Designing countrywide and regional microclimate networks

Running head: Designing microclimate networks

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Published in Global Ecology and Biogeography

https://onlinelibrary.wiley.com/doi/10.1111/geb.13290

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Acknowledgements: JJL received a postdoctoral fellowship from the Research Foundation Flanders (FWO, 12P1819N). JL received funding from the Agence Nationale de la Recherche (ANR) under the framework of the young investigators (JCJC) funding instrument (ANR JCJC Grant project N°ANR-19-CE32-0005-01: IMPRINT). PDF received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (ERC Starting Grant FORMICA 757833). We thank Stijn Van de Vondel for trying out the R code.

Biosketch: The authors all focus their research extensively on microclimates and the implications of microclimate buffering on biodiversity and ecosystem functioning in the face of climate change.

Author contributions: JJL, JL and PDF conceived and designed research. JJL analyzed the data. All authors wrote the manuscript.

Data and code: Example code is available at https://doi.org/10.6084/m9.figshare.14130116.v1. This code can be used by anyone to generate, for any country or region in the world, an optimal sampling design to launch a relevant and effective microclimate network. No own data are used for this study.

Abstract

Issue: Climate change, and its impacts on ecological, agricultural, and other societal systems, is most often studied by relying on temperature data derived from countrywide weather-station networks. Yet, these data do not capture microclimates, those arising from soil, vegetation, and topography, at spatial scales relevant to the majority of organisms on Earth. We argue that a unified strategy is missing to design regional or countrywide networks to measure microclimates and thus provide ecologically relevant and sound climate data, for instance for modelling biodiversity and ecosystem functions.

Evidence: Here, we develop an integrative framework to design effective microclimate networks for potential implementation at the country level. With the dawn of novel low-cost sensor technologies and modelling techniques it is time for designing standardized microclimate networks. We make an important step forward in that regard by providing a hands-on training to generate an optimal sensor distribution to capture as much microclimate diversity as possible at the regional or country-scale.

Conclusions: By implementing our framework to design countrywide or regional microclimate networks, strategically positioned to capture a representative picture of microclimates available within the focal country or region, governments could lay the foundation for the development of a next generation of modelling and synthesis of landscapes, to serve a range of societal needs now and into the future as climate change accelerates.

Keywords: biogeography, climate change, data loggers, location selection, microclimate, microweather, sensors, temperature

Introduction

Our knowledge of the ongoing changes in the climate system predominantly relies on a global network of countrywide weather-station networks. For their establishment, meteorologists generally follow the World Meteorological Organisation's guidelines that sensors should be installed in open landscapes where the wind mixes the air, above short grass, well away from trees, buildings or topographic features (World Meteorological Organization 2008, De Frenne and Verheyen 2016). Representativeness of a meteorological observation (the degree to which it accurately describes the value of the variable needed for a specific purpose) is thus key: synoptic observations have to represent an area up to 10-100 km around the weather station (referred to as 'free-air temperature', 'atmospheric temperature' or 'macroclimate') (World Meteorological Organization 2008). While meteorologists did their best to remove what they consider as local sources of "noise" (trees, buildings and topographic features) in the data, these sources of "noise" are home to many organisms and thus are highly relevant for ecologists. Indeed, it is the local temperatures near the ground or below the vegetation that set the bounds of organisms' range limits and dictate ecosystem processes such as primary production and hydrological, nutrient, and carbon cycles (Lenoir et al. 2017, Suggitt et al. 2018, Burrows et al. 2019, Laskin et al. 2019, Pinsky et al. 2019). For instance, temperatures below the canopies of forests are buffered by up to 10-20°C across the globe and depend on forest structure, season, tree species, latitude and management practices (Alkama and Cescatti 2016, De Frenne et al. 2019, Zellweger et al. 2019). Likewise, surface temperatures on mountain slopes can also deviate by several degrees from the macroclimate due to vegetation and topography (Scherrer and Körner 2010, Lenoir et al. 2013), while urban structures in cities can create regional-scale heat islands, and meter-scale heterogeneity in climate conditions (Dimoudi et al. 2013). In conclusion, the vertical, horizontal and temporal complexity of the surrounding landscape, all of which directly or interactively influence microclimates, makes microclimate prediction from synoptic weather stations very complex (Lembrechts *et al.*, 2020).

Recent progress in the field of microclimate ecology and biogeography has improved predictions of microclimate based on statistical downscaling of existing weather station data (Meineri and Hylander 2017) as well as on mechanistic models (Kearney and Porter 2017). The problem with both approaches is, however, that actual measurements in non-standardized environments are needed to validate predictions (Lembrechts et al. 2020). We thus argue that our hands-on training to design microclimate networks at the country or regional level – the level where existing weather station networks are currently established and maintained – is critical and necessary if we are to provide reliable future scenarios for biodiversity and ecosystem services in the context of the growing demands for resources on ecosystems. Indeed, accurate microclimate data should provide the foundation of any effort to implement key transnational policies such as the Intergovernmental Panel on Climate Change (IPCC), the Intergovernmental Panel on Biodiversity and Ecosystem Services (IPBES), and in light of the on-going discussions around drafting the post-2020 Global Biodiversity Framework under the Convention on Biological Diversity (CBD). We will indeed struggle to achieve the ambitious goals of the 2050 Vision of "Living in harmony with nature" under the CBD as long as we do not have the necessary and basic information to understand microclimate dynamics within habitats occupied by diverse life forms.

Microclimate networks

Here we propose an integrative framework to design countrywide or regional microclimate networks to monitor microclimate complementary to the existing weather station networks. Note, however, as implementation and associated costs of acquisition and maintenance can vary widely from country to country, we focus our framework on planning and design rather than addressing the actual implementation (however, see Supplementary Table S1 for some details on implementation costs). Measuring microclimate at the country level using standardized protocols across the globe would result in a dramatic step-change for the nascent field of microclimate ecology and biogeography, which aims at better understanding biological and ecosystem responses to climate change. Such networks of microclimate sensors could serve to validate microclimate modelling approaches (Maclean et al. 2019), as well as create micro- and mesoclimatic grids (e.g. 25-250 m, Bramer et al. 2018). The proposed framework is also applicable at smaller spatial extents, for example to design microclimate networks at the landscape level, where one can then aim for much finer spatial resolutions. Noteworthy, our framework is not limited to applications in ecology and can span environmental and agricultural sectors to serve a broad range of societal needs. For example, high-resolution microclimate data, when extended to agricultural land-cover types, can inform a next generation of soil-crop simulation models to help decision-making in agriculture, such as conservation tillage practices or precision agriculture, or provide real-time growth metrics for crops, all of which would maximize farmer returns.

To help governments and scientists establish efficient countrywide and regional microclimate networks, we propose a multidimensional sampling design following gradients in macroclimate, as well as in the main drivers of microclimatic variability, topography and vegetation structure (Naudts et al. 2016, Bramer et al. 2018, Graae et al. 2018, Senior et al. 2019, Zellweger et al. 2019, Lembrechts et al. 2020). Hereafter, for illustrative purposes, we focus on the country level, yet the same approach can be implemented at any spatial level. In our sampling design, the goal is to capture the greatest variability of microclimates with the fewest number of country-level monitoring locations possible, thus optimising the costs. To do this, we implement a systematic sampling design within the environmental space (Hattab et al. 2017). More specifically, we generate a principal component analysis (PCA) of the environmental space using available gridded products of the most important drivers of microclimate heterogeneity (i.e. variables reflecting the variation in macroclimatic conditions as well as in topography and vegetation structure, see Supplementary Information Table S2), and distribute our selected locations equally along the first three principal components from the PCA. This way, we ensure maximal spread of sampling locations throughout the environmental space, and selection of preferential locations that are representative of microclimatic conditions available within the focal country.

The number of locations needed within one country can be decided based on the existing macroclimatic gradient within the country (e.g. 25 locations per degree of variation in mean annual temperature at a 1 km^2-resolution, see Supplementary Information 1 for full methodological details). Countrywide microclimate networks could be plugged in the existing national networks of weather stations in order to assess the spatiotemporal dynamics of the offset between macroclimate and microclimate (Lembrechts et al. 2018, De Frenne et al. 2019) and to limit the need for sampling in areas with little microclimatic heterogeneity that are already well-covered by the existing weather station networks. Finally, each local ‘microweather’ station can incorporate a vertical gradient of sensors at different soil depths and heights above the ground. For example, some microclimate loggers are readily equipped with several built-in sensors that measure air, surface and soil temperature simultaneously (Wild et al. 2019), while a new generation of wireless and autonomous sensors can integrate several sensors across multiple depths and heights (nkeWatteco 2019).

Proof-of-concept

To show proof-of-concept, we applied the above-mentioned concept of a multidimensional sampling design (see Table S2 for data sources) to twelve example countries, in four different and contrasting regions of the world: Europe (the Netherlands, Belgium and France); South America (Chile, Argentina and Uruguay); Africa (Morocco, Algeria and Tunisia) and Asia (India, Nepal and Bangladesh) (Fig. 1). Altogether these countries make exemplar case-studies in that they: (i) represent a broad range of political, social, economical and geographical entities, (ii) have contrasting topographic scenarios from topographically simple and flat to topographically complex and mountainous and (iii) they host contrasting conditions in terms of land use and vegetation structure. To populate our framework, our approach used as an example (Supplementary Information Table S2): (i) macroclimatic data in the shape of the mean annual temperature (MAT) and precipitation (MAP) from CHELSA (Karger et al. 2017) (at a spatial resolution of 1 km^2 for the period 1979-2013), (ii) elevation, northness (the orientation of the slope relative to a northern bearing), the topographic position index (TPI), and the topographic roughness index (TRI) from Amatulli et al. (2018) (derived at 1 km^2 resolution from a global digital elevation model (DEM) at 250 m^2 resolution (GMTED2010)); and (iii) the annual Fraction of Absorbed Photosynthetic Radiation (FAPAR, COPERNICUS) to capture vegetation structure (Hengl 2018) (at a spatial resolution of 250 m^2 for the period 2014-2019). This sampling strategy resulted in between 42 (the Netherlands) and 520 (Chile) sampling locations per country (Figs. 1-3, Supplementary Figures 1-5, see Supplementary Information 1 for full methodological details). These microweather stations would complement existing weather station infrastructure maintained by their national meteorological services.

Importantly, our framework does not aim to measure microclimate at the finest possible gridded resolution (which can range from loggers placed every 100 m all the way down to 0.01 m, Geiger et al. 2009, Bramer et al. 2018). As has been argued before (Bennie et al. 2014, Lembrechts et al. 2018), we emphasize that such a run for increasingly fine resolutions is not necessary: microclimatic precision or resolution is only valuable down to the level at which an increased resolution does not affect the actual pattern or process anymore. Rather, our framework takes on the much more critical task of accounting for the most important drivers of micro- and mesoclimate and measuring within environments that are representative of organism's habitats (Lembrechts et al. 2020), achieved here using in-situ data with data loggers placed in the most characteristic environments, up to several kilometres apart. Our approach thus allows for the creation of trustworthy gridded micro- and mesoclimate maps at the regional and global scale (Lembrechts et al. 2019). While the resolution of these final gridded microclimate maps at the country-level can be as high as the available remotely sensed products at the country-level (e.g. digital elevation models at 30 m resolution), it will not necessarily increase the resolution of gridded climate products compared to the literature, as high-resolution datasets based on macroclimatic measurements are now readily available (Bramer et al. 2018, Lembrechts et al. 2018). However, the resulting products will have the direct links to the ecology of organisms and ecosystems, as well as reduced error at the local scale, that are currently lacking. Also, if required, our approach could be reproduced at finer spatial resolutions (e.g. 1 m or finer) over smaller spatial extents when such environmental data is available (e.g. through LiDAR, George et al. 2015, Randin et al. 2020).

Importantly, the goal of our approach is to create a network that captures the most representative microclimates for a given country or region. When the main research goal is to disentangle the interactive role of a specific set of environmental drivers on microclimate variability and thus minimize correlation across these variables (Ashcroft and Gollan 2012), this can be achieved by adding additional PCA axes to the selection procedure (and preferably also increase the number of sensors to reach more unique and peculiar microclimates), or by limiting the number of variables to those of principal interest and build a specific and orthogonal sampling design around these variables.

The resulting microclimate networks will also allow calibration of existing and developing mechanistic microclimate models (Kearney et al. 2019, Maclean et al. 2019). Indeed, one can predict the microclimatic conditions at all sensor locations across the environmental gradient using these models, and use the in-situ measured data from the established network for validation. In general, the output from all the above-mentioned modelling approaches will allow better calibration of species distribution and ecosystem modelling and increase our understanding of reproductive ecology or energetics of ectotherms (Lembrechts et al. 2020). Finally, it also provides a step forward towards accurate predictions of future microclimate (Lembrechts and Nijs 2020). Note however that the proposed approach is suitable for those organisms living on, in and around the soil surface (e.g. soil micro-organisms like fungi, ground arthropods, herbs, mosses, tree seedlings and small vertebrates), yet does not cover more peculiar habitats like those of invertebrates living under the bark of a tree, or parasites living in the fur of a mammal (Pincebourde and Salle 2020).

Challenges

There are of course geographical, technical, as well as financial challenges that may hamper the rollout of such countrywide, regional or landscape-level microclimate networks. Geographically, study sites can be located both on private and/or public lands, equally accessible or remote, just as with existing weather stations. Technically, several approaches exist with regard to sensor choice and station management for recording soil and near-surface temperatures and soil moisture (e.g. Wild *et al.,* 2019) ranging from: (i) fully-automated stations powered by solar cells, that remotely record and send data online; (ii) miniature battery-powered loggers; to, finally, (iii) manual 24h-readings of maximum and minimum temperatures by dedicated volunteers (as is currently done in many meteorological stations) (Supplementary Information Table S1). Of course, specific advantages and drawbacks are associated with each of these three approaches, and solutions might depend on local situations. For example, countries with substantial wilderness and willing to invest more money in the long-term monitoring of microclimate might opt for robust automated stations with a remote connection, while countries with limited economic resources could opt for cheaper battery-powered loggers or dedicated volunteers.

To ensure commitment and implementation by as many governments as possible, a promising solution would be to make the establishment of a microclimate network part of governments' obligations under international treaties such as the Paris Agreement. Ideally, intergovernmental organisations such as the European Union (EU) or the Association of Southeast Asian Nations (ASEAN) could coordinate the international roll-out of such networks. But who will pay the bill? The proposed 43 micro-weather stations for the Netherlands, 76 for Belgium and 457 for France in our European set of countries, for example, can be achieved without too much extra costs, given that miniature sensors to log in-situ microclimate are readily available at low prices per unit (e.g., < $100 USD), and final station numbers are in line with the number of existing weather stations in these countries (c. 46, 200 and 554 official weather stations for the Netherlands (KNMI), Belgium (RMI) and France (Météo France), respectively). The establishment, maintenance and data management of microclimate networks aligns seamlessly with synoptic weather stations and thus could be part of the tasks already ensured by national meteorological institutes. Besides, national meteorological institutes will directly benefit from data that incorporate microclimate to better inform the general public about microclimatic conditions in, for example, urban parks, gardens and residential areas. Installation in large and less wealthy countries might be harder to achieve, yet here again integration with existing meteorological networks could provide opportunities. As argued above, such microclimate networks do not necessarily need excessive amounts of loggers, nor focus on the most inaccessible locations, so long as climate is measured in-situ, i.e. at locations and scales relevant to the organisms of interest, and not in standardized environments that artificially filter away local climatic variability. Importantly, our approach allows flexibility in the final number of loggers used, making it feasible to match the optimal measurement strategy to any level of financial investment and research question (Supplementary Figure S4).

Finally, it remains important to find a representative location within a selected grid cell to install the microclimate sensors. Indeed, one should aim to achieve a location with average conditions for that grid cell (e.g. avoiding forest clearings in a pixel dedicated as forested habitat). For this, all assessed environmental variables in that pixel should be taken into consideration. Finding such a suitable location is far from trivial, especially in large regions where coarse-resolution environmental layers have been used. In such a case, selection could be facilitated through the use of finer-grained local or regional layers.

Conclusions

In sum, we propose a framework to generate an optimal sampling design for countrywide, regional or landscape-scale microclimate networks to lay an important foundation necessary for future implementation. Even with limited implementation by governments, organizations and/or ecologists, it will establish a necessary benchmark for climate monitoring at scales appropriate for understanding impacts to organisms (Suggitt et al. 2018). If implemented widely, our proposed approach would provide landscape, regional and even global information on local climatic conditions in forests, mountains, cities and all other habitats where such in-situ climate data is currently critically needed. Indeed, if we are to provide reliable future scenarios for climate change, biodiversity and ecosystem services as aimed for by IPCC and IPBES, we urgently need to better quantify how temperatures are changing in mountains, cities, croplands, shrublands, forests and other habitats or microhabitats that are not well captured by standard terrestrial weather stations. Only then will we be able to detect and attribute climate change impacts with confidence and certainty.

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Figures

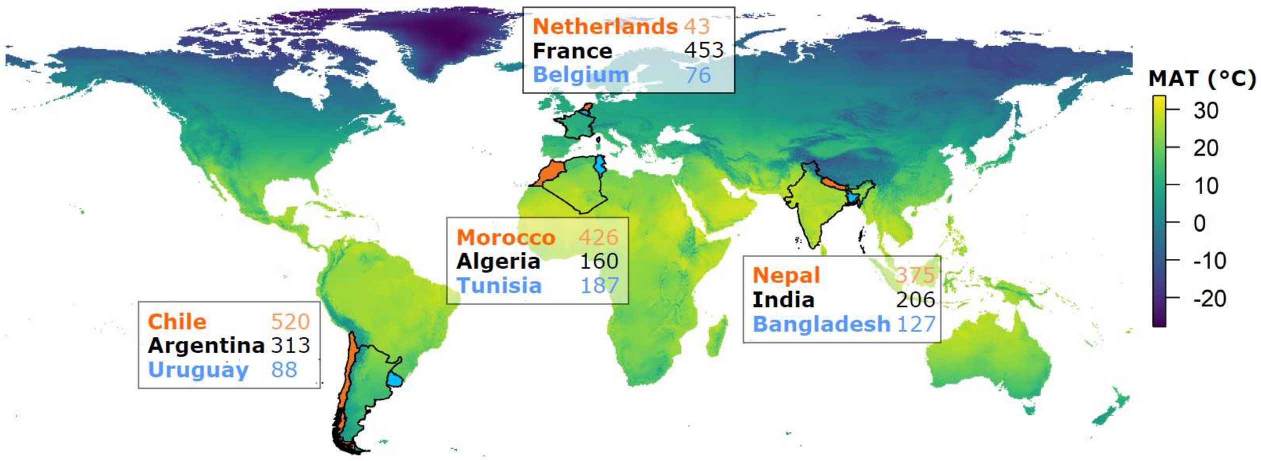

Figure 1. Location of the four triptychs (in South America, Africa, Europe and Asia) used to exemplify our framework. Background map of mean annual temperatures (MAT, °C) from CHELSA (Karger et al. 2017). Numbers behind each country's name indicate the number of data loggers for each country following our approach, which aims for 25 locations per degree Celsius of mean annual temperature range at a 1 km²-resolution within the focal country (see Fig. 2 for details).

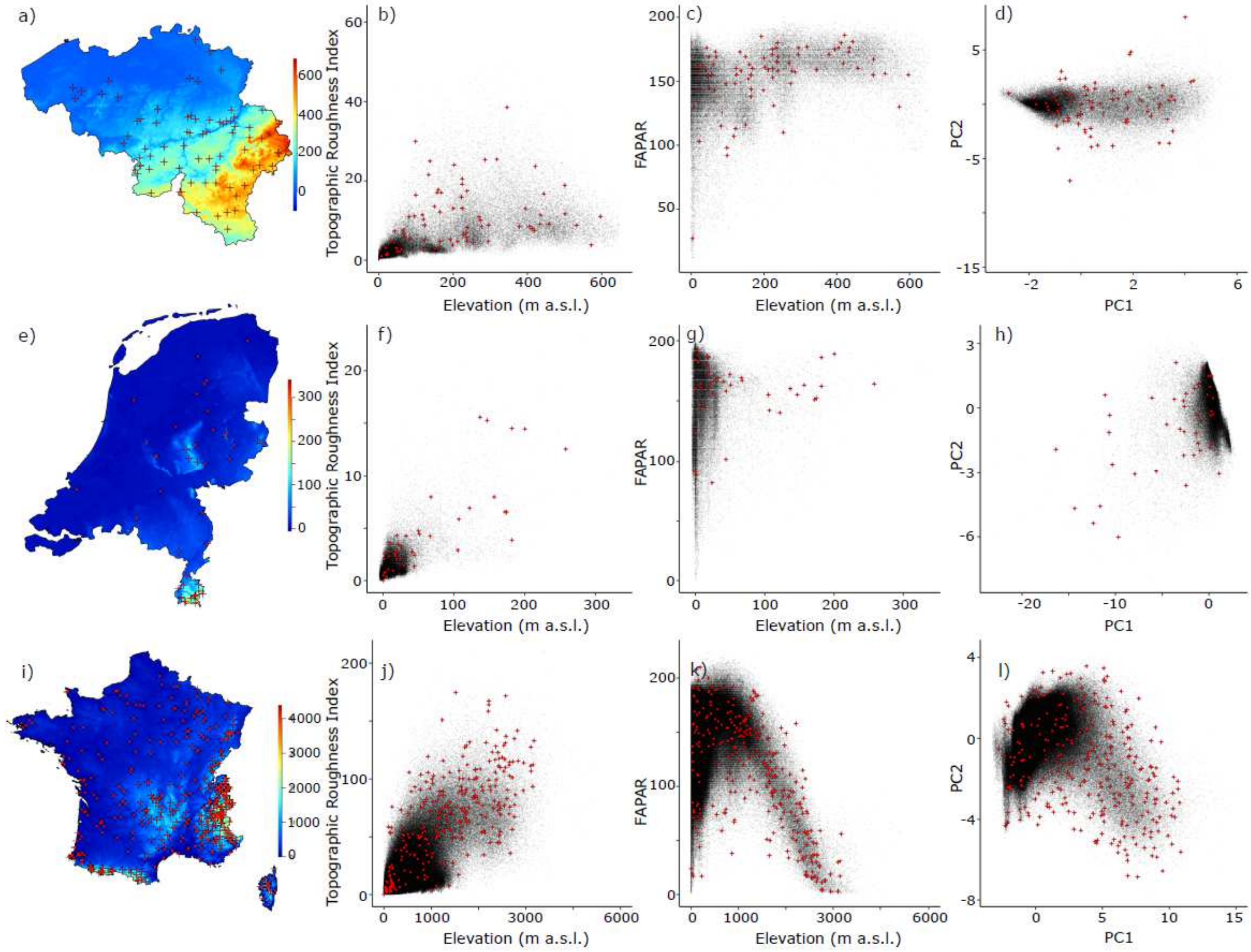

Figure 2. A framework to establish country-wide microclimate networks. Maps portray the potential locations of microweather stations, stratified according to the three main axes of a PCA of environmental variables (see Supplementary Information 1, Table S2), for a-d) the Netherlands, e-h) Belgium and i-l) France on a background map of elevation (m a.s.l.). The PCA was created using environmental conditions derived from gridded products at all points from a 1 km-resolution grid over the whole country (see Supplementary Information 1 and Fig. S5 for detailed methodology). Final selected locations are plotted with a red dot on the map. Scatterplots show for each country two example environmental drivers (Topographic Roughness Index and Fraction of Absorbed Photosynthetic Active Radiation (FAPAR)) as a function of elevation within the country, and the two main axes of the PCA. Small black dots in the scatterplots give the existing variability within the country – each dot represents one location of the grid – red crosses mark the selected locations. For results of the other triptychs, see Fig. 3.

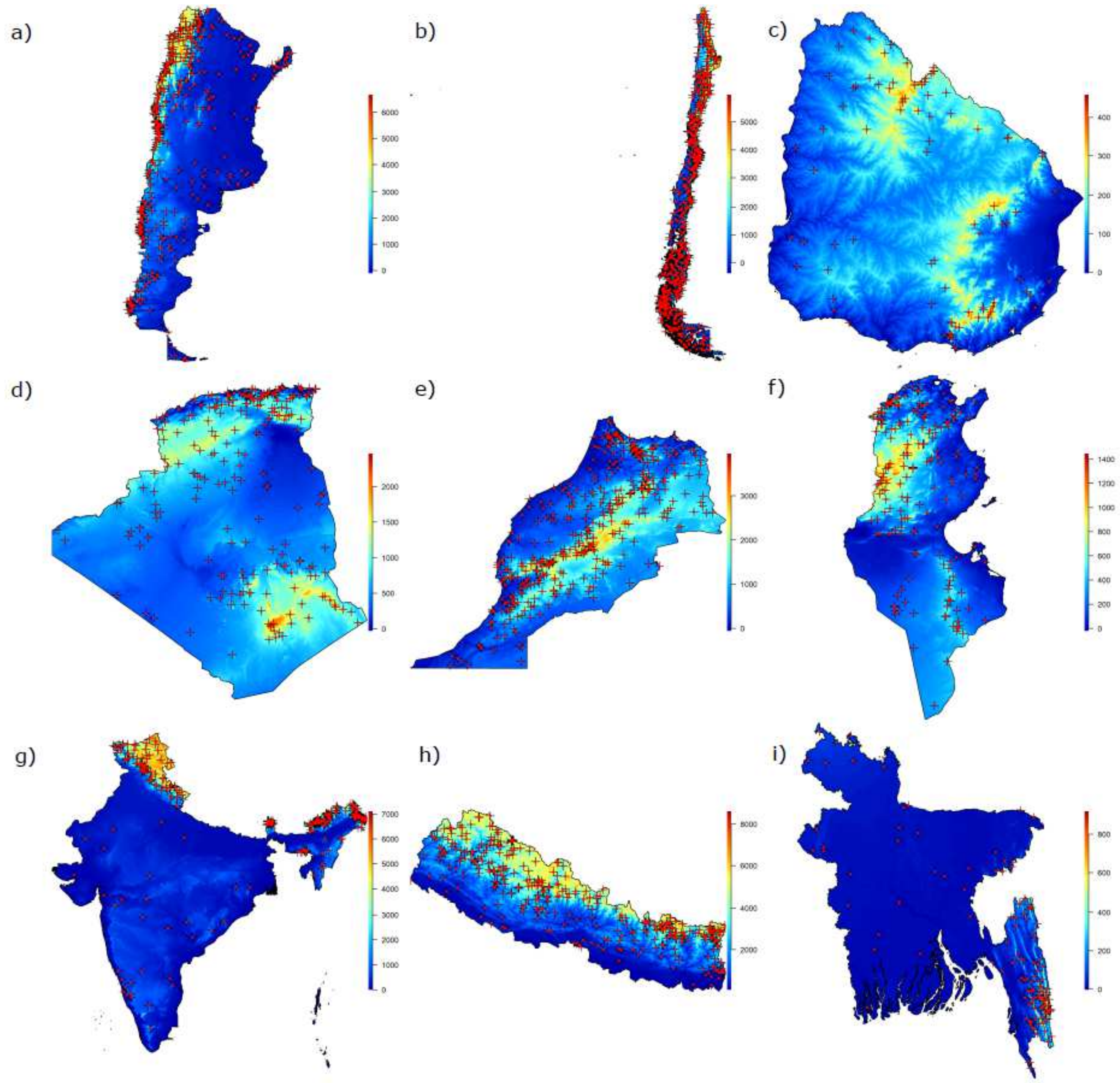

Figure 3. Examples of location selection following our framework to establish country-wide microclimate networks for the triptychs in South-America: a) Argentina, b) Chile, c) Uruguay; Africa: d) Algeria, e) Morocco, f) Tunisia and Asia: g) India, h) Nepal and i) Bangladesh. Maps portray the potential locations of microweather stations, stratified according to the three main axes of a PCA of environmental variables on a background of elevation (m a.s.l.). For methodological details, see Supplementary Information 1, for exemplary scatterplots, see Supplementary Figures S1-3.

Supplementary Figures

Fig. S1. Scatterplots for a selection of environmental drivers (Topographic Position Index, Topographic Roughness Index and FAPAR) as a function of elevation within the country for Argentina (a-c), Chile (d-f) and Uruguay (g-i), with selected locations marked with a red dot. Small black dots in the scatterplots give the existing variability within the country – each dot represents one location of the 1 km grid – red dots mark the selected locations.

Fig. S2. Scatterplots for a selection of environmental drivers (Topographic Position Index, Topographic Roughness Index and FAPAR) as a function of elevation within the country for Algeria (a-c), Morocco (d-f) and Tunisia (g-i), with selected locations marked with a red dot. Small black dots in the scatterplots give the existing variability within the country – each dot represents one location of the 1 km grid – red dots mark the selected locations.

Fig. S3. Scatterplots for a selection of environmental drivers (Topographic Position Index, Topographic Roughness Index and FAPAR) as a function of elevation within the country for India (a-c), Nepal (d-f) and Bangladesh (g-i), with selected locations marked with a red dot. Small black dots in the scatterplots give the existing variability within the country – each dot represents one location of the 1 km grid – red dots mark the selected locations.

Fig. S4. Comparison of location selection for France in scenario's where only a lower number of microweather stations can be achieved. In a), the same approach as in Fig. 2 is used – aiming for 25 loggers per degree range in Mean Annual Temperature (457 locations), in b) and c) respectively 15 and 7 locations per degree are used, resulting in respectively 424 and 186 locations. Maps portray the potential locations of the microweather stations, stratified according to the three main axes of a PCA of environmental variables on a background of elevation (m a.s.l.). For methodological details, see Supporting Information 1.

Fig. S5. Location selection for the European triptych (a-d, Belgium, e-h, the Netherlands, i-l, France) as in Fig. 2, yet without the square-root correction of the principal components. Maps portray the potential locations of microclimate stations, stratified according to the three main axes of a PCA of environmental variables on a background of elevation (m a.s.l.). Scatterplots for a selection of environmental drivers

(Topographic Position Index, Topographic Roughness Index and FAPAR) as a function of elevation within the country for Argentina (a-c), Chile (d-f) and Uruguay (g-i), with selected locations marked with crosses with a red dot. Small black dots in the scatterplots give the existing variability within the country – each dot represents one location of the grid – red dots mark the selected locations. Note that in this approach, more weight is given to outliers in the environmental space, with thus more investment in the topographically more complex regions of the countries.