dominance was more widespread (Figure 3a), especially P Pressures close to 0 or without significant trends were accompanied by noise dominance (Figure S 3a, c). Due to the generally lower P Pressure values under RCP4.5 noise dominance extended further South and North. Nonetheless, for RCP4.5 and RCP8.5 respectively 87.7 % and 92 % of cells agreed with the MM trend (Figure S 4, Figure S 5).

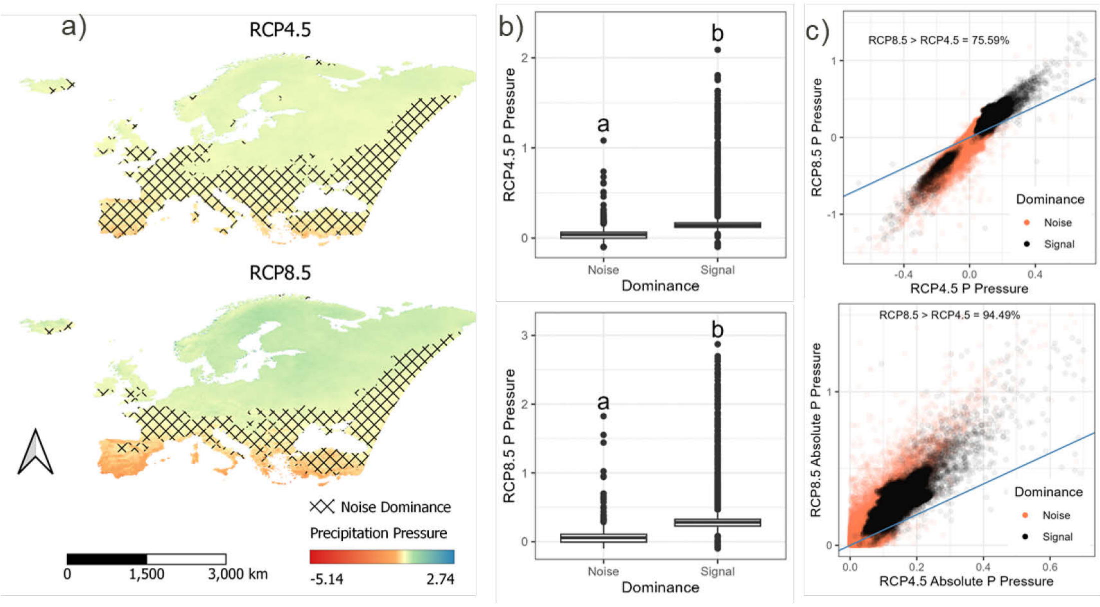

Figure 3: (a) Precipitation (P) Pressure for respectively the RCP4.5 and RCP8.5 scenarios. The colour scale diverges around 0. Hatching depicts areas where the noise is stronger than the signal. (b) Boxplots indicating the P Pressure value distribution where the noise is stronger than the signal and vice versa for the RCP4.5 and RCP8.5 scenarios. The bold horizontal line indicates the median, the hinges the 25th and 75th percentile, the whiskers extend 1.5 times the interquartile range from the hinges and the bold points are outliers. Different letters reveal significant differences. (c) Scatterplot of the P Pressure values of each raster cell for the RCP8.5 and RCP4.5 scenarios. The upper panel shows the determined P Pressure, the lower panel the absolute P Pressure, the blue line is the 1:1 line. Orange colours depict noise dominance, black colours signal dominance.

The ratio of BT to P Pressure again produced consistent spatial patterns between scenarios (Figure 4) with most regions experiencing higher BT than P Pressure (Figure 4b). The same trend in both scenarios was observed for 89.7 % of cells and the log-transformed datasets correlate well (R^2 = 0.60, Figure 4c). Highest BT-P-ratios were found where P Pressure was noise-dominated and in the Scandes, Iceland and the UK. Lowest BT-P-ratios were found in Eastern Europe and along the Mediterranean coastline.

SPEI Pressure

For SPEI Pressure a high correlation (R^2 = 0.65) with accordingly similar spatial patterns between the scenarios was observed (Figure 5). However, this correlation is weaker than for the BT and P Pressure leading to less consistent spatial patterns. Most cells experienced positive SPEI Pressures, i.e. soil water availability throughout the year becomes increasingly variable due to dry months getting drier and/or wet months getting wetter. Only 27.76 % and 13.67

% of cells for RCP4.5 and RCP8.5, respectively, revealed a negative SPEI Pressure. SPEI Pressure was higher for 88.53 % of cells under RCP8.5, thus water availability will vary more strongly within a year than for RCP4.5. The absolute SPEI Pressure shows that this pattern holds true for negative SPEI Pressures, i.e. where interannual soil water availability becomes less variable, it is more pronounced for RCP4.5. Thus, interannual water availability generally becomes more variable under RCP8.5.

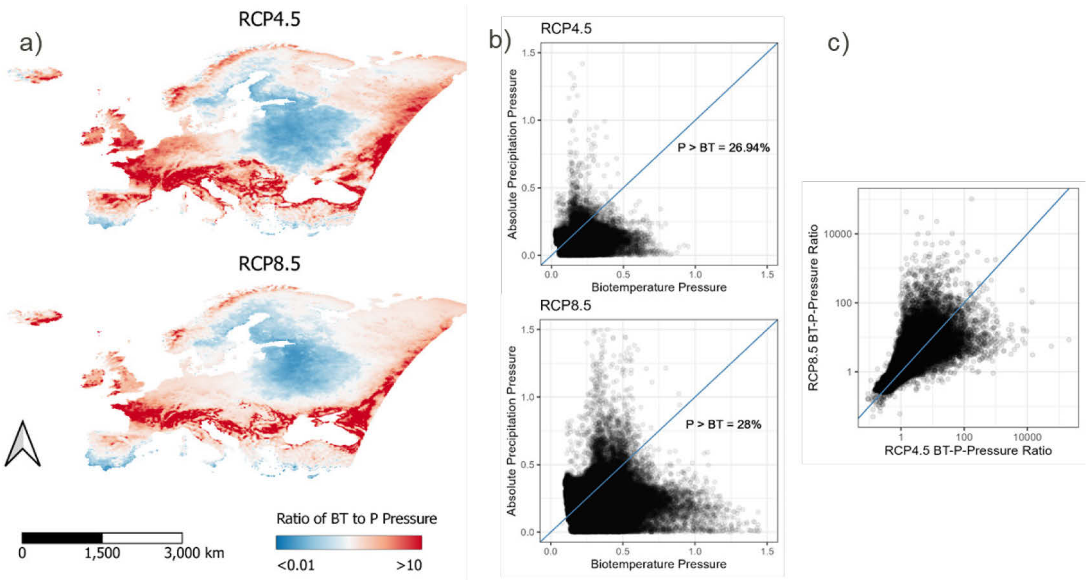

Figure 4: (a) Ratio of Biotemperature (BT) to absolute Precipitation (P) Pressure for respectively the RCP4.5 and RCP8.5 scenarios. The colour scale diverges around 1, white colours indicate ratio 1, red colours higher BT than P Pressure and blue colours higher P than BT Pressure. Stronger saturation of these colours shows stronger dominance of the respective Pressure. (b) Scatterplot with dots representing the BT Pressure and absolute P Pressure for each cell. Blue line depicts the 1:1 line. (c) Depicts a scatterplot with the logarithmic BT-P ratio for both scenarios.

The development of monthly SPEI values did not necessarily follow a significant trend (Figure S 6). Similarly, the minimum and maximum SPEI values computed for 2098 did not necessarily deviate from the baseline value (Figure S 7). Thus, even when notable SPEI Pressures were observed, often either the driest month became drier or the wettest month wetter, but not both simultaneously. The SPEI Pressure did not correlate with the P and BT Pressures of the respective RCP scenario, indeed, for the same BT or P Pressure a wide range of SPEI Pressures emerged (Figure S 8).

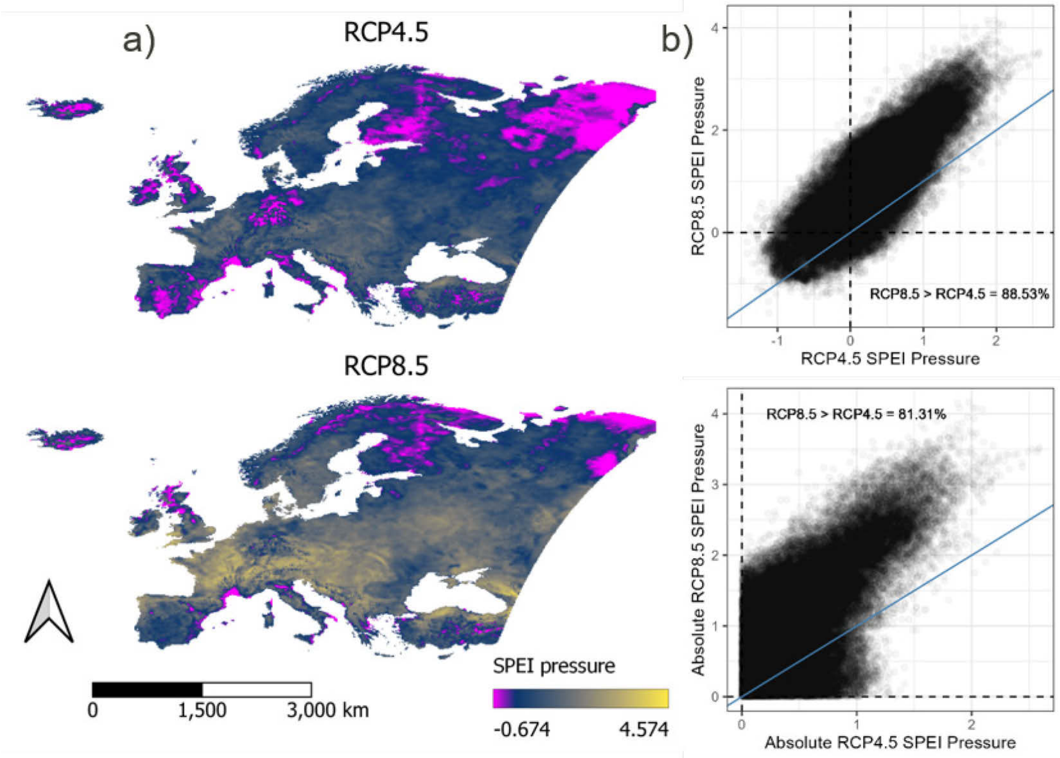

Figure 5: (a) SPEI Pressure for the RCP4.5 and RCP8.5 scenarios. Colour scale diverges around 2, yellow colours illustrate values > 2, blue between 0 and 2, pink depicts negative SPEI Pressure. (b) Scatterplot with dots representing the RCP4.5 and RCP8.5 SPEI Pressures for each cell. Blue line depicts the 1:1 line. Dotted lines depict 0.

3.2 Pressure from Land Use Change

The spatial patterns of projected Land Use Change Pressure were consistent between scenarios (Figure 6, R^2 = 0.82), with notable regional differences. Little or no Land Use Change Pressure was observed for larger parts in Fennoscandia and Iceland, while for vast regions of Russia and Finland cells underwent a substantial change of land use (Figure 6a). Strong Land Use Change Pressure is also projected for Southern Norway, Turkey, Eastern Europe, Southern Portugal, parts of Spain as well as the Alps, Apennines, Dinarides and Carpathians. Since Land Use Change Pressure is stronger under RCP4.5 for most cells (Figure 6b) strong Land Use Change Pressure was additionally observed in the Balkan, Ukraine, Western France, the UK and Ireland. Despite the high correlation, different trajectories in the relationship of RCP4.5 and RCP8.5 emerged.

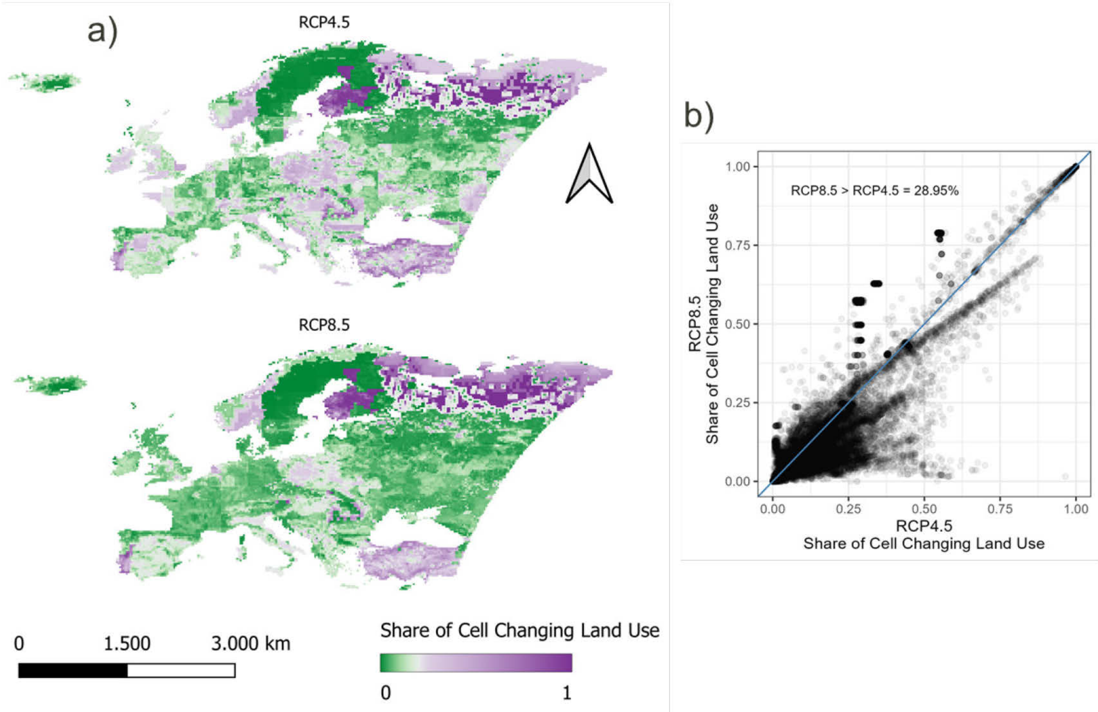

Figure 6: (a) Land Use Change Pressure depicted as share of cell changing land use between the baseline period 1971–2000 and the future period 2091–2100 for the RCP4.5 and RCP8.5 scenarios. The colour scale diverges around 0.2, with green and purple cells showing respectively lower and higher land use change. (b) Scatterplot with dots representing the RCP4.5 and RCP8.5 Land Use Changes for each cell. Blue line depicts the 1:1 line.

3.3 Hotspots of Climate and Land Use Change Pressure

Hotspot locations were very consistent for each Pressure independent of scenario (Figure 7). For BT Pressure, Hotspots were most pronounced in mountain ranges, but were additionally found in the Iberian Peninsula, Scotland and Italy. For P Pressure, Hotspots were located in northern Scandinavia and the Southern Mediterranean. For SPEI Pressure, Hotspots were generally observed in a band through Central Europe from West to East, with additional Hotspots in Denmark, the UK and the Northern Iberian Peninsula. Land Use Change Pressure Hotspots were located in Finland, Norway, Poland, Romania, Austria, the Netherlands, the UK and Portugal. Hardly any overlap between Hotspots was observed.

3.4 Representation of Climate and Land Use Change Pressures through the eLTER RI

In the following analysis the geographical distribution of projected pressures was compared with that on eLTER RI facilities (see subsection Representation of Global Change aspects by the eLTER Research Infrastructure, Figure 8). The general objective of the representativity analysis is to identify regions where expected Pressures are underrepresented in the existing geographical distribution of eLTER RI. These underrepresented areas can be interpreted as high priority areas for future network expansion. Conversely, regions where the investigated Pressures are well represented in the existing network are identified as low or medium priority areas for network expansion.

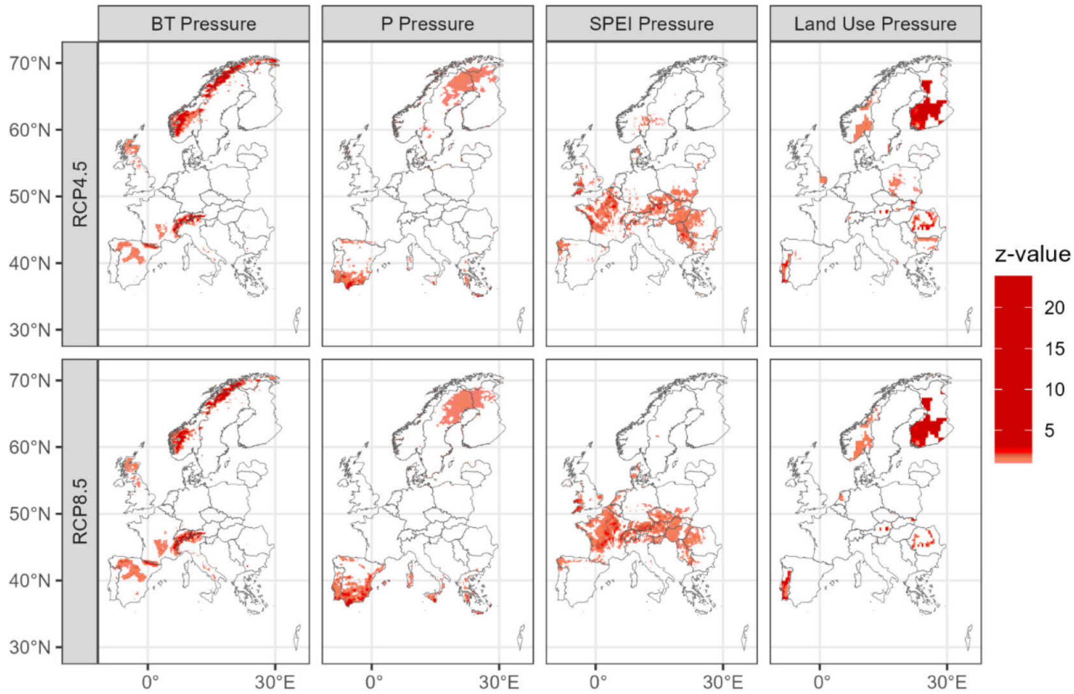

Figure 7: Hotspots computed from the Biotemperature (BT), Precipitation (P), SPEI as well as Land Use Change Pressure datasets for the RCP4.5 (top panels) and RCP8.5 (bottom panels) scenarios. Hotspots are defined as all cells with a value of +1 or higher after z-transformation. As background the reference area is illustrated. Map lines delineate study areas and do not necessarily depict accepted national boundaries. Colour scale saturation increases step-wise with every 12.5% of the dataset.

The regions being subjected to highest BT Pressures were overrepresented, meaning eLTER RI facilities cover these regions more often than their value distribution suggested. These highest BT Pressures consistently occurred in the Scandes, the Alps, the Pyrenees, the Dinarides, the Apennine and Northern Scotland. Contrary, areas experiencing lowest BT Pressures were underrepresented, i.e. they are less covered than the value distribution

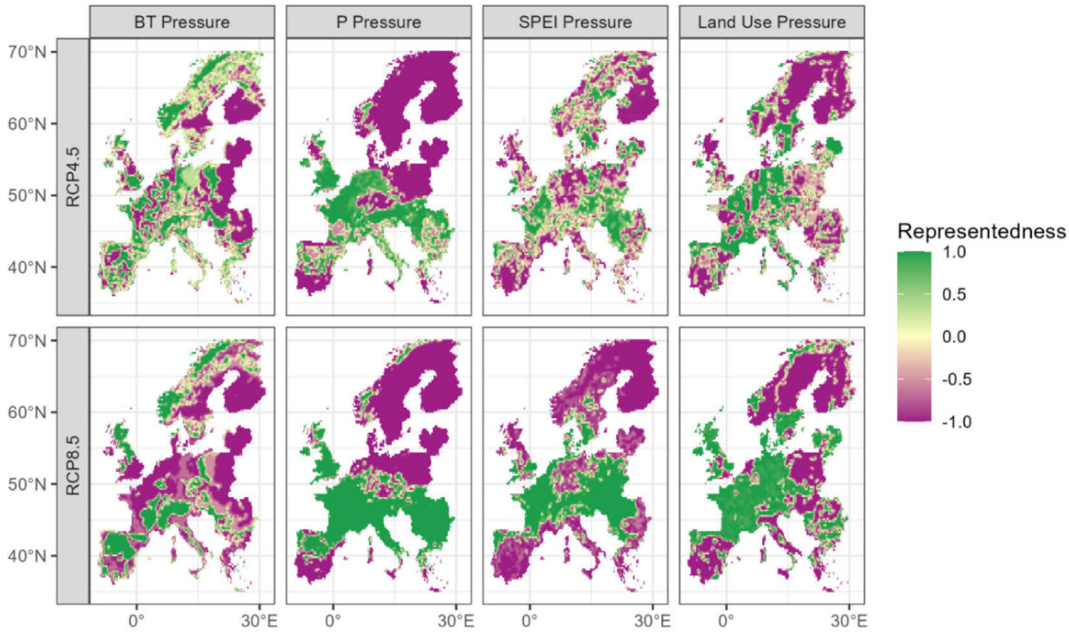

Figure 8: Geographic Representedness for the Biotemperature (BT), Precipitation (P), SPEI and Land Use Change Pressures for RCP4.5 (top panels) and RCP8.5 (bottom panels). The colour scale diverges around 0, purple colours depict underrepresentation, green colours overrepresentation.

suggested. Spatially, underrepresentation of BT Pressures was observed in vast parts of Sweden and Finland and throughout Eastern Europe. For P Pressure, both areas with most negative and most positive P Pressure were underrepresented, while regions with very low projected changes in P (P Pressures around 0) were overrepresented in both scenarios. Underrepresented areas were mainly located in the southern Mediterranean, Scandinavia, Finland and North-Eastern Europe. Regarding SPEI Pressure, highest pressures were overrepresented and lowest underrepresented in both scenarios. SPEI Pressures overrepresentation was located in a band from West to East through Central Europe, while underrepresentation was especially pronounced in Southern Finland, Scotland, Germany and the Mediterranean. For Land Use Change Pressure, both the regions with highest and lowest projected values were underrepresented in both scenarios. Overrepresentation of Land Use Change Pressure is found for a band through Western and Central Europe, while the Iberian Peninsula and parts of Northern and Eastern Europe are underrepresented. Notably, all categories of Climate and Land Use Change Pressures were covered by eLTER RI sites.

Due to the identified underrepresentation regions with high priorities for densifying the eLTER RI network emerged. Regions of high and very high priority for the establishment of additional eLTER RI sites were found in the North in Scotland and Fennoscandia, in the East in Lithuania, Poland, Romania and Bulgaria as well as along the Mediterranean in Portugal, Spain and Greece (Figure 9a). For RCP8.5, contrary, Scotland, Romania and Bulgaria are not of high priority, while along the Mediterranean, in Fennoscandia and in Poland the priority is increased (Figure 9b). Occasionally, high priorities were observed scattered along the edges of the reference area in both scenarios. Lowest priorities were persistent from Southern Sweden in the North to Northern Italy in the South and Northern Spain in the West to Slovakia in the East, irrespective of the scenario. A weak correlation between scenarios was observed (R^2 = 0.38).

The share of well represented regions (low and medium priority for network expansion) is greater under RCP4.5 than RCP8.5, irrespective whether Land Use Change Pressure was included in the analysis or not (Figure 10). Combining Land Use and Climate Change Pressures improved the representation of RCP8.5 compared to considering Climate Change Pressures alone. Nonetheless, an anticipated future under RCP4.5 is better represented within eLTER RI.

4 Discussion

4.1 Climate Change Pressures and their Hotspots

The projected BT Pressures (Figure 2) align with the projections for global warming and the temperature increase in Europe (IPCC, 2023). Strongest warming in Eastern Europe and the Mediterranean was expected before (Lionello and Scarascia, 2018), with notably enhanced local warming towards the north in winter (Dosio and Fischer, 2018; Kjellström et al., 2018; Schaller et al., 2018; Teichmann et al., 2021). Other works suggested strongest increase of heatwaves over the Mediterranean and Scandinavia (Forzieri et al., 2016; Abaurrea et al., 2018; Dosio and Fischer, 2018; Rohat et al., 2019), with Southern and Central European cities especially subjected to these events (Guerreiro et al., 2018; Junk et al., 2019). While extreme heat events are not specifically considered in the present study, their effects do influence the determined MM values.

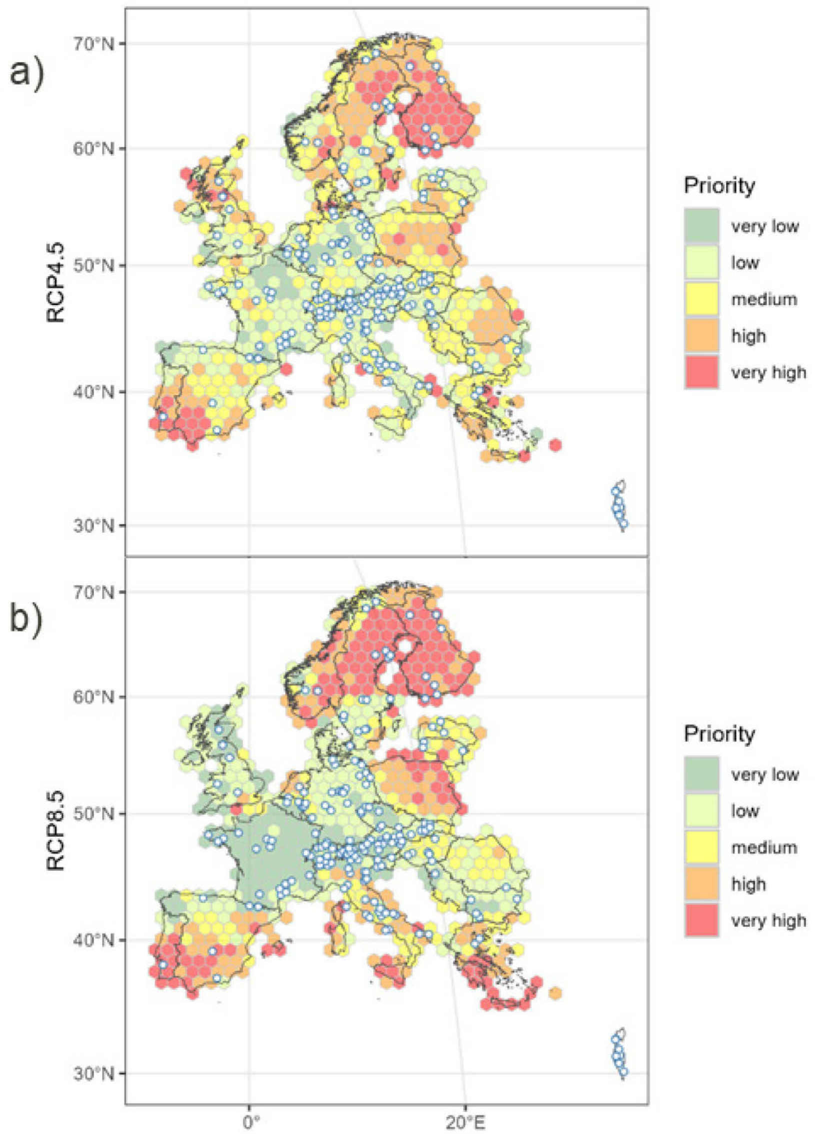

Figure 9: Priority for the establishment of new sites in the eLTER RI regarding Climate and Land Use Change Pressures for (a) the RCP4.5 scenario and (b) the RCP8.5 scenario. Hexagon colours depict the priority, white dots the eLTER RI in-situ facilities analysed. As background the reference area is illustrated. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

Expressing warming relative to baseline temperatures as BT Pressure suggests that the Mediterranean, Northern and Easternmost Europe are likely subjected to most notable ecological consequences due to rising temperatures. The BT Pressure Hotspots were especially the high altitudes (Figure 2, Figure 7). The BT Pressure results indicate that the projected warming will have a lesser ecological impact on most of Eastern Europe compared to other regions. This contrasts with Lionello and Scarascia (2018), who observed significantly stronger effects. However, Lionello and Scarascia (2018) regarded the period of 1901 to 2100, thus a large part of the signal observed in their study is attributed to a historical period which was not regarded in the present study.

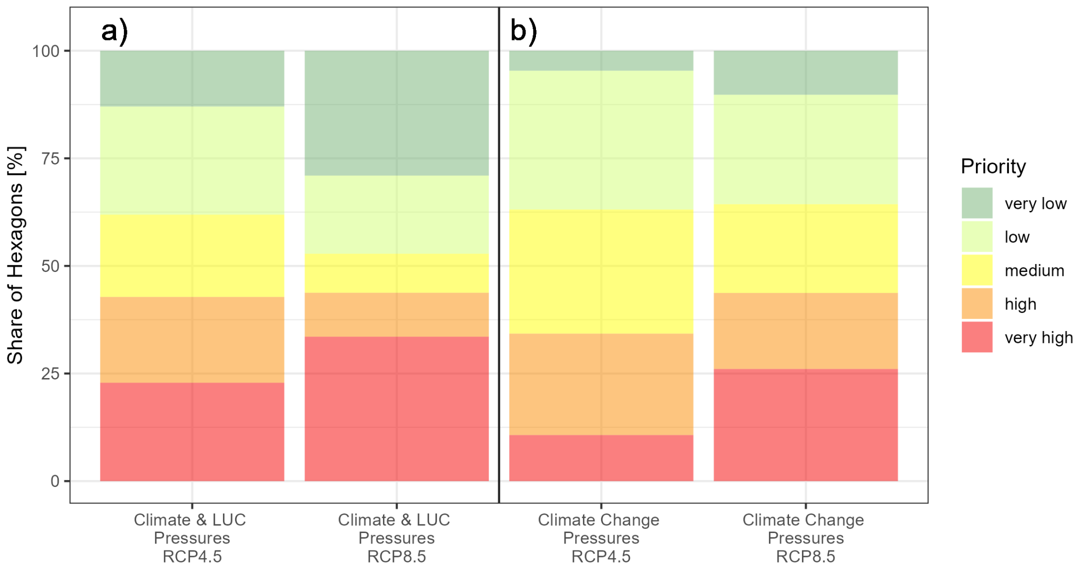

Figure 10: Barplots indicating the share of hexagons of each priority within the priority regions datasets for RCP4.5 and RCP8.5: (a) for the Climate Change Pressures and the triple-weighted Land Use Change (LUC) Pressure and (b) for the Climate Change Pressures only.

Regarding P changes, a meridional gradient over Europe was identified before, with increasing P in the North and decreasing P in the South (IPCC, 2023). This gradient is also pronounced when expressing P changes as P Pressure (Figure 3). Drying in southern Europe was found to be consistent among models (Russo et al., 2013; Hertig and Tramblay, 2017; Guerreiro et al., 2018; Raymond et al., 2019), while for Western and Central Europe, in

CMIP5 projections a wide range from hardly any trend to very strong drying is known (Vogel et al., 2018). Previous quantitative estimations of climate change features in Eastern Europe were of low confidence due to limited GCM/RCM runs and limited evaluation of model performance in this region (Partasenok et al., 2015; Kattsov et al., 2017). Stronger deviations between single model runs regarding P projections were frequently observed (Faggian, 2021; Adib et al., 2022) and explain the more widespread noise dominance for P Pressure (Figure 3). Importantly, on average, hardly any P change is projected for these areas (Figure 3, Figure S 3), thus even slight deviations of single models can lead to noise dominance and even different trends (Figure S 4). Thus, MM values close to zero with noise dominance still appear reliable.

Importantly, P changes over Europe are subjected to pronounced seasonality (IPCC, 2023), which is reflected in the SPEI Pressure (Figure 5). Indeed, regarding seasonality is of great importance, since for the same P and BT Pressures, respectively, the SPEI Pressure can differ strongly (Figure S 8). For Southern Europe, it is expected that there will be practically no change in water availability during winter, but a decrease in summer P (Jacob et al., 2018; Lionello and Scarascia, 2018) will lead to an increase in ecological drought occurrence (IPCC, 2023). Since water is already scarce in this region in summer, accordingly SPEI Pressures are close to 0 or slightly negative. Also, for Western and Central Europe a decrease in summer water availability is expected (Jacob et al., 2018; Lionello and Scarascia, 2018), which will increase droughts with medium confidence by mid-century and high confidence by the end of the century (IPCC, 2023). In this region increasing winter P is projected, accordingly the SPEI Pressure suggests a strong increase in seasonality of water availability. In Northern Europe, vast areas reveal negative SPEI Pressure. This is consistent with the projection of higher water availability in driest months (Spinoni et al., 2018) while no clear future trend for the rest of the year is observed (IPCC, 2023). For Eastern Europe increases in winter precipitation are projected (Jacob et al., 2018; Lionello and Scarascia, 2018), with low confidence in further seasonality projections (IPCC, 2023). This again leads to rather high SPEI Pressures. In brief, the SPEI Pressures obtained agree well with findings of previous studies.

Importantly, annual spatial patterns were more consistent between scenarios than seasonal ones (Figure 2, Figure 3, Figure 5). This indicates that even for future pathways aligned with CMIP6 (e.g. RCP7.0 or RCP6.0) similar spatial patterns on annual scale can be expected, but with differing magnitudes of pressures on ecosystems. Seasonal spatio-temporal patterns might be subjected to greater differences. Summarising, Climate Change Pressure Hotspots on annual timescale were found especially in highly elevated areas for BT and in the Mediterranean, Northern Sweden and Finland for P (Figure 7). On seasonal timescale, Hotspots are located mainly in Central Europe. These patterns agree well with the literature, but we introduced a novel metric translating climatic changes according to the prevalence of PFTs to pressures on ecosystems.

4.2 Choice of Baseline

On multi-decadal timescales, the manifestations of climatic parameters can change dramatically (Legates and Willmott, 1990). Consequently, different multi-year periods can lead to regionally differing climatic baselines (Hulme and New, 1997; Visser et al., 2000) and hence to different conclusions derived from climatic data (Baker et al., 2016). The baseline period from 1971 – 2000 used for the present study misses recent increases in global temperature and spatio-temporal precipitation and temperature shifts (Ma et al., 2021; Daramola and Xu, 2022; Yuan et al., 2023). Nonetheless, this baseline was chosen since i) CORDEX, which provided the data for the climate scenarios, did not provide historical data from the year 2001 onwards and ii) other historical datasets covering the years 2001 - 2020 could introduce data inconsistencies between the baseline and the scenario periods.

Furthermore, this work aims to create a new perspective on the representativity of the eLTER RI. While a previous study took the *current* perspective on relevant environmental and socio-ecological gradients in Europe (Ohnemus et al., 2024), this study takes the 'future' perspective and considers the representativity of eLTER RI to address Global Change research questions. The reference datasets chosen to elucidate current gradients (Ohnemus et al., 2024) assume a 'static' state. Therefore, the present study uses a more 'conservative' baseline of 1971-2000, which aligns better with the temporal reference used in the previous study.

4.3 Land Use Change Pressure

Land Use Change Pressure revealed two marked differences to the Climate Change Pressures. First, the relationship between the scenarios followed several different trajectories (Figure 6b) instead of just one. The SSPs focus on the variability of future socio-economic drivers including several sources for diverging land-use futures (O'Neill et al., 2016; Riahi et al., 2017). Thus, assumptions for societal development differed within the European domain. Importantly, SSPs are based on qualitative narratives, which would benefit from extended assumptions for more spatially precise LUC analyses (van Ruijven et al., 2014). These differing assumptions led to sharp shifts in Land Use Change Pressure observed along national borders between e.g. Portugal and Spain, Norway and Sweden or Russia and Finland. While SSPs assume differences in regional regulations and global governance (O'Neill et al., 2017), national policies are not mentioned as explicit input for LUH2. Therefore, sharp boundaries between countries cannot be explained by national policies alone. Indeed, distinct Land Use Change Pressure boundaries were also observed within countries. For example, in Finland, Land Use Change Pressure ranges from 0 to 100% of a cell. The different Land Use Change Pressure trajectories between scenarios suggest a varying response in Land Use Change Pressure with different climate forcing scenarios.

The second marked difference relates directly to the different RCPs: Although stronger climatic changes are expected in RCP8.5, the projected Land Use Change Pressure is stronger in RCP4.5 (Figure 6). RCP4.5 is based on the assumption that the world follows a path in which social, economic and technological trends do not differ markedly from historical patterns. In contrast, RCP8.5 is driven by the economic success of both industrialised and less industrialised economies. Thus, in RCP8.5 the extent of agricultural land stabilises due to agricultural production shifting from extensive to more intensive management (Popp et al., 2017). Contrary, under RCP4.5 agricultural land can expand. Generally, most LUC can be attributed to agricultural land (Rounsevell et al., 2006). Thus, without a metric accounting for changes in land use intensity, Europe is affected by stronger Land Use Change Pressure under RCP4.5. We are currently not aware of any data projecting land use intensity. However, a metric that accurately represents the pressure of land use change should entail both land use intensity and LUC.

Therefore, while with P, BT and SPEI three aspects summarise the pressures of climate change on ecosystems, in this study Land Use Change alone summarises direct human pressures on ecosystems. Consequently, Climate and Land Use Change Pressures should enter a representativity analysis with the same weight to encounter the second aim of this study: assessing eLTER RI’s fitness for the future.

4.4 eLTER RI's Fitness for Future

Ohnemus et al. (2024) identified gaps in coverage of current environmental and socio-ecological gradients of Europe. They defined gaps as clusters of regions with very high priority for the establishment of additional sites, including adjacent high priority regions. These gaps are areas where infrastructural expansion is most effective in improving the representativity of the eLTER RI. Given the historical 'bottom-up' development of the eLTER RI, which took place independently of questions of representativity in the European context (Mirtl et al., 2018), a spatial bias regarding the representation of climate and land use change was expected.

Following the same definition, three gaps regarding eLTER RI's representation of projected climate and land use change were identified in this study. For RCP4.5, a *Nordic Gap* manifested, encompassing Finland, Sweden and Norway, an *Eastern Gap* manifested in Poland and an *Iberian Gap* manifested in the South of Portugal and Spain. For RCP8.5, again a *Nordic Gap* manifested encompassing Finland, Sweden and Norway, an *Eastern Gap* was observed in Poland and Lithuania and a *Mediterranean Gap* extended along the Southern Mediterranean from Portugal all the way to Greece. Gaps overlapped in most areas for both scenarios, e.g. the South of Portugal and Spain, in Poland, Finland, Sweden, and Norway. These gaps can be assumed to be consistent for a variety of potential futures, since RCP4.5 and RCP8.5 are based on widely differing assumptions (Hausfather, 2019). Thus, additional in-situ facilities are desirable within gaps to improve the suitability of eLTER RI for ecosystem studies in times of Global Change, regardless of the RCP.

The persistence of gap locations between scenarios is based on the similar spatial patterns found for individual reference parameters, which differed mainly in their magnitudes between scenarios. Especially the observed pressure hot spot locations were remarkably persistent (Figure 7). Indeed, if the individual reference parameters would correlate perfectly between scenarios, the exact same priority regions map would be produced for a given site network.

Thus, while the persistence of gap locations is, in this case, related to the persistence of spatial patterns in the reference parameters, the occurrence of areas with a very high priority for the establishment of additional in-situ facilities itself indicates a strong spatial bias of the eLTER RI site network.

A lack of sites was observed in both scenarios in areas with low BT Pressure, i.e. in coastal Mediterranean regions, Sweden and Eastern Europe. Also, regions with most positive and most negative P Pressures were underrepresented (Figure S 9), due to only few sites in Scandinavia and the Mediterranean, respectively. These regions were identified as P Pressure Hotspots (Figure 7, Figure 9). For RCP4.5 negative SPEI Pressures were underrepresented (Figure S 9). They again mainly occurred in the Mediterranean, and also in the UK and parts of Germany, despite a high site density here, suggesting that the lack of sites in the Mediterranean drives this underrepresentation. For RCP8.5, the lack of sites in the Mediterranean, northern UK and Scandinavia, where SPEI Pressures are low, drives underrepresentation. The underrepresentation of highest Land Use Pressure, including its Hotspots, is again related to a lack of sites in Scandinavia, especially Finland, and the Mediterranean, especially Portugal. Under RCP8.5, mainly more pronounced underrepresentation regarding the BT Pressure and Land Use Change Pressure led to the increased extent of the "*Mediterranean" Gap* (Figure 9), while increased underrepresentation of the BT and SPEI Pressures led to a more pronounced *Nordic Gap.*

However, the spatial bias of the eLTER RI is most pronounced for the Alps with an exceptional high density of in-situ facilities. This forces the overrepresentation of highest BT Pressures (Figure S 9), and therefore of BT Pressure Hotspots, and of high SPEI Pressures. However, in certain BT Pressure hotspot regions, e.g. the Scandes and the Pyrenees, eLTER RI sites are scarce (Figure 1). SPEI Pressure Hotspots were generally overrepresented within the eLTER RI, due to a rather high site density in Central and Western Europe. Despite this pronounced bias, all categories of investigated Climate and Land Use Change Pressures were covered by the eLTER RI (Figure S 9).

The representativity of the geographical design of an in-situ RI cannot be assessed solely based on the occurrence of gaps, other factors should be considered as well. It should be noted that this study did not explicitly include climate extreme events as a layer of information that the eLTER RI should represent. However, size distribution characteristics of climate extremes influence their representation in distributed RIs (Mahecha et al., 2017). Hence, in addition of the representation of Climate Change Pressures the spatial density of the eLTER RI is relevant to detect ecosystem effects due to climate extreme events. Furthermore, explicitly regarding hotspots as another layer of information revealed underrepresentation of ecosystems that will experience substantial pressures due to LUC and P changes. Counteracting the persistent gaps would also target the underrepresented P Pressure Hotspots and partially the LUC Pressure Hotspots. Therefore, adding sites within the gap areas will most improve eLTER RI's fitness for the future.

4.5 Recommendations for eLTER RI Development

Since the eLTER RI strives to represent major environmental and socio-ecological gradients, the fitness for the future - i.e. climate and land uses changes - should be regarded as an additional layer of information determining the infrastructural development. Consequently, clearest recommendations for the eLTER RI development can be derived combining the findings of the present study (projected futures) with the findings by Ohnemus et al. (2024), who analysed the eLTER RI representativity with respect to current environmental and socio-ecological gradients (anthromes, bioclimate, biogeoregions, economic density, land cover and landforms). The gaps in the coverage of climate change and LUC identified by the present study mostly overlap with the *current* gaps (Ohnemus et al., 2024, Figure S 10), i.e. in the North of Finland, Sweden and Norway, in Poland and in the South of Portugal and Spain. The similarity in spatial gap patterns between the two studies despite different spatial patterns of their reference parameters further indicates the current spatial bias resulting from the historically evolved geographical distribution of eLTER RI's in-situ facilities (Mirtl et al., 2018).

Closing these gaps is a precondition to fulfil one of the main goals of eLTER: using the eLTER RI, in combination with a whole systems approach (Collins et al., 2011; Mirtl et al., 2021), to scale ecological patterns and processes. In essence, this is a prerequisite for an envisioned macrosystems ecology approach (Heffernan et al., 2014). This explicitly recognises local interactions and feedbacks between biotic and abiotic elements, cross-scale interactions and emerging patterns, macro-scale feedbacks, and teleconnections. A network that is neither representative nor provides transferable results can hardly achieve the goals needed for macrosystems ecology.

Based on this study's findings, fulfilling the study's final aim, we recommend the following for eLTER RI development:

- **Primarily target overlapping gaps**: Additional sites here will counteract lacking coverage of environmental and socio-ecological gradients and simultaneously improve eLTER RI’s fitness for the future

- **Target hotspot areas**: Especially the P Pressure Hotspots are clearly underrepresented. However, the overrepresentation of BT Pressure Hotspots is driven by the high density of sites in the Alps. Especially in the Scandes and the Pyrenees eLTER RI facilities are scarce, and site additions here should be considered.

5 Conclusions

The study demonstrates the potential to assess the spatial design of environmental in-situ research infrastructure, not only based on current conditions but also in terms of their suitability for future aspects, such as climate change or changing land use. The novel metrics relating climate change and LUC to pressures on ecosystems enabled us to sharpen the recommendations for eLTER RI development derived from the current coverage. While the novel metrics allow for further spatial ecological analyses, we encourage other research infrastructures and monitoring networks to adapt a representativity analysis to optimise their spatial design towards their target regions.

Furthermore, representativity analyses will allow to derive specific recommendations for potential additional sites to close identified gaps, both for current and future conditions. When selecting additional sites, costs can be minimised and benefits (e.g. long-term legacy data) maximised by upgrading already existing in-situ facilities to the needs of RIs like eLTER (Futter et al., 2023). These existing sites comprise the core of European environmental monitoring and research networks (Vuorenmaa et al., 2018; Wandinger et al., 2020; Ferretti, 2021; Heiskanen et al., 2022), of which many sites already participate in the development of the eLTER RI (Mirtl et al., 2018). Targeted co-location of key-sites would be a significant step to improve not only research capacity but also the ability to transfer shared data and knowledge into a truly useful continental-scale policy support (Kulmala, 2018).

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Supplement

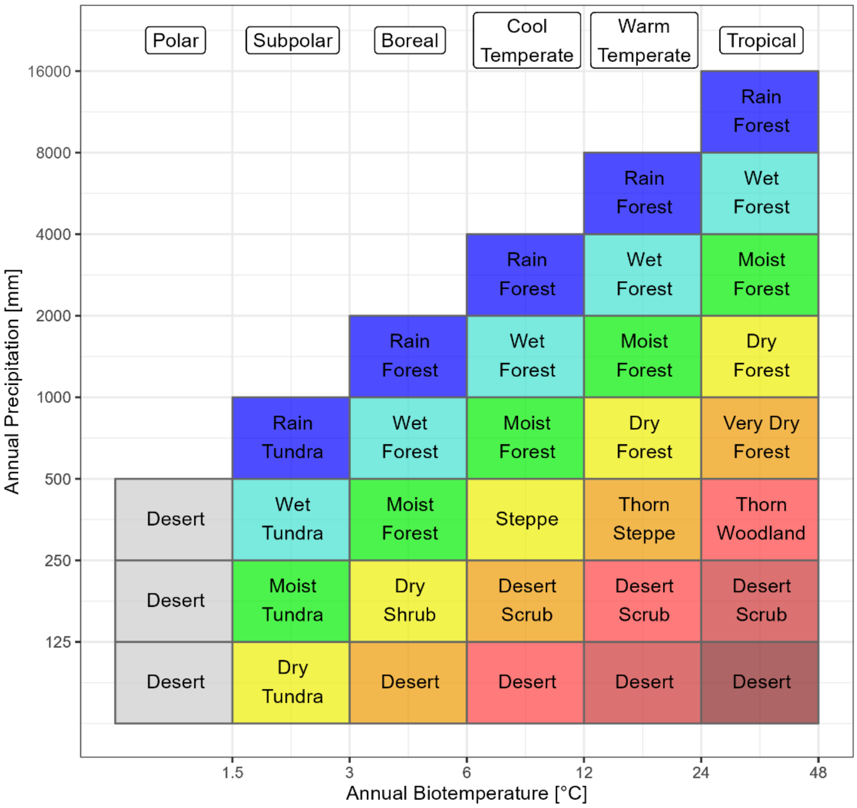

Figure S 1: Holdridge Life Zones named after Tekin et al. (2021) defined within a binary logarithmic data space consisting of annual precipitation and annual biotemperature.

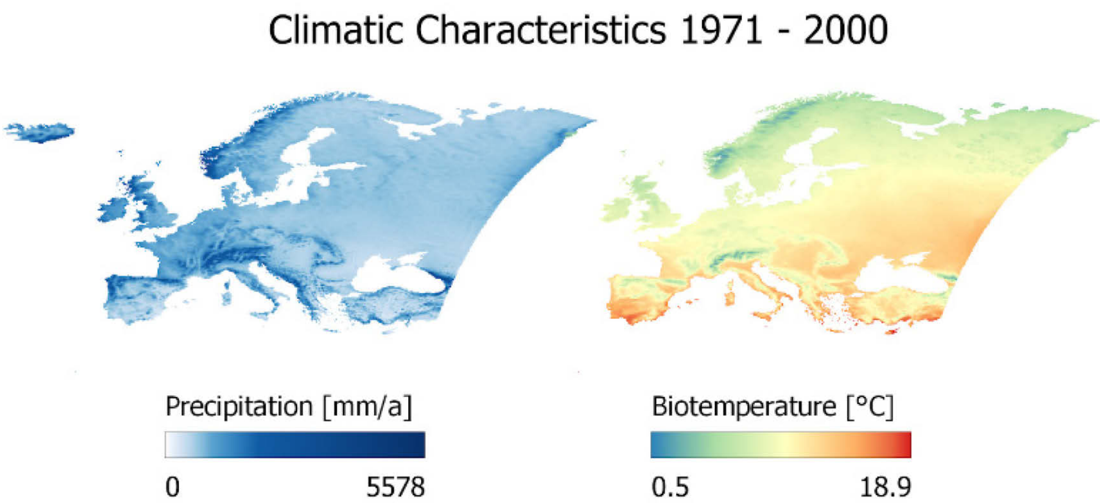

Figure S 2: Mean precipitation and biotemperature for the baseline period 1971 – 2000

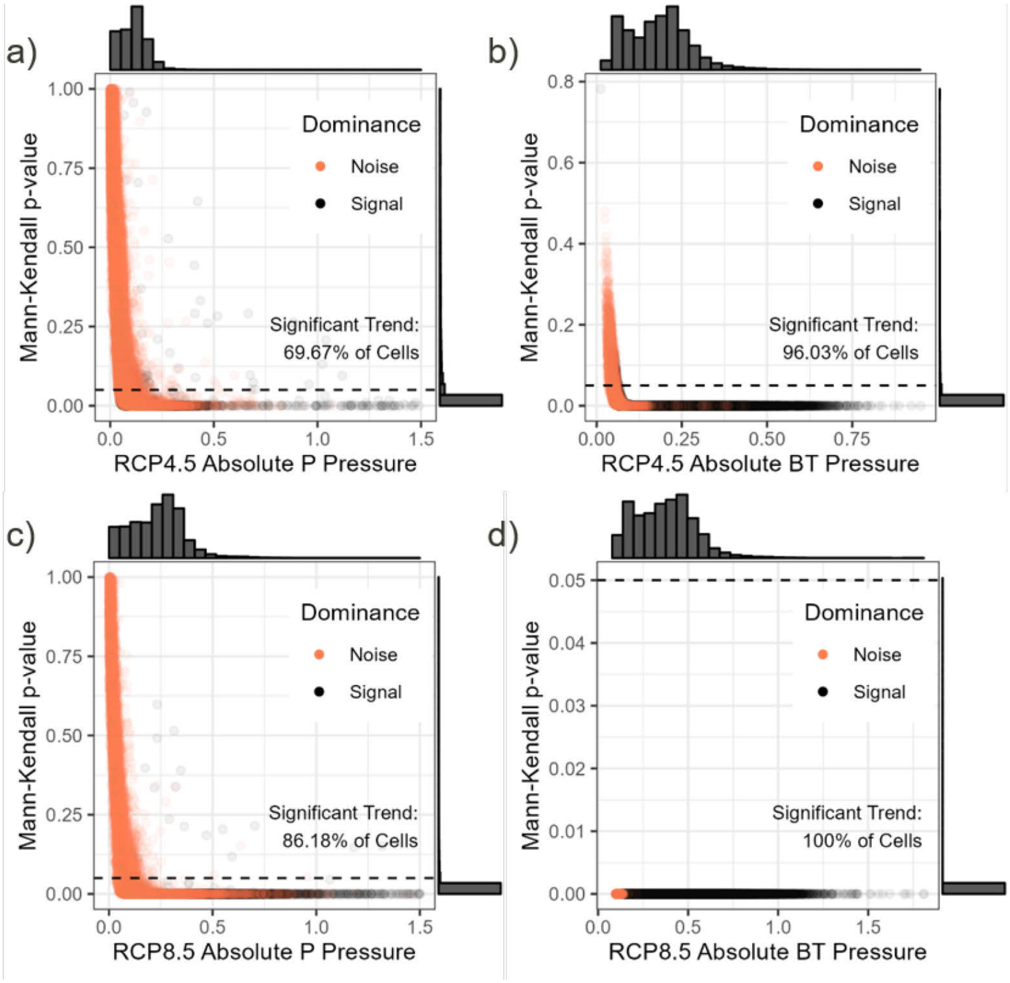

Figure S 3: The p-value of Mann-Kendall trend analysis and the respective a) RCP 4.5 Absolute Precipitation (P)Pressure, b) RCP 4.5 Absolute Biotemperature (BT) Pressure, c) RCP 8.5 Absolute P Pressure, d) RCP 8.5 Absolute BT Pressure illustrated as points. Orange colours depict Model Mean values with noise dominance, black colours with signal dominance. Dashed lines mark the 0.05 significance level. The share of cells below the significance level is denoted in the plots. Marginal histograms illustrate the value distribution for the x- and y-axes.

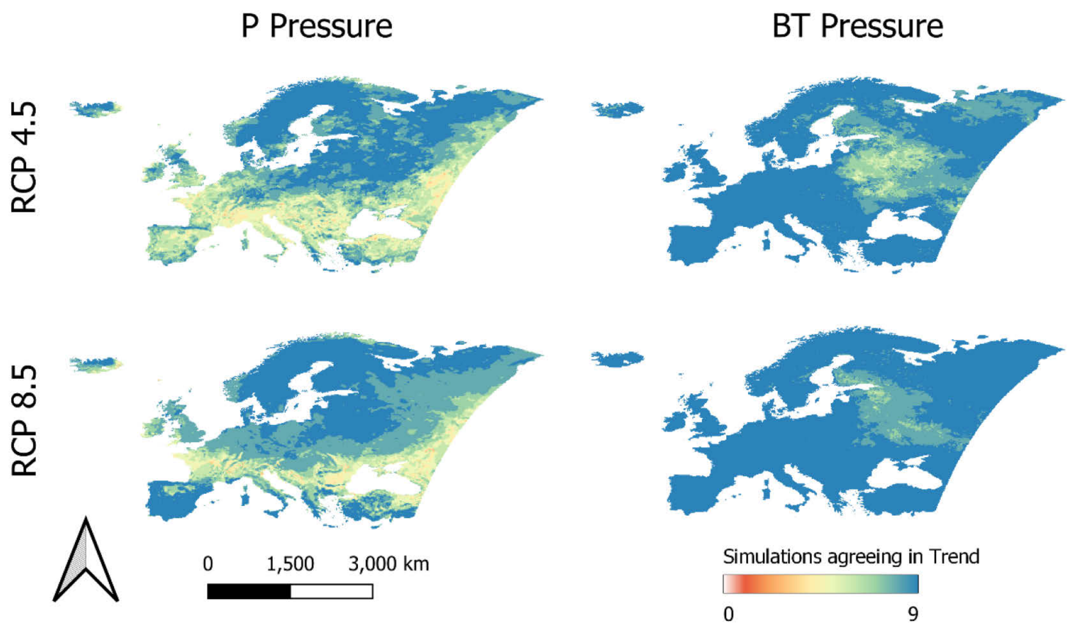

Figure S 4: Number of single simulations agreeing with the trend of the Model Mean for the Precipitation (P) an Biotemperature (BT) Pressure datasets for the RCP 4.5 as well as the RCP 8.5 scenario.

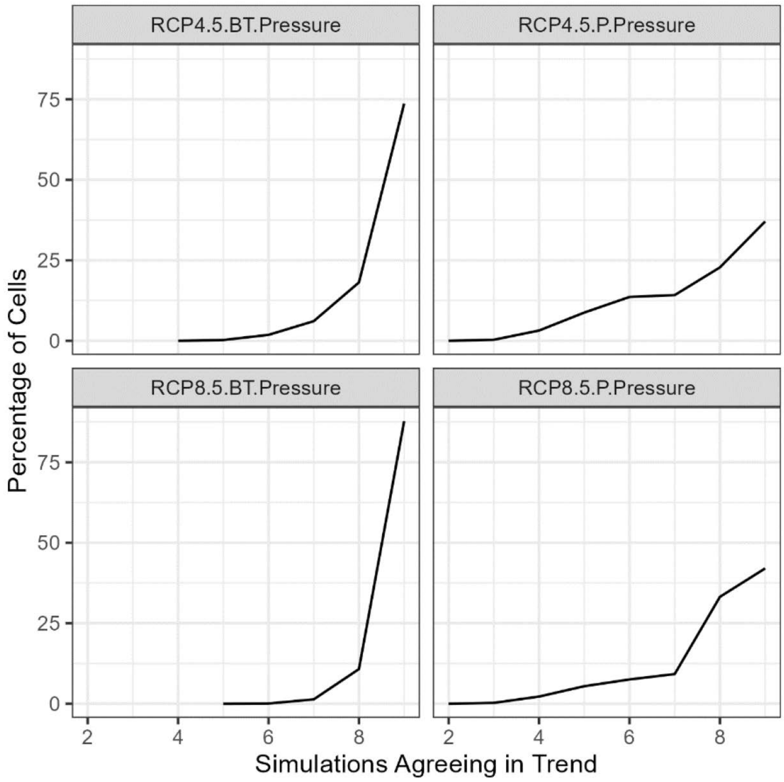

Figure S 5: Share of cells illustrated as a line for each number of simulations agreeing with the trend of the Model Mean in percent for each RCP scenario and the Biotemperature (BT) and Precipitation (P) Pressures.

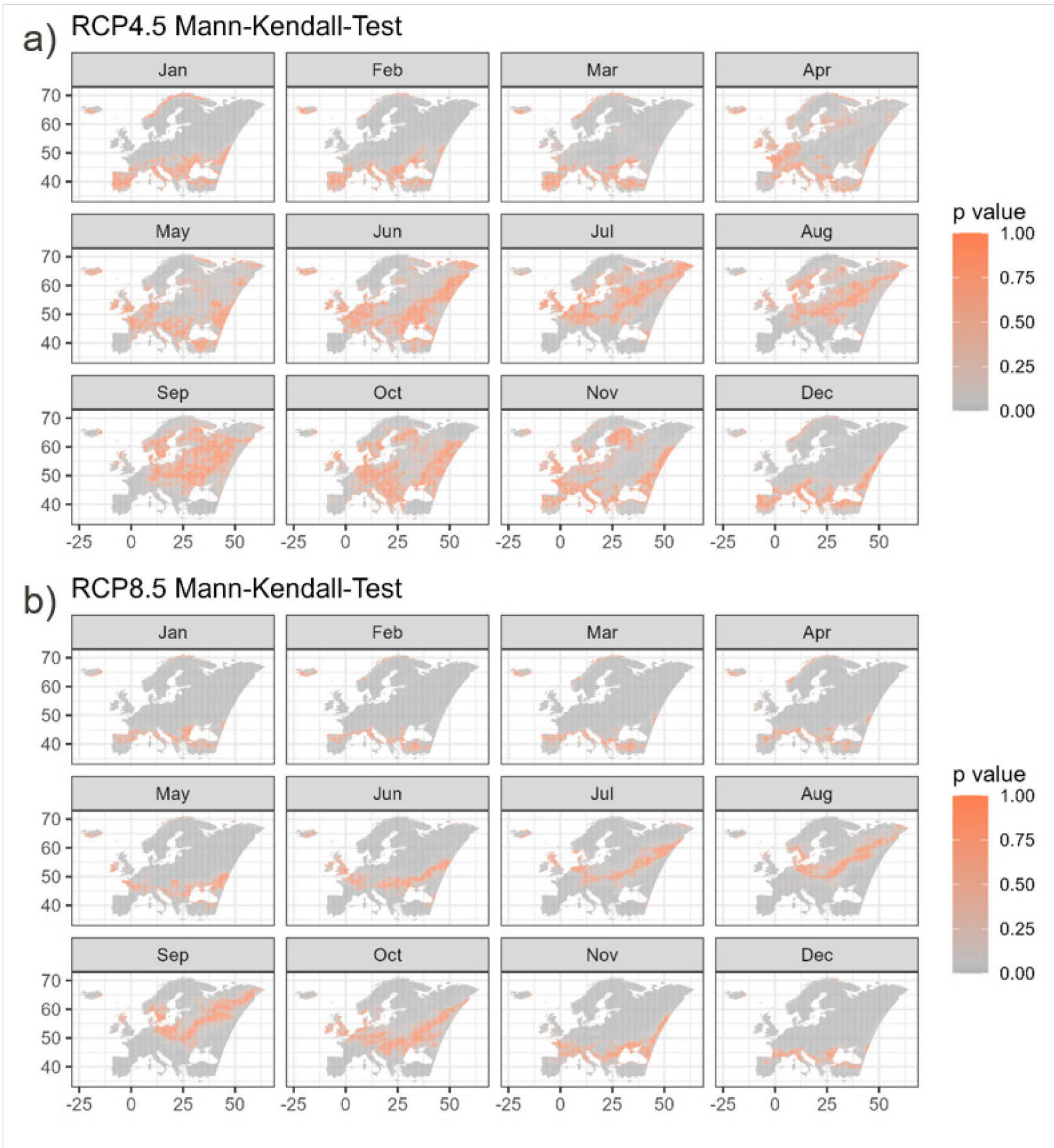

Figure S 6: The p-values of the Mann-Kendall trend analysis for the monthly slopes underlying the SPEI Pressure computation for a) the RCP 4.5 and b) the RCP 8.5 scenario. Each panel depicts a different month. The colour scale diverges around 0.05, with grey values lying below 0.05 and indicating significant trends.

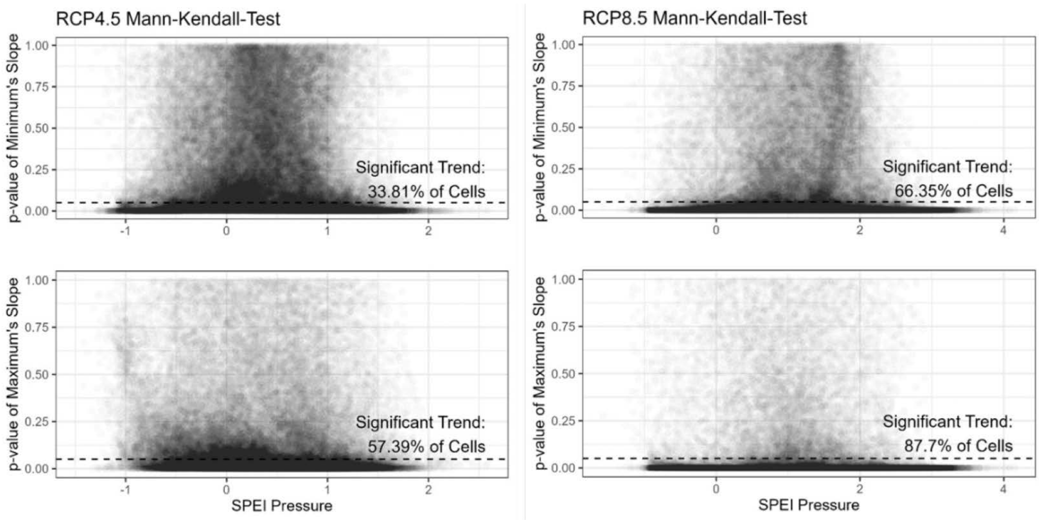

Figure S 7: p-values of Mann-Kendall trend analysis of the respective slope of the minimum (upper panels) and maximum (lower panels) monthly SPEI value illustrated as points for the RCP 4.5 (left panels) and RCP 8.5 (right panels) scenarios. The dashed line marks a p-value of 0.05, the significance threshold, and the share of cells with a significant trend is denoted within the plot panels.

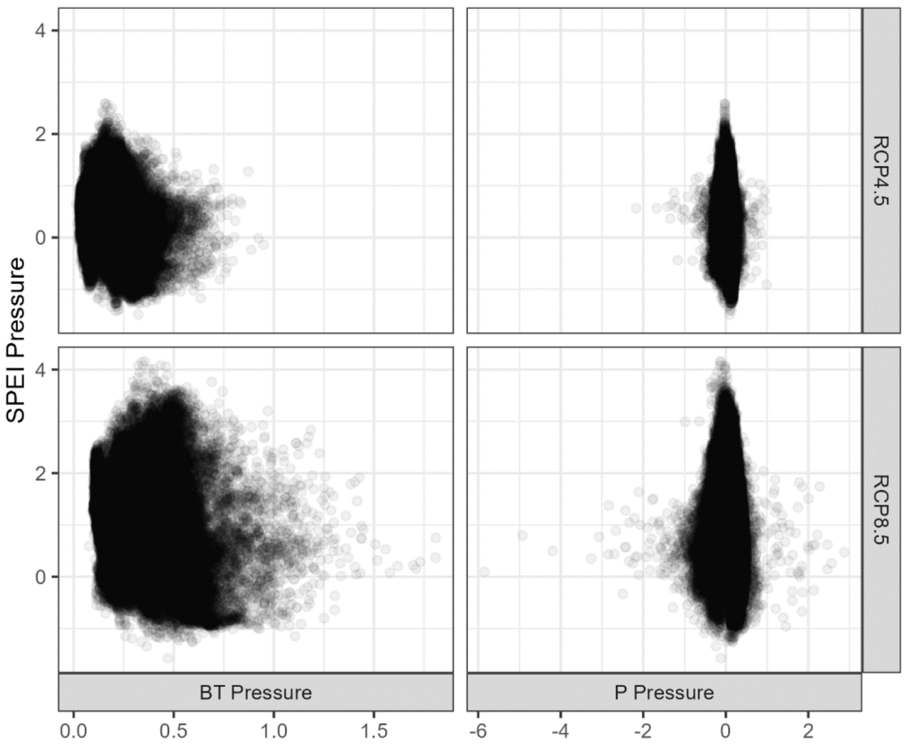

Figure S 8: Scatterplots with points illustrating the respective Precipitation (P), Biotemperature (BT) and SPEI Pressures of each cell for the RCP4.5 and RCP8.5 scenarios.

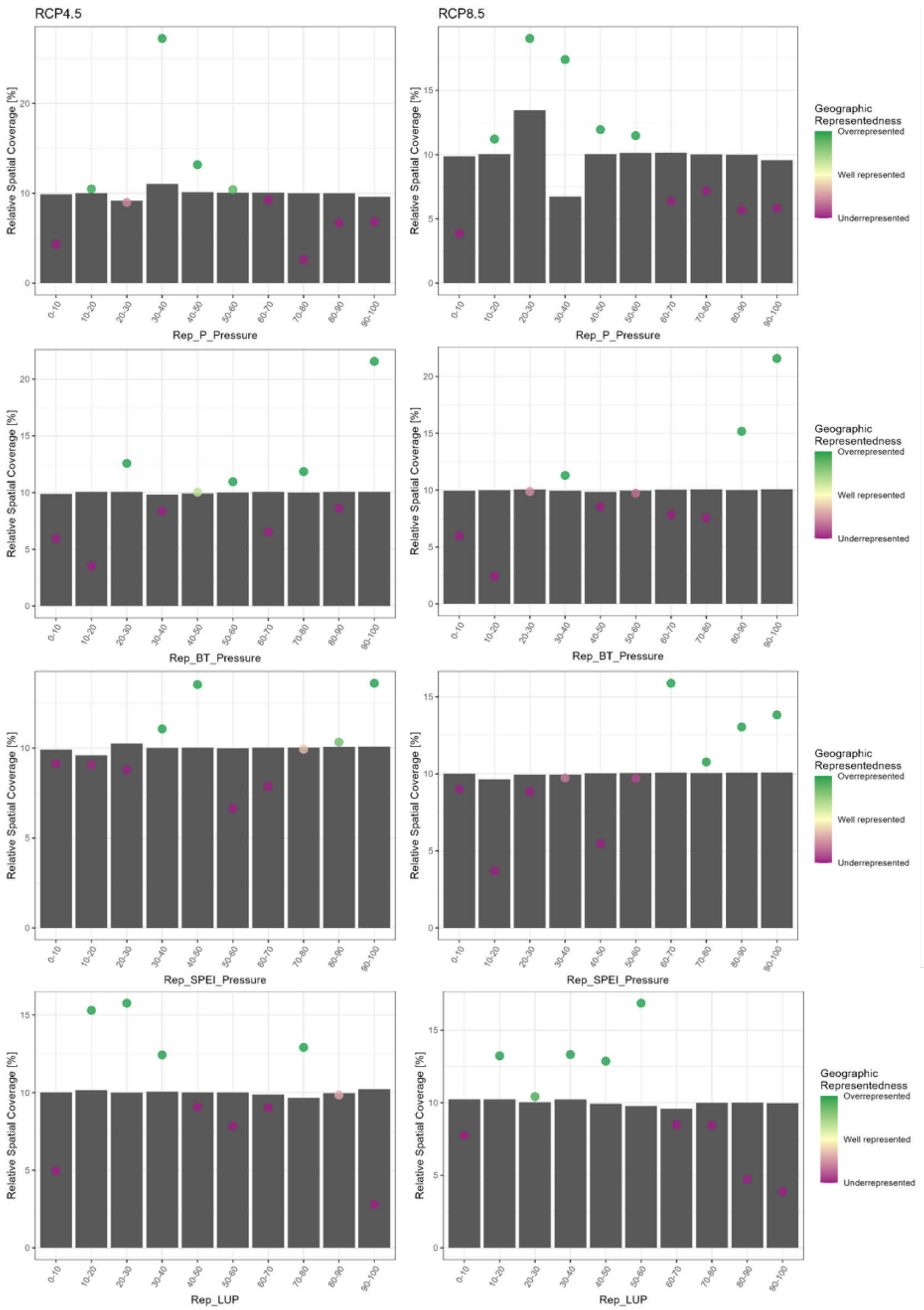

Figure S 9: Geographic Representedness of the Precipitation (P, first row), Biotemperature (BT, second row) and SPEI (third row) Pressures as well as Land Use Pressure (fourth row) for the RCP 4.5 (left panels) and RCP 8.5 (right panels) scenarios. The bars represent the relative spatial coverage of each quantile, each representing approximately 10% of the dataset. The dots illustrate the relative spatial coverage within the eLTER RI, with the colours indicating over- (green colours), under- (purple colours) or good (yellow colours) representation of a quantile.

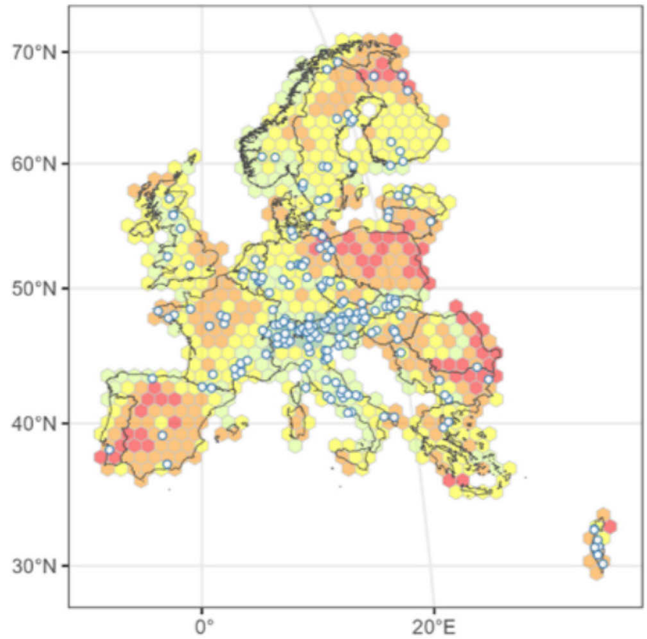

Figure S 10: Priority for the establishment of new Sites in the eLTER RI regarding the current environmental and socio-ecological coverage taken from Ohnemus et al. (2023). Hexagon colours depict the priority, white dots the eLTER RI in-situ facilities analysed. As background the 26 LTER member countries are illustrated. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

Table S 1: Depicts the threshold values based on quantiles used for the reclassification of the Biotemperature (BT), Precipitation (P), SPEI and Land Use Pressures of the RCP 4.5 and RCP 8.5 scenarios to be suitable as input parameters for the representativity analysis. Numbers in bold indicate manually-chosen threshold values of 0 to distinguish positive and negative values.

Quantiles	0	10	20	30	40	50	60	70	80	90	100
RCP4.5 P	-3.09	-0.12	-0.05	0	0.04	0.06	0.09	0.12	0.14	0.16	1.62
RCP4.5 SPEI	-1.34	-0.30	0	0.22	0.39	0.56	0.71	0.87	1.04	1.25	2.08
RCP4.5 BT	0.03	0.10	0.13	0.16	0.18	0.20	0.22	0.23	0.25	0.29	0.79
RCP4.5 LUP	0	0.03	0.07	0.09	0.12	0.15	0.18	0.22	0.27	0.38	0.99
RCP8.5 P	-9.30	-0.35	-0.17	0	0.07	0.14	0.20	0.23	0.29	0.34	2.56
RCP8.5 SPEI	-1.23	0	0.41	0.71	1.02	1.31	1.56	1.81	2.12	2.46	3.83
RCP8.5 BT	0.12	0.24	0.30	0.33	0.37	0.41	0.44	0.47	0.50	0.56	1.37
RCP8.5 LUP	0	0.02	0.05	0.06	0.08	0.10	0.12	0.15	0.19	0.25	0.99

Table S 2: R Session Info including R version and all the version info for "other attached packages" obtained with sessionInfo() for the Representativity Analysis and all other scripts associated with this study.

Representativity Analysis	All other Scripts
R v. 4.2.2	R v. 3.6.1
sf_1.0-9	sf_0.9-8
data.table_1.14.8	data.table_1.14.0
terra_1.7-3	terra_1.2-5
ggfortify_0.4.15	ggfortify_0.4.10
gridExtra_2.3	gridExtra_2.3
tidyr_1.3.0	tidyr_1.3.0
dplyr_1.1.0	dplyr_1.1.2
raster_3.6-14	raster_3.4-10
rgeos_0.6-1	rgeos_0.5-5
rgdal_1.6-4	rgdal_1.5-23
sp_1.6-0	sp_1.6-1
ggplot2_3.4.1	ggplot2_3.4.2

Manuscript 3

The Potential of Co-location to mitigate Sampling Bias in Research Infrastructures

Submitted to Ecological Indicators

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Abstract

Research Infrastructures (RIs) are key to face the grand environmental challenges humanity encounters by providing standardized, large-scale data. However, the in-situ facilities of RIs frequently exhibit a sampling bias. A promising and cost-efficient approach to mitigate sampling bias is "co-location", i.e. the usage of in-situ facilities by more than one RI.

We investigated the bias mitigation potential of co-location in Europe exemplarily for eLTER RI. Therefore, we added 50 candidate facilities from seven pan-European RIs and peer networks to the eLTER RI and investigated bias reduction for current environmental conditions and anticipated changes under RCP4.5 and RCP8.5. Additionally, we investigated which facilities contribute to bias reduction.

It required 5, 10 and 25 of 832 candidate facilities, respectively, to reduce sampling bias for RCP8.5, RCP4.5 and current conditions. However, after the addition of 50 sites, 60 % (RCP4.5) to 80 % (current conditions) of the initial bias remained. Bias reduction was most conclusive in Eastern Europe and Fennoscandia, while bias in the Mediterranean was only removed for RCP4.5. The analysis recommended 197 candidate facilities for bias reduction, 156 in Fennoscandia, Poland, Lithuania and Spain.

Thus, co-location alone can mitigate but not overcome bias in eLTER RI. The mitigation potential was limited by the small number of candidate facilities in the Iberian Peninsula. Therefore, for eLTER RI we recommend: i) aim to co-locate the facilities recommended by this analysis, ii) search for or establish further facilities in the Iberian Peninsula and iii) mitigate bias in data analyses by using less biased or unbiased subsets.

1 Introduction

Humanity faces grand environmental challenges (Reid et al., 2010; Da Rounsevell et al., 2012; Kulmala, 2018), affecting the earth system on various temporal and spatial scales. While each single observation has an important contribution (Lovett et al., 2007), these multi-scale challenges cannot be comprehensively tackled by in-situ research and observations of a single facility (Futter et al., 2023). Thus, compiling in-situ data gathered at several in-situ facilities can uncover processes and large scale patterns in the earth system beyond the potential of a single in-situ facility (e.g. Hautier et al., 2014; El Yaacoubi et al., 2016). Yet, especially compiling data from different in-situ facilities can be challenging due to observational protocols varying between them, which can lead to the determination of differing or potentially even contrasting effects (Forster, 2014; Gould et al., 2025). Hence, developing and implementing standardized observational protocols and coordinating single in-situ facilities is crucial to collect and collate environmental knowledge. Loosely and not formally organized peer networks like Fluxnet (Baldocchi et al., 2001) and the International Long Term Ecological Research Network (ILTER, Mirtl et al., 2018) can by definition not accomplish this challenge of standardizing observations. This has been one of the key drivers for the establishment of Research Infrastructures (RIs) like the US National Ecological Observatory Network (NEON, Kampe, 2010), the Integrated Carbon Observation System (ICOS, Storm et al., 2023), the Aerosol, Clouds and Trace Gases Research Infrastructure (ACTRIS, Laj et al., 2024), the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research Infrastructure (eLTER RI, Ohnemus et al., 2024), the Chinese Ecosystem Research Network (CERN, Huang and Niu, 2005), the South African Environmental Observation Network (SAEON, van Jaarsveld et al., 2007) or the Terrestrial Ecosystem Research Network (TERN, Cleverly et al., 2019). These RIs observe and investigate different compartments and geographies of the earth system, creating comprehensive, standardized and accessible data (Futter et al., 2023). Consequently, RIs have become an indispensable prerequisite for investigating and facing these grand environmental challenges.

Besides the standardization of observations within and across in-situ facilities of an RI, also their geographic arrangement must be considered. In an ideal scenario, the conditions of the earth system encompassed by the in-situ facilities of an RI would be a precise reflection of the RI target region. This would result in the in-situ facilities being, in essence, a geospatial replica or twin of the conditions present in the target region. Following the definition of the term representativeness by Sulkava et al. (2011), a geospatial twin should reproduce the characteristics of processes and quantities of the target region. Additionally, no ecosystem at a given place is completely similar to another, hence there is an infinite number of unique ecosystems that would ideally be observed, which is practically impossible with the finite number of facilities RIs can operate. While, therefore, each and every single ecosystem observation is valuable, the spatial network design must be crafted carefully so the finite number of facilities approximates a geospatial twin.

Contrary, biases regarding the spatial distribution of research observation locations are common in ecological research (Martin et al., 2012) and were also identified earlier for RIs and peer networks (Václavík et al., 2016; Villarreal et al., 2018; Wohner et al., 2021; Kumar et al., 2023; Ohnemus et al., 2024; Ohnemus et al., 2025). In this context, the conditions represented by observation locations can be seen as a sample from the population of conditions in the target region, therefore this bias can be described as sampling bias. Uncovering sampling bias was thus far achieved using approaches that either follow concepts of representativity or concepts of transferability (Diogo et al., 2023). Both investigate the distribution of in-situ facilities compared to the spatial distribution of certain conditions deemed relevant for the type of investigation, thus they go beyond simple spatial distance analyses. Representativity approaches (e.g. Schmill et al., 2014; Malek and Verburg, 2017; Meyfroidt et al., 2018; Villarreal et al., 2018; Wohner et al., 2021; Ohnemus et al., 2024; Ohnemus et al., 2025) compare value distributions covered by in-situ facilities with value distributions of the target region, while transferability approaches (e.g. Hargrove et al., 2003; Sulkava et al., 2011; Václavík et al., 2016; Villarreal et al., 2019; Piemontese et al., 2020; Villarreal and Vargas, 2021) investigate the similarity of conditions covered by in-situ facilities with that of the target region. While each approach independently offers distinct advantages in developing a network design that approximates a geospatial twin, the integration of the different perspectives offered by the representativity and transferability approaches appears to be particularly valuable for spatial network design. However, to the best of our knowledge, representativity and transferability approaches have not been integrated for this purpose previously.

Although numerous studies have exposed sampling biases, few developed clear strategies to rectify or mitigate such biases. Villarreal et al. (2018) showed that combining AmeriFlux and NEON prompted improved coverage for the conterminous United States compared to facilities of each network alone. Likewise in the United States, Kumar et al. (2023) revealed notable benefits of co-location between LTAR (long-term agricultural RI) and NEON. This concept of several RIs using a single in-situ facility is referred to as "co-location". Futter et al. (2023) investigated co-location conceptually regarding carbon cycling research. Beyond the potential to address sampling bias in RI spatial network design, co-location has advantages, for i) ecosystem understanding since it provides information of a wider array of earth system variables, ii) for site coordinators and researchers to engage in different RIs, iii) for RIs as a cost-efficient approach to densify their networks of in-situ facilities. Despite this suite of benefits of co-location, we are currently not aware of any publications regarding the potential of co-location to mitigate sampling bias in pan-European RIs or investigating the potential of several RIs to be co-located. Yet, for the European research landscape, where a range of continental scale long-term RIs and peer networks are operative, co-location seems especially promising.

In this study, we elucidate the potential of co-location for terrestrial environmental RIs in Europe by implementing both a representativity as well as a transferability approach, exemplarily for eLTER RI, the Integrated European Long-Term Ecosystem, critical zone and socio-ecological Research infrastructure. eLTER RI is a pan-European RI focusing on long-term ecological research in terrestrial, freshwater and transitional water ecosystems. It seeks to provide researchers across Europe and beyond with access to long-term environmental data, facilities, and expertise. Furthermore, it aims at deriving actionable knowledge to support environmental policy makers at the local, regional and continental scale (Futter et al., 2023).

Importantly, eLTER RI first developed in a bottom-up manner as part of the European contribution to ILTER and the in-situ facilities have only later been consolidated within an RI with common scientific goals and a derived mandatory observational design (Mirtl et al., 2018; Ohnemus et al., 2024; Zacharias et al., 2025). With the interoperability achieved, which is typical for a top-down approach (Vargas et al., 2017), eLTER RI now unites strengths of the bottom-up and top-down approaches (Holzer et al., 2018). This contrasts with the approach taken by e.g. NEON, which was developed strictly top-down (Schimel et al., 2007; Keller et al., 2008; Schimel and Keller, 2015). Many of the eLTER RI facilities were founded in locations where research activities have been ongoing in the past, some more than 100 years. Therefore, the spatial organization and continental coverage reflect aspects of institutional and national research agendas. These independent agendas, in turn, largely disregarded the aspect of continental coverage and representativity. Nonetheless, eLTER RI covers the major gradients in European environmental and socio-ecological conditions, but it was already found to exhibit sampling bias, both concerning current (Ohnemus et al., 2024) as well as anticipated future (Ohnemus et al., 2025) conditions of its target region. Thus, eLTER RI and other bottom-up developed RIs - which are most distributed environmental RIs - could especially benefit from the potential of co-location as a cost and labor-efficient pathway to sampling bias reduction.

To investigate the potential of co-location for eLTER RI we first identify candidate facilities from other RIs that could be co-located with eLTER RI. Then, we apply analyses of representativity and transferability to investigate the potential of sampling bias reduction by incorporating candidate facilities. Finally, we identify specific in-situ facilities that eLTER RI would most benefit to incorporate.

2 Material and Methods

2.1 Data

eLTER RI facilities

For this study and to develop the analytical approach, eLTER RI was chosen. eLTER RI is in the final stages of formal establishment and the findings of this paper have been of practical and strategic relevance. eLTER RI comprises a network of in-situ facilities spread over its target region, i.e. the area eLTER RI strives to represent, which is most of Europe (Figure 1) covering a variety of habitats and ecosystems. These facilities feature an observational design and are equipped with the instrumentation to support research on all spheres of the socio-ecological system. The present study considers 204 eLTER RI sites as the eLTER RI in-situ facilities (Figure 1a), the information on these facilities was compiled by Ohnemus et al. (2024) and all associated geodata, including the complex polygon geometry of eLTER RI facilities, are available online. The spatial extend of facilities varies in complexity and in accordance to the habitat type, terrain properties and within-site heterogeneity to be covered.

Candidate facilities

For the investigation of potential candidate facilities that could be co-located with eLTER RI, geodata depicting in-situ facility locations from seven spatially distributed pan-European environmental RIs and peer networks was obtained. For ICOS (Storm et al., 2023), FLUXNET (Baldocchi et al., 2001), ACTRIS (Laj et al., 2024), INTERACT and the International Cooperative Programme on assessment and monitoring of the effects of air pollution on rivers and lakes (ICP Waters, Kvaeven et al., 2001) these data were extracted from their respective data portals (EBAS, n.y; FLUXNET, n.y; ICOS, n.y; ICP Waters, n.y; INTERACT, n.y). For the International Cooperative Programme on assessment and monitoring of air pollution effects on forests (ICP Forests, Ferretti, 2013) and the International Cooperative Programme on integrated monitoring of air pollution effects on ecosystems (ICP Integrated Monitoring, in this study abbreviated as ICP IM, Vuorenmaa et al., 2018) site coordinates were provided by their program centers upon request. All candidate facilities were depicted with a point representation, none as complex polygon geometries. These data were then projected and cropped (Hijmans, 2024) to the coordinate reference system and spatial extent of the target region.

For some RIs, the candidate facilities had to be further filtered according to their fundamental suitability for co-location with eLTER RI. For ICOS, we removed stations that were not labeled as ecosystems stations. For ICP Forests, only facilities providing data for the last time in 2022 or more recently were regarded, as other sites can be deemed inactive. Likewise, for ICP IM and INTERACT only facilities respectively labeled active or open were regarded.

Importantly, already established co-location of candidate facilities with eLTER RI, as well as other RIs or peer networks needed to be considered to avoid regarding the same facility more than once in our analysis. The cleaning procedure was performed in two steps, one based on metadata and one based on geodata. To identify already existing co-location using metadata, we relied on the eLTER Site Registry, DEIMS (Wohner et al., 2019). DEIMS has over the past decade been established as globally used service not only for eLTER, but also for the site documentation of a range of other projects, RIs and peer networks. Being compulsory only for eLTER RI and ILTER, it is not complete, but the most comprehensive catalog of RI in-situ facilities available. Candidates were either removed, if i) a co-location to eLTER RI was already listed in DEIMS, or ii) if already existing co-location with eLTER RI could be identified by a combination of facility name and geographic proximity. Therefore, names were compared manually, since same facilities were occasionally spelled differently in different RIs. Importantly, procedure ii) was also performed to identify co-location between other RIs or peer networks. Notably, ICP Forests data did not entail names, thus identifying existing co-location based on name similarities was not possible in this case. Yet, some already co-located ICP Forests facilities were identified and removed from the candidate dataset based on DEIMS metadata. With the different reporting standards of metadata and without a complete metadata repository, identifying co-location by metadata alone would be insufficient. Therefore, co-location was also identified based on geodata, if a geographic overlap between facilities from different RIs or peer networks existed. This overlap was identified using the function "mask" (Hijmans, 2024). Therefore, the point data provided for RIs and peer networks was buffered (Hijmans, 2024) to a 1 ha circle. This was necessary, since point data would only be identified as co-located between different RIs, if different RIs would report coordinates in exactly the same format, which is not the case (e.g. ICP Forests coordinates were rounded to geographic minutes). Thus, due to the different coordinate reporting standards, a geographic subset using point coordinates would be insufficient. Consequently, the 1 ha buffer zone was regarded as adequately large to overcome discrepancies in reported geographical coordinates and as sufficiently small to minimize erroneous identification as co-location between RIs. Due to the generally inconsistent reporting of metadata, the geographical subset appeared more reliable for all RIs. While candidates identified as co-located to eLTER RI were removed from the candidate facility dataset, those co-located between other RIs or peer networks were reduced to one occurrence for the subsequent analysis.

2.2 Methods

2.2.1 Representativity Analysis

In two previous studies sampling bias within the in-situ facility network of eLTER RI was investigated regarding three facets: (i) current socio-ecological conditions of Europe (from now on referred to as current, Ohnemus et al., 2024), as well as anticipated changes in socio-ecological conditions (Ohnemus et al., 2025) following (ii) an RCP4.5 and (iii) an RCP8.5 scenario. In the present study, we followed the same approach and used the representativity analysis introduced by Wohner et al. (2021) for the global scale with refinements by Ohnemus et al. (2021) to adapt to the European scale. In brief, this representativity analysis compares the value distribution of a so-called thematic dimension, which depicts categorical data, in a defined target region with the value distribution covered by in-situ facilities of an RI. Before getting into the details of the representativity analysis, first the thematic dimensions chosen for this study are discussed.

Defining the thematic dimensions that an RI shall represent is a prerequisite for a sound analysis of co-location potential, and determines the results of such an analysis. Therefore, their usage must be thoroughly justified. We used the same thematic dimensions as in the aforementioned studies, i.e. for current conditions we investigated sampling bias regarding anthromes, bioclimate, biogeographical regions, economic density, land cover and landforms (Ohnemus et al., 2021; Ohnemus et al., 2024). We consider these aspects to be pertinent to the evolution of ecosystems and the associated developmental processes that occur within them. In previous studies, the coverage of target region conditions was judged compared to soil, vegetation or climatic parameters (e.g. Hargrove et al., 2003; Sulkava et al., 2011) or to the distribution of a target variable like gross primary production or evapotranspiration (as e.g. Villarreal et al., 2019). However, other studies suggest that a functional description beyond regarding simple parameters or variables is important for a thorough ecosystem understanding (Reichstein et al., 2014). Therefore, other authors used ecosystem functional types (Villarreal et al., 2018; Villarreal et al., 2019), an approach comparable to the parameters approximating a description of ecosystem functioning investigated in the present study. Importantly, Ohnemus et al. (2024) deemed the human influence on ecosystem development relevant, as codified in the thematic dimensions economic density and anthromes. This stands in contrast with the parameters used by NEON to stratify their ecological domains, where human influence is not an explicit factor (Hargrove and Hoffman, 2006). Yet, these current conditions are subjected to Global Change, and e.g. Villarreal et al. (2019) suggested future conditions should be considered in the classification of ecosystems. Therefore, we additionally regarded the thematic dimensions biotemperature pressure, precipitation pressure, SPEI pressure and land use change pressure for the RCP4.5 and RCP8.5 scenarios as developed by Ohnemus et al. (2025). This suite of thematic dimensions describing current ecosystem functioning as well as the changes ecosystems are projected to be subjected to is a solid foundation for a functional ecosystem description, as required for this analysis.

The distribution of each thematic dimension within the target region is then compared statistically to the distribution on the in-situ facilities. Following Schmill et al. (2014), for each category the statistical (dis)similarity between these distributions is calculated based on a chi^2-test of homogeneity. This calculation leads to a parameter Schmill et al. (2014) termed "representedness" that has a continuous value range of +1 (overrepresented on RI facilities compared to the target region distribution) to -1 (underrepresented), where values around 0 indicate that a category is well represented on RI facilities. Then, each category is reclassified (Hijmans, 2024) to display the representedness value for each thematic dimension. Finally, the representedness values of the individual thematic dimensions are summarized to a parameter called "aggregated representedness" (AR) (Wohner et al., 2021). Since for the RCP scenarios the thematic dimension land use change pressure was weighted trifold (Ohnemus et al., 2025), the AR value range is +6 (all thematic dimensions overrepresented) to -6 (all thematic dimensions underrepresented) for all facets. For further details on the representativity analysis and associated calculations, please refer to Wohner et al. (2021).

Network Optimization

To elucidate the sampling bias reduction potential, an iterative network optimization procedure was established. At the start of each iteration, the AR for each candidate facility location was extracted. The starting AR values were taken from (Ohnemus et al., 2024) for current conditions, and from (Ohnemus et al., 2025) for the RCP4.5 and RCP8.5 scenarios. Then, from all candidates with an AR of minus 4 or lower or – if none such facilities existed – of the 1 % quantile with the lowest AR one candidate was sampled and added to the eLTER RI. This sampling procedure was introduced, since several candidates could display the same AR values meaning there is no "perfect" or preferable solution of this optimization problem. Yet it still allowed to choose candidates exhibiting the most underrepresented conditions. Since the candidate facilities themselves are spatially biased (Figure 1b), a random sample would bias the results towards areas with higher facility density. Thus, the candidate facility density was calculated for each candidate facility as the mean Euclidean distance to the respectively nearest ten candidate facilities. This mean distance was used as weight for the sampling procedure, i.e. the higher the mean Euclidean distance, the higher the sampling probability (Supplemental Figure 1). The candidate sampled was then added to the eLTER RI and the representativity analysis was performed again for the resulting eLTER RI in-situ facility network leading to a new AR distribution. Based on these new AR values the next iteration was performed. Iterations were performed, until 50 candidates had been added to the eLTER RI. Due to the relative value distribution as base of this analysis, each additional candidate chosen influences the resulting AR, and therefore the selection of the candidates chosen in the subsequent iterations. Importantly, the addition of facilities in one region could lead to stronger underrepresentation in another region due to the according manifestations of the thematic dimensions. It is indispensable for an analysis of bias, that the methodology is able to produce such a result, as e.g. the addition of 50 facilities in a similar ecosystem type would undoubtedly be considered a sampling bias introduced for eLTER RI. Thus, the representativity analysis is an ideal framework to investigate sampling bias manifesting in geographic space. To account for the randomness introduced by the sampling procedure, this iterative process was repeated 500 times for each of the three facets current conditions, RCP4.5 and RCP8.5.

Quality Markers

Since each candidate site chosen will influence all subsequent iterations and therefore all other candidate sites chosen, the different runs will not be similarly effective regarding bias reduction. Thus, to quantify how well each run counteracted sampling bias, we first defined sampling bias within eLTER RI. Raster cells were classified as biased when they exhibited an AR value of -4 or lower for a given facet, i.e. when all or all but one thematic dimension were underrepresented on a cell. Then, we calculated the area classified as biased at the beginning and after each iteration. Consequently, we expressed the percentage in area that was classified as biased after each iteration compared to the initial area classified as biased as "bias remaining". The results were reduced to the 5 % of runs with the strongest bias reduction, i.e. to the best performing 25 runs. For visualization purposes, bias remaining was displayed as the mean and the standard deviation of these 25 best performing runs for each iteration. In addition, the raster cells classified as biased within these runs were mapped. Therefore, the 25 single runs were overlain and the probability that a cell is still classified as biased after the addition of 50 facilities was calculated, e.g. if a cell is classified as biased in 5 of 25 runs, its probability is 20 %. We refer to this metric as "remaining bias probability".

Candidate Facility Recommendations

Similarly to the remaining bias probability, for each candidate the suitability for eLTER RI was calculated. Any candidate is deemed more suitable for eLTER RI, if it is more likely to contribute to bias reduction. Therefore, the suitability is calculated as the probability of a candidate to contribute to the 25 best runs. This probability was first calculated for each facet independently, e.g. if a facility was added in 5 of 25 runs of the current facet, its probability would be 0.2. To regard the suitability over all facets, the mean over all facets was calculated, if the same candidate had a probability of 0.7 for RCP4.5 and of 0 for RCP8.5, its overall probability, i.e. its suitability, would be (0.2+0.7+0)/3 = 0.3. The higher its suitability, the higher the potential of a candidate to reduce sampling bias within eLTER RI. Additionally, the number of facets for which a candidate can contribute regarding bias reduction was recorded, i.e. the number of facets for which a candidate had a probability of >0. In the example from above, this would be two facets.

2.2.2 Transferability Analysis

The representativity analysis was designed and performs well in investigating sampling bias. However, it cannot address the (dis)similarity between conditions covered by in-situ facilities and the conditions within the entire target region of a given RI or peer network. For this purpose, a transferability analysis, which is rather designed to illustrate conditions that are not covered at all by an RI's in-situ facilities was conducted as an additional layer of information regarding candidate facility selection.

On this account, a multiple correspondence analysis (MCA) was performed. An MCA can be understood as the equivalent to a principal components analysis in the case of categorical data (Abdi and Williams, 2010). Again, this analysis was implemented as an iterative process. First, for all facets (current conditions, RCP4.5 and RCP8.5) the conditions covered by eLTER RI and candidate facilities were extracted (Hijmans, 2024). Then, the MCA was run based on this dataset. The MCA creates an n-dimensional data space, with new dimensions created until all variance of the dataset is explained. In the MCA, each extracted raster cell is represented in each dimension by a numerical value, which represents its coordinates in the MCA data space. The same position of different cells or facilities in all dimensions of the MCA data space means that all manifestations of the different thematic dimensions were the same for these cells or facilities. Indeed, respectively 300, 194, and 216 candidate facilities showed manifestations identical with at least one eLTER RI facility for the current, RCP4.5 and RCP8.5 facets. Thus, the transferability analysis does not suggest these candidates.

After establishing the MCA data space for each facet, the iterative addition of sites was performed. The minimum distance of each candidate facility to any eLTER RI facility was calculated for each dimension, then the mean over all dimensions was calculated. This results in the mean statistical distance between any candidate and all eLTER RI facilities. The higher the distance, the more dissimilar are the conditions covered by a candidate facility to any conditions on eLTER RI facilities. Then, we randomly sampled one candidate from the 1 % facilities with the highest distance and added it to the eLTER RI. Afterwards, again the statistical distance to eLTER RI facilities in the MCA data space was calculated for all remaining candidates and again one candidate from the 1 % of facilities with the highest distance was sampled and added to the eLTER RI. This iterative process was performed, until 50 facilities were added. The entire iterative procedure was repeated 1,500 times for each facet to account for the randomness introduced. A notably higher number of runs was performed for the transferability analysis which is based on absolute distances, while the representativity analysis investigates relative distributions. Thus, any facility added to the representativity analysis has a greater influence on all further 49 facilities chosen. Therefore, with the same number of runs the representativity analysis investigates a "more random" array of possibilities than the transferability approach. To account for this, the transferability approach was forced into more runs, to create a wider array of random outcomes.

Candidate Facility Recommendations

Similarly to the representativity analysis, the 25 best runs were chosen to identify the candidate facilities the transferability analysis recommends. On this account, for each of the 1500 runs the maximum distance between the eLTER RI facilities and the remaining candidate facilities was calculated after 50 facility additions. Then, the 25 runs with the smallest maximum distance, i.e. with the least dissimilarity between conditions covered by eLTER RI and remaining candidate facilities, were chosen. Then, again, the probability of a facility to be added was calculated for each facet as the number of occurrences within one the best runs divided by the number of best runs (n = 25). Then, the mean of the three probabilities of the individual facets was assigned to each candidate. Finally, the candidate facilities recommended by the transferability analysis were used as a second layer of information for the candidate facilities recommended by the representativity analysis. Consequently, candidate facilities were only recommended to be incorporated into the eLTER RI if both analyses recommended them.

2.3 Software

Data was handled and analyses were performed in R v. 4.4.0 (R Core Team, 2024), geodata processing was performed using the terra package (Hijmans, 2024), for geodata visualization the sf package was used (Pebesma, 2018; Pebesma and Bivand, 2023) and all visualizations were performed using the package ggplot2 (Wickham, 2016), to arrange several plots the library patchwork was utilized (Pedersen, 2024). The MCA was performed using the packages FactoMineR (Lê et al., 2008) and factoextra (Kassambara and Mundt, 2020). All code created for this work is available online (Ohnemus, 2025).

3 Results

3.1 Candidate Facilities

In total, 832 individual candidate facilities spread all over Europe from the seven different RIs could be tested regarding their potential to mitigate bias of the eLTER RI in-situ facility network (Figure 1b). Notably, most candidates cluster in Central Europe, Poland and southern Sweden, while candidate facility density was low in the Mediterranean, Hungary, Romania, Serbia, Bulgaria, most of Fennoscandia and the UK. The vast majority of candidate facilities were associated with ICP Forests (n = 536), followed by ICP Waters (n = 111), ACTRIS (n = 64), ICOS (n = 55), FLUXNET (n = 54), ICP IM (n = 29) and INTERACT (n = 10). Of these facilities, 27 were co-located between two of the RIs or peer networks.

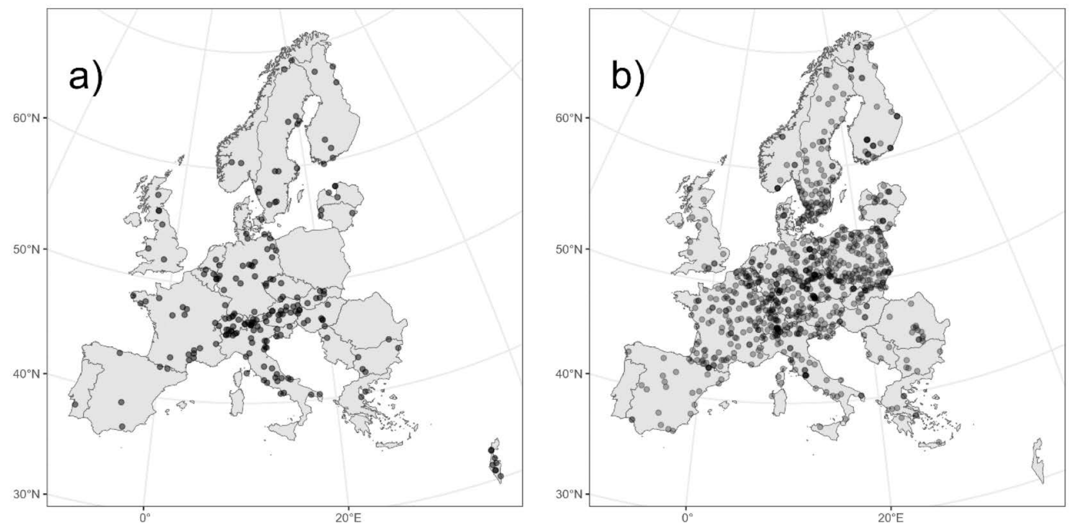

Figure 1: Map showing the target region the eLTER RI strives to represent as gray polygons, borders do not necessarily depict accepted national boundaries. Dots depict the centroid of a) the eLTER RI in-situ facilities and b) the potential candidate facilities. Dots are depicted with slight transparency to illustrate facility density for the two datasets.

3.2 Bias Reduction

The addition of facilities from other RIs was able to reduce bias for all facets (Figure 2). Yet, several facilities are required until notable bias reduction occurred. While for RCP8.5 bias reduction was observed already after the addition of ~5 facilities, ~15 and ~25 facilities were required for RCP4.5 and current conditions, respectively, until biases were reduced. After the respective number of additional facilities was reached, a continuous reduction of bias was observed with further facility addition. Nonetheless, the extent to which bias could be counteracted differed between facets, with a reduction of bias by 40 % for RCP4.5, 30 % for RCP8.5 and 20 % for current conditions. Furthermore, when reaching the addition of ca. 50 facilities, a tendency to plateauing is evident for current conditions and RCP8.5.

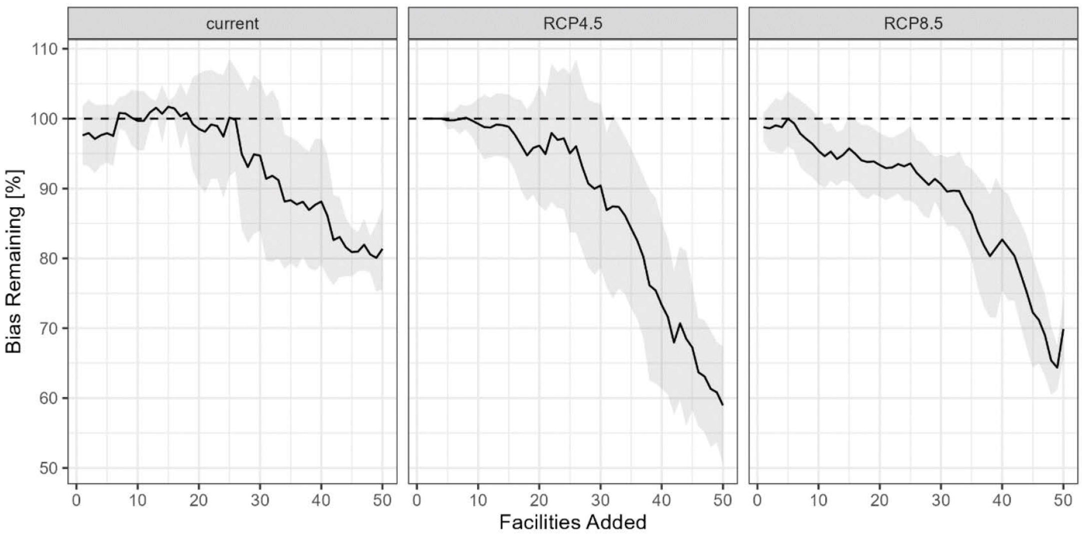

Figure 2: Bias remaining in percent in dependence of the number of candidate facilities added to the eLTER RI based on the representativity analysis. Solid lines depict the mean of the 25 best runs, ribbons depict the standard deviation around the mean. Facets illustrate the different dimensions, i.e. the current state as well as the anticipated conditions under RCP4.5 and RCP8.5. Dashed line marks the initial bias.

Since the spatial extent of initial biases before the addition of candidate facilities differed markedly between facets (Figure 3a), also the bias remaining after the addition of 50 candidate facilities to the eLTER RI differed notably in space (Figure 3b). For current conditions all areas that initially exhibited a bias would in some runs still exhibit a bias. Nonetheless, in most runs the bias initially observed in Eastern Europe and northern Scandinavia was rectified.

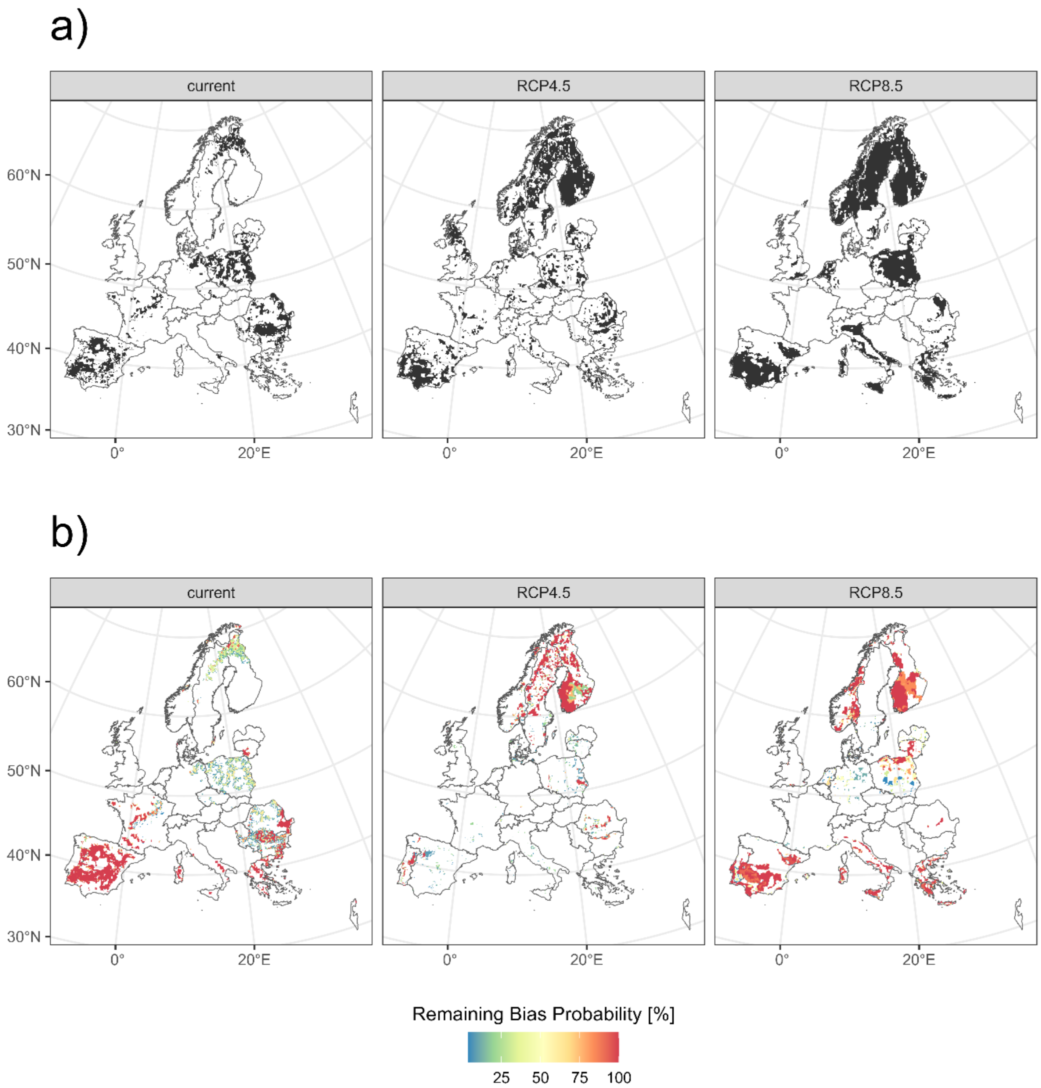

Figure 3: Maps illustrating a) the areas initial classified as biased, before the addition of candidate facilities, b) the remaining bias probability after the addition of 50 candidate facilities for the three facets current, RCP4.5 and RCP8.5 based on the representativity analysis. The remaining bias probability depicts in which share of best quality runs areas are still classified as biased. Boundaries depict the study region and not necessarily accepted geographic boundaries.

Contrary, even more regions in the Mediterranean exhibited a bias after the addition of candidate facilities. This phenomenon was also observed for smaller patches in Northern Spain and Norway for RCP4.5. This can be explained since the addition of facilities in areas with conditions different to that in the Mediterranean will lead to stronger underrepresentation there. For a bias analysis, the methodology must be capable of producing such a result. Nonetheless, for both RCP4.5 and RCP8.5 in vast areas initial bias was completely removed, and especially Eastern Europe was targeted well by the co-location approach. Contrary, two main regions could be identified where the co-location approach alone appears insufficient to completely counteract bias: the Iberian Peninsula (for current conditions and RCP8.5) and Fennoscandia (especially for RCP4.5 and RCP8.5).

3.3 Facility Recommendations

The representativity analysis suggested 282 candidate facilities that could contribute to bias reduction, yet facility suitability differed widely (Figure 4a, b). The higher the suitability, the more relevant a single facility is in counteracting bias. Of the facilities recommended by the representativity analysis, 69.9 % were also identified by the transferability approach (Figure 4a). While the facilities recommended are spread throughout Europe, they mainly cluster in Eastern Europe, Fennoscandia, parts of Eastern Europe and Central Europe (Figure 4c). The latter, however, were less suitable and were, therefore, not most relevant for counteracting bias.

The transferability approach did mainly not choose some facilities in Central Europe, Southern Sweden, Eastern Europe and Italy (Figure 4c). Especially the cluster of candidate facilities in Poland was thinned out. Of the 197 candidate facilities suggested by both analyses, respectively 17, 71 and 111 facilities were important in reducing bias regarding three, two and one facet. The 50 candidate facilities with the highest suitability, i.e. those candidates with highest potential to counteract bias, were found in Poland (n = 13), Finland (n = 12), Sweden (n = 10), Spain (n = 5), Norway (n = 4), Italy (n = 3), Denmark (n = 1), Bulgaria (n = 1) and France, specifically Corsica (n = 1). With a suitability of >0.27 these facilities were chosen in more than one in four runs, and 45 of these facilities contributed to bias reduction in at least two of three facets.

4 Discussion

4.1 Candidate Facilities and chosen RIs

The recommendations of suitable candidate facilities for bias reduction through co-location as elaborated in our analyses strictly capitalized on the seven environmental RIs and peer networks investigated. Therefore, the properties of these RIs and peer networks and the documentation of these properties both enabled and limited the achievable improvements. Consequently, some limitations of the meta- and geodata utilized must be addressed.

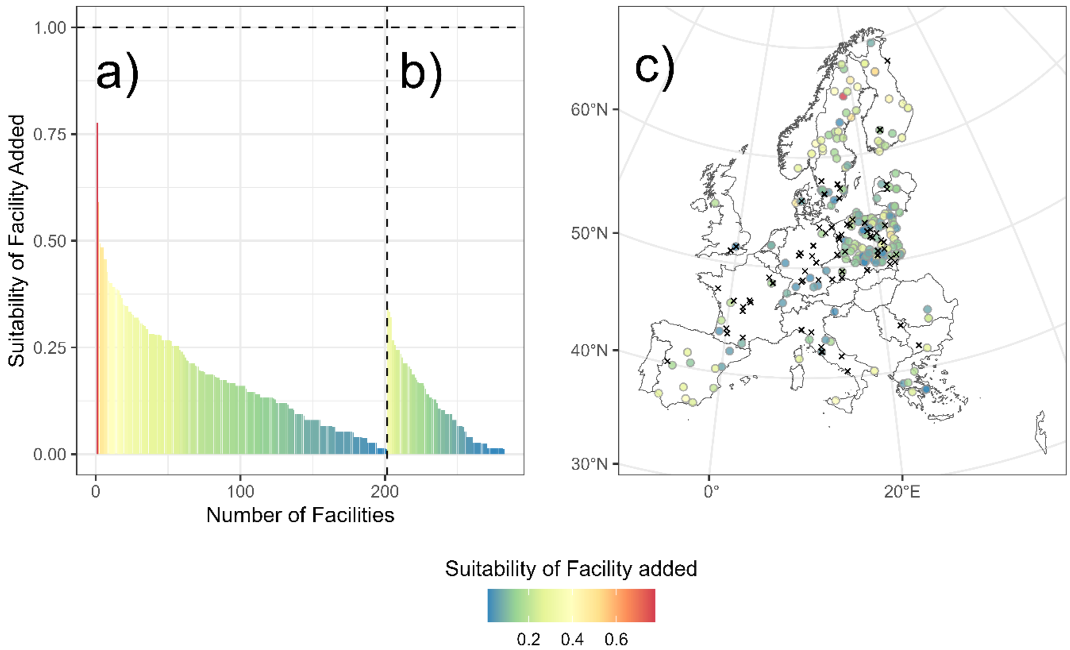

Figure 4: Suitability of a facility added, i.e. the probability that a facility is added in one of the best performing runs (n = 25), illustrated in color. The suitability depicted here is the mean of the three individual probabilities of addition in either the current, the RCP4.5 or the RCP8.5 facet. The dashed horizontal line depicts the maximally possible suitability of 1. a) Includes all facilities that are suggested by both the representativity and the transferability analysis, b) includes all facilities that are only suggested by the representativity analysis. The dashed vertical line separates the sub-panels a) and b). c) Coloured points illustrate candidate facilities in a) with their suitability of addition to eLTER RI. Black crosses illustrate all candidate facilities depicted in b). Boundaries depict the study region and not necessarily accepted geographic boundaries.

The first limitation is the lack of accurate information on complex geometries. The representativity and transferability approaches were developed to also consider such complex geometries with single facilities potentially covering several raster cells (Wohner et al., 2021; Ohnemus et al., 2024). While eLTER

RI in-situ facilities mandatorily report their complex geometries, all RIs investigated regarding co-location only provided point coordinates. Furthermore, the reporting standard of geographic coordinates differed between RIs or peer networks. However, reporting only point coordinates bypassed the tedious question of the actual geographic extent of a facility, i.e. which measurement devices, measurement campaigns or sensor footprints belong to the geographic extent? Since the investigated RIs and peer networks serve different purposes, they might come to different conclusions regarding what the extent of their facilities is. Therefore, complex geometries of different RIs might not be easily comparable. In fact, these issues may appear regarding RIs operating beyond the plot scale such as ICP IM (small catchments), ICP Waters (lakes) as well as FLUXNET and ICOS with their potentially large footprints, yet it might not be of particular relevance for ICP Forests.

This leads directly to the second limitation. We are aware that the geographic subsetting procedure may have flagged valid candidate facilities as co-located to other RI facilities, and some facilities that were already co-located with eLTER or other RIs might not have been properly removed. For the present analysis it was of superior importance to clearly identify and remove already established co-location facilities from the candidate facility dataset. Thus, we chose a methodology that rather removed valid candidates than keeping invalid ones. Importantly, for most candidates in the co-location dataset distances to the next facility were far beyond the spatial extent that can be expected for these facilities (Figure 1b). Thus, if any invalid facilities were indeed investigated regarding their co-location potential, their number should be small. Therefore, the influence on the identified patterns should be marginal. Improved standardization of reporting coordinates and metadata between the different RIs, at best in an overarching site registry like DEIMS (Wohner et al., 2019), would allow for a more comprehensive candidate dataset, where no none co-located facilities would be identified as co-located and vice versa.

The third limitation relates to the spatial bias present in the candidate facility dataset (Figure 1b) due to facilities clustering mainly in Central Europe. We tried to address this issue using the candidate facility density for weighted sampling (Supplemental Figure 1) before the addition of a facility to eLTER RI. This weighting procedure was very successful in addressing the spatial bias, e.g. a truly random sample was 5.3 times as likely to be drawn from Poland than from Spain, while for the weighted sample this ratio changed to 1.6 (Supplemental Figure 2). However, the analysis suggested seven times as many suitable facilities in Poland than in Spain. Thus, there is still some bias present in drawing samples, but the differences in facilities suggested lie mainly in the availability of suitable candidates. While in Poland the weighted iterative approach identified 77 facilities of interest, only 3 were chosen with a suitability of >0.3. Contrary, of the 11 facilities identified in Spain, 6 were chosen with a suitability of >0.3. Therefore, the weighted iterative approach apparently allowed to target the bias in the candidate facility dataset. Nonetheless, a less biased candidate facility dataset with more suitable candidates in the Mediterranean could provide a clearer pathway to bias mitigation within eLTER RI.

The fourth limitation relates to the RIs investigated. We were interested in facilities embedded in environmental RIs that feature long-term operation and, in principle, measure variables similar to eLTER RI. Therefore, facility coordinators are already used to and have already established necessary infrastructure for working within an RI environment. We acknowledge, while co-locating candidate facilities from other RIs with eLTER RI is promising from a bias reduction perspective, additional facilities would require an adaptation of the observational design to meet eLTER RI standards (Zacharias et al., 2021; Zacharias et al., 2025). The effort necessary for facilitating co-location differs from facility to facility and from RI to RI. For example, ICP Waters facilities are mainly aquatic. Therefore, to comply with the eLTER RI facility design ICP Waters facilities would have to adapt a terrestrial catchment approach. While we made efforts to consider the most relevant RIs and peer networks, we acknowledge that there might be other RIs with facilities suitable for this approach that were not regarded in this study. Again, a site registry like DEIMS (Wohner et al., 2019) should be used by more RIs and peer networks to allow for, inter alia, a more comprehensive investigation of suitable candidate facilities. Importantly, for all RIs investigated we assume that co-location can be implemented regarding the observational facility design. Thus, as aimed for in this study, despite the addressed limitations we were able to derive a comprehensive dataset of potential candidate facilities to thoroughly investigate the potential of co-location exemplary for eLTER RI.

4.2 Methodological Approach to Bias Reduction

To investigate the co-location potential, we focused on a representativity approach and only used the transferability approach as a second layer of information. The representativity analysis (Wohner et al., 2021) is based on a chi²-test of homogeneity for each thematic dimension. This feature generally allows to classify bias and to judge improvement based on a real-world meaning. Contrary, calculating statistical distances in transferability approaches cannot be easily translated back to real-world properties, a general feature of PCA or MCA methods. Therefore, (dis)similarity is in these approaches usually judged by arbitrary thresholds, e.g. by dividing the target area into 25 % brackets of (dis)similarity (Václavík et al., 2016). Thus, these arbitrary thresholds can be used to classify areas as dissimilar, however, they clearly hamper the ability to judge improvement in terms of bias reduction within an RI.

However, also the representativity analysis has shortcomings. Since it compares relative distributions on RI facilities with those of a target region, it is well equipped to uncover bias. However, it does not address the dissimilarity between ecosystems covered by RI in-situ facilities and in the target region. Thus, combining both analyses allows to mitigate bias while simultaneously identifying candidates in ecosystems with conditions most different to those on eLTER RI facilities. More than 70 facilities the representativity analysis would have suggested were not suggested by the transferability analysis. These were mainly located in France, Germany, Czechia, Italy, Southern Sweden and Poland (Figure 4c). Especially in Poland, this analysis allowed refining facility recommendations. Under certain circumstances, e.g. if an RI is specifically developed to cover extremes rather than mirror image the target region, transferability approaches could be the primary choice when further developing the in-situ facility network. Nonetheless, we deem representativity approaches generally superior in addressing bias and advise adding the information of a transferability approach to refine network development recommendations.

4.3 Tackling Bias of the eLTER RI in-situ facility network

The methodological approach presented in this study successfully identified many potential candidate facilities in regions where initial bias was strongest (Figure 3a). In previous work, where sampling bias within eLTER RI was investigated (Ohnemus et al., 2024; Ohnemus et al., 2025) the addition of facilities in the Iberian Peninsula, Fennoscandia, Poland and Lithuania was suggested as most important to reduce bias. The present study confirms these past suggestions, with 156 of 197 recommended candidate facilities lying in these countries. Notably, while sampling bias manifests in these regions, the underlying drivers of sampling bias lie in the thematic dimensions investigated. Ohnemus et al. (2024) found a few general patterns causing underrepresentation in current conditions. First, agricultural lands were underrepresented. Even within an anthropogenically dominated region like Europe, a tendency towards studying more natural sites is apparent (Martin et al., 2012; Ohnemus et al., 2024), coming at the expense of agricultural facilities. Second, remote areas with little direct anthropogenic impact, e.g. in Fennoscandia, were underrepresented. This pattern is also widespread in ecological research and is especially evident on the global scale (e.g. Martin et al., 2012; Li et al., 2017; Wohner et al., 2021; Wolf et al., 2022). Third, areas with low economic density were underrepresented. The underrepresented areas in the Iberian Peninsula, Fennoscandia, Poland and Lithuania all reveal GDP per Capita below European average (Solís-Baltodano et al., 2021). Ohnemus et al. (2024) postulated that economic strength might be an especially strong determinant for the locations in long-term research, since these facilities are often in proximity to their operating institutions.

Nonetheless, especially arctic and antarctic long-term research facilities show that special research foci lead to the deployment of funding, independent of simple spatial GDP per Capita patterns. Regarding anticipated future changes (Ohnemus et al., 2025), a lack of in-situ facilities within eLTER RI was observed for areas with low change in annual biotemperature, strongest increases and decreases in annual precipitation and strongest changes in land use. Thus, all these conditions identified before drive the observed initial bias (Figure 3a). We are not aware of any RI that specifically included anticipated global change aspects in its network development. However, we strongly recommend this, and for some RIs like e.g. NEON with the domain delineation based on climatic conditions only (Hargrove and Hoffman, 2006) it could be rather quickly implemented. The methodology in the present study was successfully designed to identify European long-term research facilities covering conditions that eLTER RI underrepresents. Consequently, the candidate facilities suggested here are not chosen based on simple geographical distance, but on a wide array of current and anticipated future conditions that eLTER RI strives to represent better.

Importantly, not all 197 identified facilities are suggested to be incorporated into eLTER RI, as - even if it was possible to incorporate such a high number of facilities - not all identified facilities would necessarily reduce bias, since the bias reduction depends on the facilities chosen before. Rather, this approach allows to address policy and decision makers with a clear prioritization of candidate facilities down to country and RI-level using the calculated suitabilities. We are aware that political and funding constraints will not necessarily allow to incorporate candidate facilities with the highest impact in terms of bias reduction. Nonetheless, the suitability clearly ranks facilities in their importance. We argue that this analytical framework should be used after any addition of in-situ facilities to eLTER RI to create an updated facility recommendation list.

Only after the addition of >25 facilities a bias reduction in all facets was observed (Figure 2). Importantly, that bias is not reduced already with the addition of the first facility can be explained by the categorical data. With every facility added, some categories of the thematic dimensions investigated approach a better representation, based on the underlying chi²-test of homogeneity, but do not necessarily reach it. Therefore, several facilities must be added until the first categories reach a new representation state. Even after the addition of 50 facilities notable bias persisted. While the trend of bias reduction suggests that the addition of more than 50 facilities could further counteract bias, it seems unrealistic that more than 50 facilities could be added to eLTER RI. This appears to be in line with the study of Villarreal and Vargas (2021), where already an optimal distribution of 60 flux towers over Latin America reached a similar representativeness to 200 towers. This points to an obvious feature that with increasing network density, improvements in coverage become increasingly smaller. Yet, since ecosystems are complex each additional facility would provide important insights, which might not be the case if only one parameter was of interest (Sulkava et al., 2011). Consequently, with the current set of candidate facilities, overcoming bias within eLTER RI seems unlikely. The greatest limitation is the small number of candidate facilities covering conditions that prevail and are projected in the Iberian Peninsula and, less dramatic, other parts of the Mediterranean. Indeed, while the co-location analysis provided a sufficient number of suitable candidate sites in Eastern Europe to counteract bias, the addition of facilities there and in Fennoscandia even led to slightly increasing bias-classified areas in the Mediterranean. Therefore, especially for the Iberian Peninsula, the Mediterranean and to a lesser extent for Fennoscandia further facilities are required to conclusively target bias. These facilities could be part of further RIs that we did not investigate in this study, or they would have to be set up, e.g. ICOS plans to build three more facilities in Spain, and two more in Greece (Storm et al., 2023).

Yet, even if further suitable candidate facilities were found in the Mediterranean and Fennoscandia, eLTER RI will likely not be able to co-locate more than 50 further facilities. But, due to the high facility density in the Alps, adding 50 facilities might not be sufficient to counteract bias, independent of the candidate facility locations. The high alpine site density can again be explained in eLTER RI's initial bottom-up approach, where local research interests and funding opportunities largely drove the establishment of new in-situ facilities. While this facility density can lead to sampling bias on continental scale, nonetheless, the high variability in alpine ecosystems due to steep gradients and rough relief may warrant a dense facility network in the European Alps. Importantly, bottom-up approaches can still achieve good or even better coverage than top-down approaches. This can be the case, when top-down developed facilities are always placed close to cluster centers, hampering the ability to reproduce a parameter's variability (Sulkava et al., 2011). However, as long as bias is present in eLTER RI, it should also be addressed in analyses of eLTER RI data. On this account, a less biased or even unbiased subset of locations could be chosen before undertaking comprehensive meta-analyses or implementing large-scale models (e.g. Baatz et al., 2018; Forsius et al., 2023). Finding such a subset of in-situ facilities could be facilitated using the representativity analysis, with the opposing goal to the present analysis: facility removal instead of addition. Importantly, we would not advise eLTER RI to literally remove in-situ facilities from their network, but to disregard data from specific facilities to reduce sampling bias. This sampling bias can lead to dramatic misrepresentation of variables on continental scale, e.g. Sulkava et al. (2011) showed for flux towers in Europe, that upscaling from the persistent network would lead to an mean overestimation of GPP by 8 % compared to its target region, and of >20 % in certain regions. However, removing sampling bias in data would be concomitant with the loss of valuable data. Since each ecosystem is unique, each observation would contribute to functional ecosystem understanding and macrosystems ecology (Heffernan et al., 2014). To avoid loss of data, Schmill et al. (2014) suggested to assign a greater weight to data from underrepresented regions. Practically, one could multiply single data points, artificially creating data to remove sampling bias from the dataset. However, since ecosystems are unique, while removing one kind of bias this approach rather introduces another. Therefore, as long as sampling bias within an RI persists, the scalability of the in-situ data gathered by this RI is limited.

Consequently, only mirror imaging the target region in a "geospatial twin" would allow to create unbiased data without the loss of single data points, i.e. harnessing the complete data pool of eLTER RI.

5 Conclusions

In this study we showed that co-location is promising to reduce sampling bias and we were able to derive a prioritization that can help policy and decision makers in further optimizing the eLTER RI in-situ facility network, specifically towards sampling bias reduction. Nonetheless, co-location alone can - at least for eLTER RI - not eliminate all observed sampling bias. Therefore, it is important to continuously monitor sampling bias as the in-situ facility network evolves, and to address sampling bias in data syntheses and analyses, e.g. by creating less biased or unbiased data subsets.

Regarding the in-situ facilities of both the seven RIs and peer networks tested for co-location as well as of eLTER RI itself, a lack in long-term environmental research efforts in the Mediterranean compared to all other regions of Europe was identified. This suggests that sampling bias regarding continental target regions might occur in other pan-European RIs and peer networks, too. Therefore, pooling efforts and resources of several RIs to establish additional facilities in these areas can be advised. A more widespread use of the site registry DEIMS (Wohner et al., 2019) as metadata repository would also help identifying suitable candidate facilities for sampling bias mitigation by co-location. Furthermore, the bias-reducing potential is just one beneficial aspect of co-locating facilities, which also allows to measure a wider range of earth system parameters, pushing RIs collectively towards a stronger whole-systems approach.

Especially when aiming to develop a global scale earth observatory (Kulmala, 2018), as e.g. GERI tries by integrating data from different continental scale RIs (Loescher et al., 2022), strong collaboration between different RIs is necessary. While co-location is a way to reduce bias, further standardization across RIs is indispensable for producing interoperable data (Futter et al., 2023; Deshpande et al., 2025). While GERI will be a first of its kind RI, early stage work indicated that sampling bias and gaps in coverage of its global target region will be substantial (Ohnemus and Mirtl, 2025). Therefore, also efforts like GERI addressing the global scale will benefit from thorough analyses of sampling bias, to ultimately push environmental sciences to an improved, more representative understanding of the earth system.

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Supplement

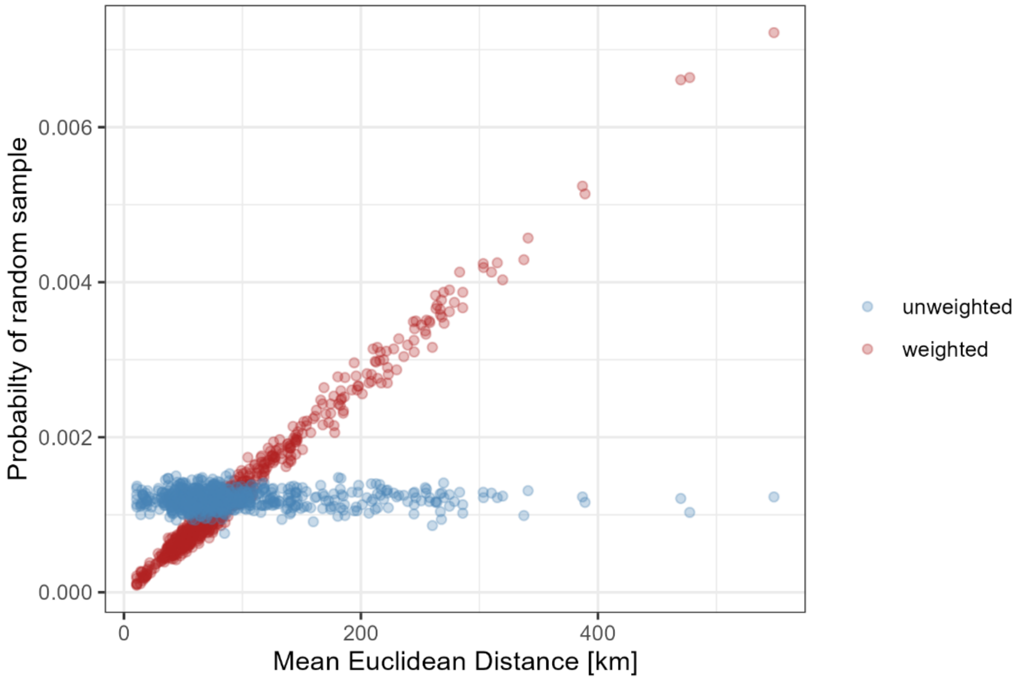

Figure S 1: Each dot displays the mean probability for a candidate site in the sampling procedure in dependence of the mean euclidean distance to the 10 closest candidate sites. Colours indicate whether the sampling procedure was random (blue) or based on the mean Euclidean distance to the next ten candidates (red). Result of 100,000 samples.

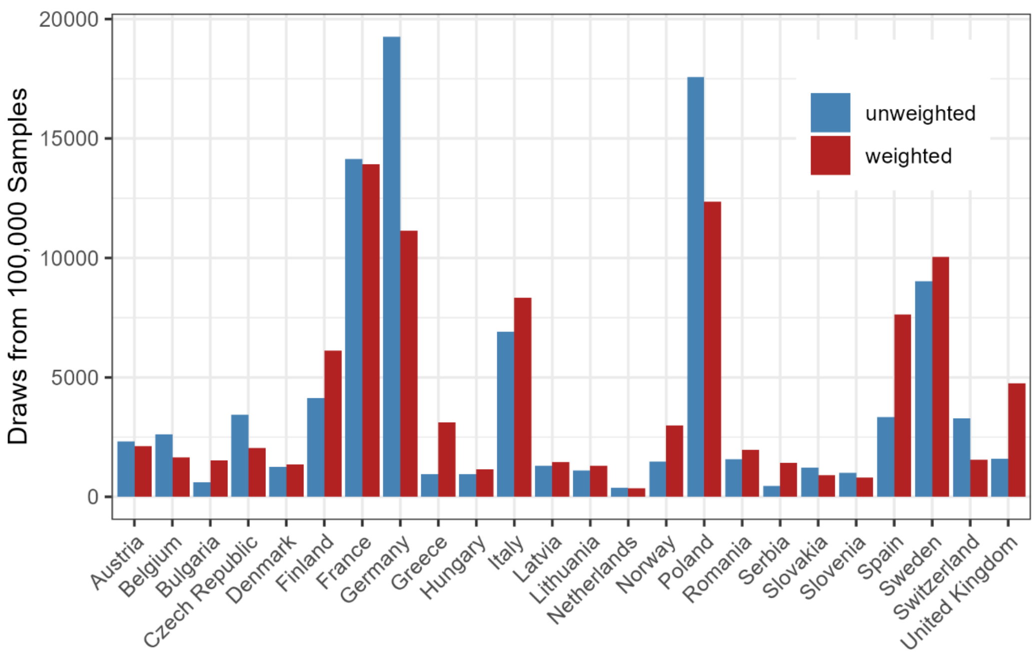

Figure S 2: Each bar displays the number of draws of candidates from 100,000 samples for each country in the eLTER RI target region. Colours indicate whether the sampling procedure was random (blue) or based on the mean Euclidean distance to the next ten candidates (red).