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BRITISH ECOLOGICAL SOCIETY Methods in Ecology and Evolution

REVIEW

Ten practical guidelines for microclimate research in terrestrial ecosystems

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Abstract

1. Most biodiversity dynamics and ecosystem processes on land take place in microclimates that are decoupled from the climate as measured by standardised weather stations in open, unshaded locations. As a result, microclimate monitoring is increasingly being integrated in many studies in ecology and evolution.
2. Overviews of the protocols and measurement methods related to microclimate are needed, especially for those starting in the field and to achieve more generality and standardisation in microclimate studies.
3. Here, we present 10 practical guidelines for ground-based research of terrestrial microclimates, covering methods and best practices from initial conceptualisation of the study to data analyses.
4. Our guidelines encompass the significance of microclimates; the specifics of what, where, when and how to measure them; the design of microclimate studies; and the optimal approaches for analysing and sharing data for future use and collaborations. The paper is structured as a chronological guide, leading the reader through each step necessary to conduct a comprehensive microclimate study. At the end, we also discuss further research avenues and development in this field.
5. With these 10 guidelines for microclimate monitoring, we hope to stimulate and advance microclimate research in ecology and evolution, especially under the pressing need to account for buffering or amplifying abilities of contrasting microhabitats in the context of global climate change.

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1 | INTRODUCTION

Most terrestrial climate data are derived from synoptic weather stations, which measure atmospheric conditions of ambient air and represent a coarse spatial grain. These stations are designed according to the standards of the World Meteorological Organization (WMO), that is, to be situated in open areas, typically at 1.5–2.0 m above the ground, where air temperature sensors are shielded from solar radiation and where airflow minimises fine-scale heterogeneity (WMO, 2023). However, many terrestrial organisms live near or below the ground or on vegetation (surfaces), experiencing near-surface microclimates (Box 1). For instance, many animals and plants inhabit either sunlit or shaded environments just centimetres above the ground, where radiation absorption and evaporation strongly influence the temperature of the surface and the air in its immediate vicinity: the proximal microclimate (Klinges, Baecher, et al., 2024). Temperature differences between north- and south-facing slopes or between open and shaded forest patches can exceed 10–20°C (Maclean et al., 2021; Suggitt et al., 2011). Similar variations are observed in other environmental variables, such as relative humidity and wind speed, which can, for example, differ markedly between forest understories and short-stature vegetation. Many organisms rely on this microclimatic variation to maintain their body temperatures and water balance within their preferred range (Mitchell et al., 2024).

Researchers in ecology and evolution face the challenge of determining if, why, what, how, when and where microclimatic conditions should be measured. Historically, ecologists have relied on macroclimate data to infer relationships between organisms and their environments. However, it is now widely recognised that these measures often provide only crude approximations and can sometimes lead to erroneous or misleading predictions (Haesen, Lembrechts, et al., 2023; Körner & Hiltbrunner, 2018; Maclean & Early, 2023; Suggitt et al., 2011). An additional challenge is that microclimate varies at fine spatial and temporal resolutions (Pincebourde & Woods, 2020), increasing the need for replication.

The WMO regularly updates guidelines for climatological practices (WMO, 2023), including location of measurements, instrumentation required and network design and management. However, these guidelines focus on reducing the very factors that microclimate researchers are interested in measuring. While several papers have already collated information on microclimate science, standardised guidelines do not yet exist for the field. De Frenne et al. (2021) discuss the drivers and importance of microclimate variation, focusing specifically on forests. Bramer et al. (2018) covered the state of the art at the time in terms of measuring and modelling microclimates, but did not consider data management or sharing. A lack of common data protocols and knowledge of measurement methods were ranked as the second and third most important challenges for microclimate science (behind funding issues) at the British Ecological Society workshop that inspired this last paper. Since then, there have been developments in sensor design (Wild et al., 2019) and understanding measurement error (Maclean et al., 2021), modelling

BOX 1 Definition of macroclimate versus microclimate

The macroclimate represents the average atmospheric conditions of ambient air across a large geographic region, independent of local topography, soil and vegetation (Stoutjesdijk & Barkman, 2014; WMO, 2023). We here define microclimate as the thermal and hydric conditions in the immediate vicinity of organisms (i.e. proximal microclimate sensu Klinges, Baecher, et al., 2024, see Section 3) or ecosystem processes of interest, as driven by atmospheric conditions interacting with the abiotic and biotic components of the Earth's surface. This is often in a relatively small area, within few metres or less above and below the Earth's surface and within canopies of vegetation (Britannica, 2024). We distinguish microclimate from 'mesoclimate' in which climatic variations are caused by the wholesale movement of air masses where variation is typically most evident at scales ranging from hundreds of metres to kilometres. Extensive discussions of the definitions of macroclimate, microclimate, mesoclimate and also other terms including topoclimate, nanoclimate and ecoclimate are available elsewhere (Barry & Blanken, 2016; Bramer et al., 2018; Geiger et al., 2009; Stoutjesdijk & Barkman, 2014).

(Gril, Spicher, et al., 2023; Kearney et al., 2020; Klinges et al., 2022; Maclean & Klinges, 2021) and data collation and sharing (Lembrechts et al., 2020) to facilitate the expansion of the discipline from local to global scales. Kemppinen et al. (2024) provide a discussion of these, but a comprehensive and practical step-by-step guide for those starting in the field is still lacking.

Here, we review standardised methods for terrestrial microclimate research, grouped in 10 practical guidelines. These range from understanding the importance of microclimates, through what, how, when and where to measure them, the design of microclimate studies and how best to analyse and deposit data for further use and collaboration (Figures 1 and 2). As such, the paper is designed as a chronological guide taking the reader through all the steps required to complete a microclimate study across ecological and evolutionary topics. We do not explain major physical, ecological or ecophysiological theories driving microclimates—these are described elsewhere (Barry & Blanken, 2016; Bramer et al., 2018; Geiger et al., 2009; Maclean et al., 2021; Monteith & Unsworth, 2013). The aim is rather to provide a practical guide for people embarking on ecological research involving microclimate data and to help avoid the pitfalls we encountered when starting ourselves. We specifically do not focus here on (distant) remote sensing methods such as airborne LiDAR or thermal infrared imagery because of the very contrasting methods associated with, for example, the data collection and analyses (reviewed in Zellweger et al., 2019). We also exclude most aquatic systems (both freshwater and marine) as they typically require very different methodologies, and we specifically do not consider financial aspects (including human resources, travelling and logistics).

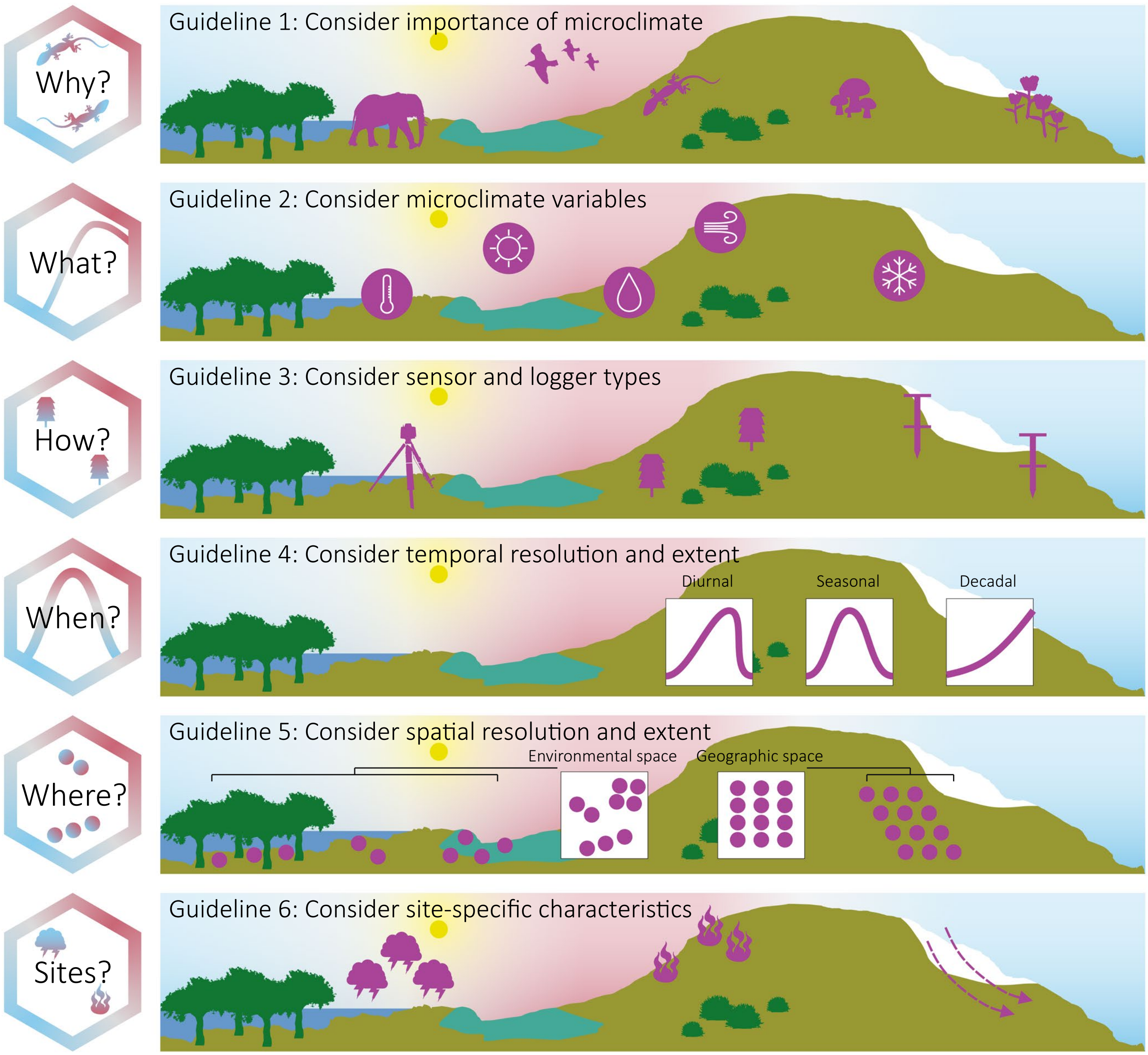

FIGURE 1 Graphical overview of guidelines 1–6 summarising why, what, how, when and where to monitor microclimate, and to consider site-specific characteristics. The colour shading of the landscape simulates a microclimatic gradient.

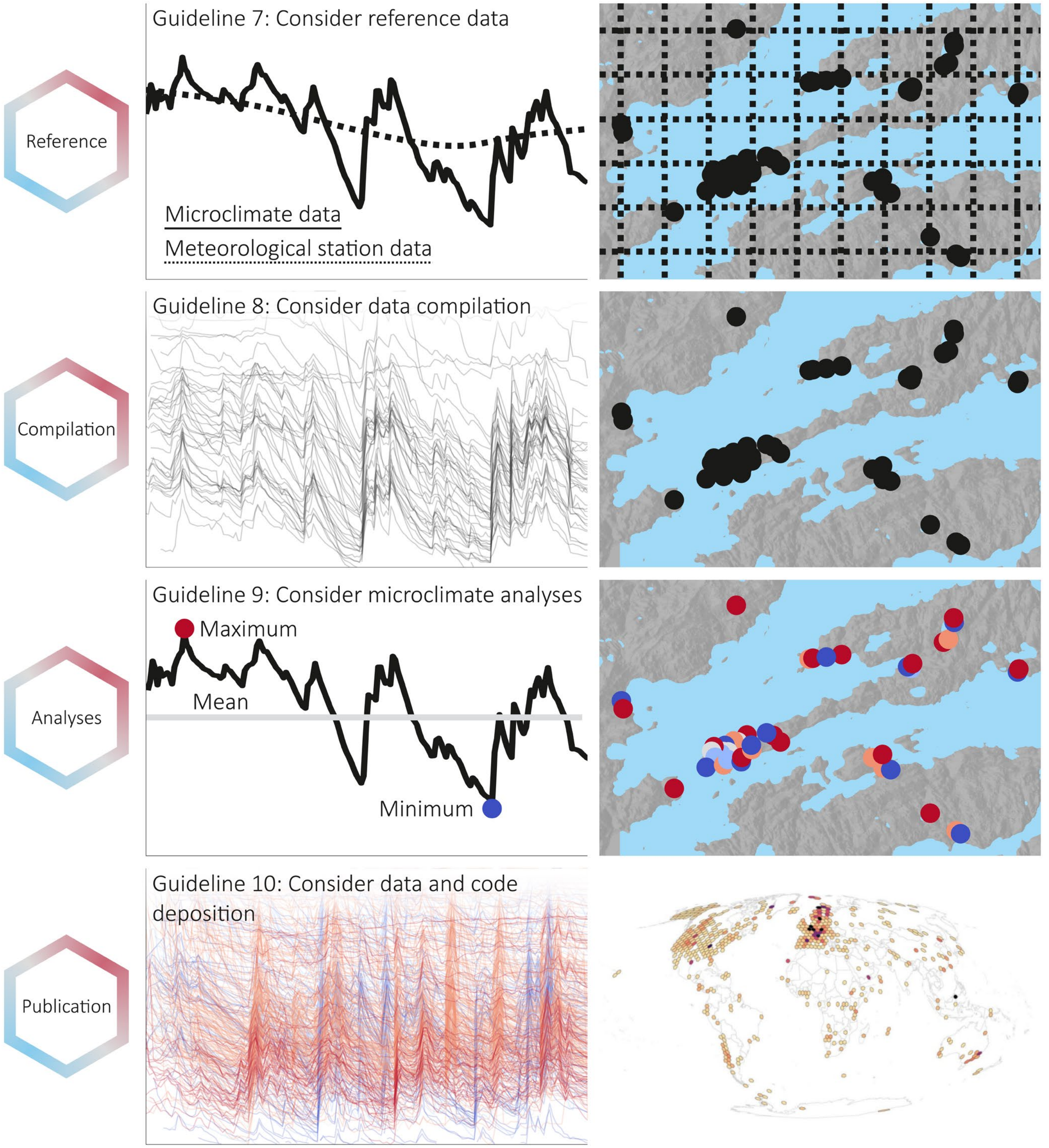

FIGURE 2 Graphical overview of guidelines 7–10 as the final steps of a microclimate study: Choosing the right reference data, data compilation, data analysis and publication of open data.

2 | GUIDELINE 1: IMPORTANCE OF MICROCLIMATE IN YOUR SYSTEM

The importance and necessity of collecting microclimate data within a particular study may range from being: (i) 'indispensable', that is, microclimate is at the heart of the study and available resources should first go to microclimate monitoring; (ii) 'relevant', that is, basic microclimate monitoring could be considered to reach the aims of the study and address the research questions; and (iii) 'optional', that is, available resources can first be spent elsewhere, but if resources are available they could go towards microclimate monitoring.

Microclimates are challenging to measure and model because of their fine spatiotemporal resolutions and often complex underlying drivers (Gates, 2012). Thus, it is important to first decide whether collecting microclimate data is even necessary. Sometimes, the combination of macroclimate variables based on weather station data (see Section 8) or gridded climate data, combined with static topographic variables at fine spatial resolutions, may be sufficiently informative (Kearney & Porter, 2009). The first key question is for the researchers to ask themselves whether macroclimate variables are adequate and meaningful predictors of the ecological response of interest (as they often are for understanding macroecological patterns such as species distributions). Microclimate is, for instance, needed when one wishes to get closer to the actual physiological constraints (Bennie et al., 2014). Hence, to determine whether microclimate should be monitored, a first key question is whether correlative or mechanistic approaches to link microclimate and the study organism or process are desired (Figure 3).

Correlative approaches rely on statistical modelling to infer relationships between the focal study organism or ecosystem process (e.g. empirical data on the geographical distribution of a species) and its habitat or environment (including soil, climate, topography and other biotic and abiotic descriptors; Morin & Thuiller, 2009). Often in these studies, the focus is not on the exact microclimatic conditions experienced by organisms. Instead, these studies aim to define a mean field approximation of the environmental conditions that explain or predict the potential occurrence of a focal species at a given location. It is nonetheless important to tailor micro- or macroclimate monitoring to the process and ecosystem that is being studied. For instance, life cycle components, physiological properties and general natural history need to be known with enough detail to formulate precise research questions or hypotheses to decide whether microclimate is necessary, or if a combination of macroclimate with topography might be sufficient to meet the requirements (Figure 3). When climate data are used to explain or predict ecological processes, it might suffice to work with information-rich microclimate variables that are likely related to the studied object (see Section 3). These variables often combine a variety of climate factors, aggregated into one or two variables that make up the microclimate of the object and give sufficient information to develop good explanatory or predictive models (e.g. Jonsson et al., 2008; Mathewson et al., 2017). Preliminary analyses of variation in specific microclimate variables from measurements, or comparison of models fit with different microclimate variables, can help to validate the choice of categories or variables to be included as factors in the statistical analyses. The relative necessity of microclimate data may also be dependent on whether researchers want to extrapolate in time or space. In cases where predictions into novel conditions are needed, the inclusion of microclimate data can improve predictions (Haesen, Lenoir, et al., 2023) and mechanistic or process-based microclimate models forced with high-resolution data represent an exciting future research avenue (Briscoe et al., 2023; Klinges, Baecher, et al., 2024).

Mechanistic approaches aim to explicitly capture the physiological links between (micro)climate conditions and the study organism or process. They are grounded in the application of biophysical models

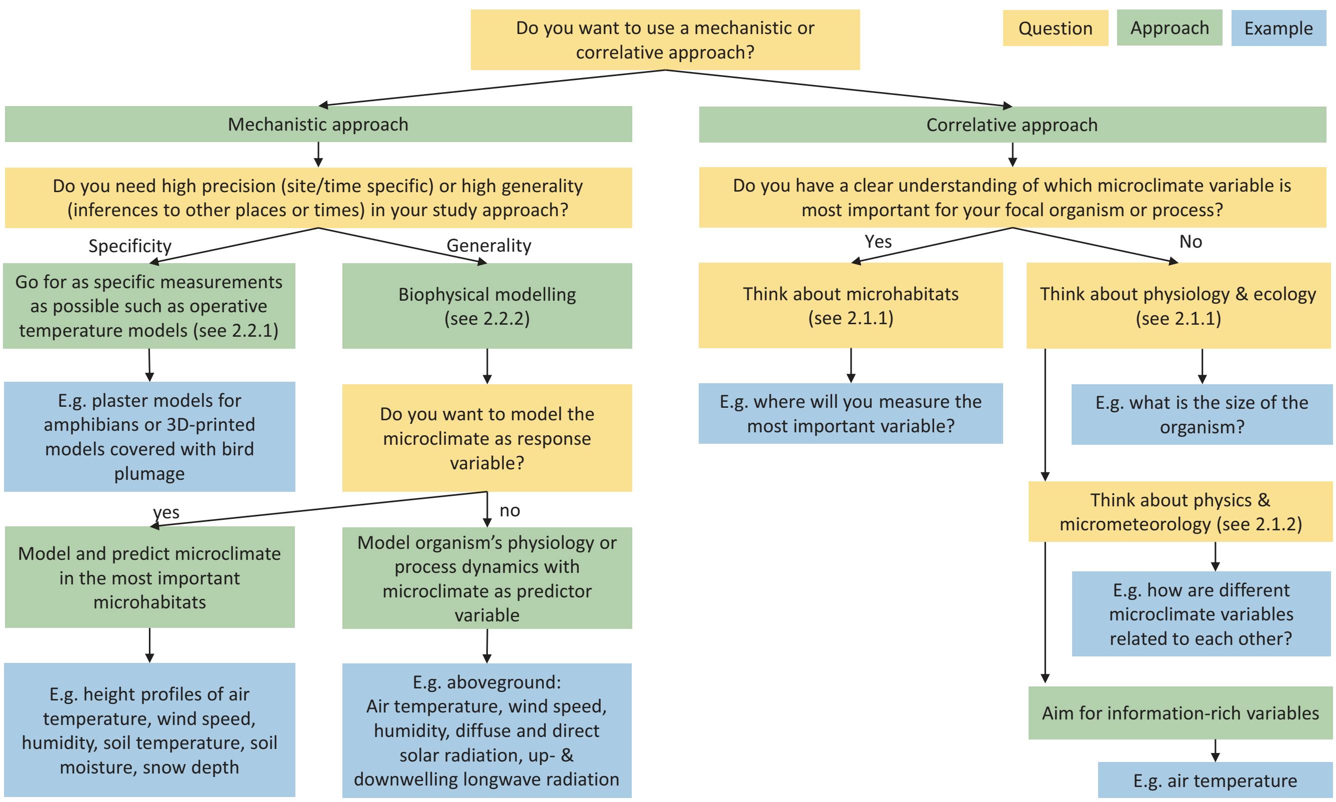

FIGURE 3 Decision tree to guide researchers in their decision when and where to monitor microclimate and which microclimate variables to measure.

of energy (heat) and mass (water, nutrients) exchange between the organism and its living environment (Briscoe et al., 2023; Kearney & Porter, 2009) and can be generalised to novel conditions with confidence (Briscoe et al., 2023). This approach defines the functional traits that matter in the processes of energy and mass exchange and their relationship to survival, growth, development and reproduction (Kearney, Briscoe, et al., 2021; Kearney, Jusup, et al., 2021), making it suitable for fine-scale analysis of processes such as survival, phenology or decomposition (Helmuth et al., 2002; Jørgensen et al., 2022; Rezende et al., 2020). The scale at which these analyses should be undertaken depends on the intrinsic characteristics of the focal species, like body size (Pincebourde et al., 2021; Pincebourde & Woods, 2020), mobility or dispersal (Tigreros et al., 2023) and on the extrinsic characteristics of the (micro)habitat (Vives-Ingla et al., 2023). Therefore, incorporating microclimate data into a study does not always ensure that the correct scale of microclimate representing an organism's exposure is captured.

We recommend that any researcher performing a study that involves climatic factors as a driver of biodiversity or ecosystem processes should at least consider whether it is worthwhile to collect their own microclimate data or to rely on available reference data (see Section 8). It is impossible to say precisely when and where microclimate should be incorporated into any given study, because the significance of microclimate is contingent upon the study's objectives, the focal organisms and processes under investigation, the ecosystem in question, the spatial and temporal resolution and extent of the study and the available resources (financial, logistical and human) for microclimate monitoring.

3 | GUIDELINE 2: WHICH MICROCLIMATE VARIABLES TO MEASURE?

> The choice of which microclimate variables to measure depends mainly on (1) the level of mechanistic insight required in the study, (2) the ecology and physiology of the focal organism or the underlying drivers of the investigated process and (3) the physics of micrometeorology and how microclimate variables are correlated.

The microclimate of terrestrial organisms and ecosystems results from the exchange of heat (energy) and water (mass) between the atmosphere and the land. Relevant variables involved in these exchanges include air temperature, substrate temperature, wind speed and direction, incoming and outgoing long- (e.g. infrared light with wavelengths longer than 700–800 nm) and short-wave radiation (e.g. visible light with wavelengths of 400–700 nm), air humidity, precipitation and soil moisture. These variables can be combined and aggregated at different resolutions of space and time to generate predictors along a spectrum of proximal (e.g. hourly soil temperature or water potential) to distal (e.g. aridity indices). Thus, the choice of which microclimate variables to measure can be challenging. The most important consideration is the biological question being addressed. In this guideline, we again refer to the question-based decision tree in Figure 3.

3.1 | Correlating measured microclimate variables to a biological process or pattern

For most approaches, the focus of measurements is mostly on efficiently capturing as much information as possible with a small set of easily measured variables. In a correlative approach, the physiological and physical processes are considered implicitly and a direct link between microclimatic measurements and the physiological processes is not necessarily needed. Correlative approaches can be especially useful for understanding species distributions and environmental conditions of species' (micro)habitats without the need to dive into the detailed mechanistic processes of the focal organism's physiology. However, good knowledge of the studied species' natural history helps in determining which microclimate variables strengthen the informative value and predictive power of models.

3.1.1 | Know your organism's physiology & ecology and the drivers of ecosystem processes

First, it is necessary to consider the habitat of the study organism or the potential drivers of the investigated ecological process. Here, we draw attention to two guiding considerations: (1) body size and (2) microhabitats (Kearney, Briscoe, et al., 2021; Kearney, Jusup, et al., 2021).

In terms of body size, for very small organisms (<1 mm high, e.g. aphids, endophytic fungi), the body temperature is mainly determined by near-surface air temperature because these small organisms dwell within the surface boundary layer and have very thin boundary layers themselves, coupling them more closely to near-surface air temperature (Pincebourde & Woods, 2020). As a result, the most relevant temperature to measure for these organisms is surface temperature (e.g. leaf surfaces, Pincebourde & Woods, 2020). For somewhat larger organisms that move or grow primarily on the ground surface, air temperature near the ground might be a suitable proxy for body temperature (e.g. for carabid beetles, woodlice). However, for organisms with high levels of evaporative cooling (e.g. plants, amphibians, molluscs) and organisms exposed to solar radiation or clear night skies, the microclimate air temperature may be a poor proxy for body temperature (Gardner et al., 2024). For the latter, it might be more relevant to measure operative temperatures as a proxy for body temperature, or to compute body temperature with a heat exchange model (Bakken & Angilletta, 2014; Tracy et al., 2007; see also Section 3.2.1). For very large organisms, such as trees, individuals sample a large temperature gradient (from the surface to tens of metres below and above the ground) and this whole gradient may need to be characterised, or specific measurements may be needed depending on the research question (e.g. studying epiphytes on the full above-ground extent of the tree vs. below-ground root growth). Sampling such broad vertical temperature gradients (e.g. from the ground to the top canopy of trees) may require novel methods such as distributed temperature sensing via fibre-optic technology (Krause et al., 2013). The microclimate requirements can also shift ontogenetically within the same individual, for instance from germinating seeds and small tree seedlings on the shaded forest floor to dominant adult trees with the top canopy in full sunlight (Schouten et al., 2020).

Ideally, one characterises the full microclimate range experienced by their study organism or process. If it occupies different microhabitats, it is important to understand which microclimate variables best describe the differences between these microhabitats. For ectotherms in deserts that move between shade-providing bushes, for example, solar radiation drives microhabitat differences (Kearney, Briscoe, et al., 2021; Kearney, Jusup, et al., 2021). For bryophyte communities in forests, and litter decomposition, variation in soil moisture might be most important (Man et al., 2022).

3.1.2 | Know the physics of the proximal environment and choose information-rich variables

To make good choices of microclimatic variables for correlative studies, it is important to understand the underlying physical principles, and we refer readers to standard texts on this topic (Bramer et al., 2018; Campbell & Norman, 2012; Geiger et al., 2009). For example, relative humidity is often used as a predictor variable to capture aspects of water exchange. However, this metric, which expresses the actual water content as a percentage of the saturated water content of the air, is very tightly correlated with air temperature. Vapour pressure deficit (VPD), the difference between actual and saturated water content, is easily calculated from relative humidity and air temperature, and may be a more informative predictor, as it is more directly linked to physiology (Grossiord et al., 2020; López et al., 2021; Trotsiuk et al., 2021). Temperature variables are also spatially and temporally autocorrelated, e.g. temperatures along an elevation gradient, or daytime temperatures of two consecutive days. However, covariation patterns can change through time. For example, minimum and maximum temperatures in forest understories may be negatively correlated in summer but positively in winter (Greiser et al., 2018; von Arx et al., 2012). Indices derived from one or two information-rich variables such as VPD, soil temperature or soil moisture may contain sufficient information to develop good predictive models because they are a combination of many more primary microclimatic variables. However, interpreting the meaning of any correlations found can be difficult and for questions regarding causality, mechanistic approaches are required.

3.2 | Using microclimate in mechanistic models

Mechanistic models explicitly characterise processes at the level of individual organisms or physical features that are driven by heat or water exchange, such as dew formation, snow melt, wilting points, desiccation thresholds, physiological thermal response curves or regulatory behavioural responses. Additionally, ecosystem processes, for example, biogeochemical processes performed by soil microbial communities, can be mechanistically modelled.

3.2.1 | When aiming for high specificity and precision: Consider operative temperature

For precise body temperature estimates of a specific organism, operative temperatures can be highly insightful as they integrate microclimate with the species' morphology (Bakken & Angilletta, 2014). This includes, for example, building 3D models that represent the shape, size and energy exchange characteristics of your organism (Leith et al., 2024), in which the temperature is measured (for some examples, see Section 4). Black or grey globe temperatures, and wet bulb globe temperatures, are other widely used methods to estimate operative temperatures for a broad range of animals (Hetem et al., 2007; Mitchell et al., 2024) and to calculate levels of human thermal comfort (Gillerot et al., 2022; Gillerot, Landuyt, et al., 2024).

3.2.2 | Microclimate measurements for mechanistic models

When calculating body temperatures, ecosystem processes or physical processes with a biophysical model, microclimate measurements are a prerequisite and there are generally two options. First, the microclimate can be modelled with a physically explicit model (Kearney et al., 2020; Kearney, Briscoe, et al., 2021; Kearney, Jusup, et al., 2021; Maclean & Klinges, 2021), using either locally measured weather data or gridded data sets (see Section 8) as forcing variables (Meyer et al., 2023). In this case, we recommend testing the output of your model against many microclimate measurements in the field, covering height and depth profiles of air temperature, wind speed, air humidity, soil temperature, soil moisture and perhaps even snow depth (e.g. see Briscoe et al., 2022; Kearney, 2020; Maeno et al., 2021). Second, one can input measured microclimate variables directly into a biophysical model. For above-ground organisms or ecosystem processes, it is important to consider air temperature, wind speed, VPD, soil surface temperature (or upwelling long-wave radiation), 'sky temperature' (or downwelling long-wave radiation) and (ideally both direct and diffuse) solar radiation, at the location or height relevant for the study organism (e.g. Pincebourde et al., 2007; see also Section 3.1). For below-ground organisms and soil processes, important variables are soil temperature and soil water potential (rather than soil water content) (Kearney & Enriquez-Urzelai, 2023).

4 | GUIDELINE 3: MICROCLIMATE LOGGERS

Choosing the most appropriate logger to use depends on the study question and the organism or process one wants to investigate. The need for shielding, protection and data calibration are contingent on the type of logger, but careful consideration is needed to achieve the highest data quality.

Ecologists have used a variety of loggers to measure and monitor the microclimatic conditions that organisms encounter. For simplicity, we here further refer to the entire device that contains one or several sensors (e.g. a thermocouple) and logging system ('memory') as 'logger'. Often, these loggers were originally engineered for industrial and commercial use, but there has been a growing trend towards developing devices better suited for ecological field studies (Wild et al., 2019; Wilmers et al., 2015). These efforts have resulted in a notable increase in the variety and accessibility but also the data quality (for instance in terms of shielding, see Section 4.2) of loggers to monitor microclimates, which makes the choice of loggers a challenge. Nevertheless, most microclimate loggers share common attributes essential for durable field deployment, including battery longevity, memory capacity and robustness to field conditions. In this guideline, we aim to outline the most frequently used microclimate loggers (noting that those most frequently used in the past might not actually be most suitable in future applications), shielding methods and logger intercalibration. Specifically, we focus on battery-powered microclimate loggers that feature internal long-term memory storage suitable for ecological field studies.

4.1 | Temperature loggers

There are many types of temperature loggers and they each exhibit different advantages and shortcomings. In Table, we list the most commonly used loggers to measure temperature among the microclimate community as indicated by metadata submitted to the SoilTemp database (Lembrechts et al., 2020). The table details their characteristics including memory capacity, operating range, accuracy, battery lifespan, as well as other strengths and limitations. Among the dozens of logger brands and many more logger models, the currently most often used loggers in ecology and evolution according to the SoilTemp database include: (1) TOMST TMS, which measures simultaneously temperature at three heights but also soil moisture; (2) Maxim iButtons which have, for example, a temperature or humidity sensor; (3) Onset HOBO Pendant with several sensor options (including temperature, light, air humidity); and (4) Lascar with mostly temperature and air humidity sensors. These four logger brands already include very different types of temperature measurements for a variety of research needs. See Bramer et al. (2018) for more details outlining considerations when choosing loggers to measure different variables. Maclean et al. (2021, see especially their Table 1) compared several commonly used temperature loggers under a range of conditions making it a valuable initial resource for selecting loggers (see also Section 4.2).

Operative temperature models (Bakken & Angilletta, 2014) that mimic the thermal and hydric properties of an organism are often used in animal ecology (see Section 2). Early versions of these were made by making moulds of live lizards out of dental plaster and using them to create hollow copper (for fast response time) models that can be painted to match absorptivity (Porter et al., 1973). Heated taxidermic mounts have been used for endotherms (Bakken et al., 1983) and plaster or agar models have been used for amphibians to capture evaporation (Tracy et al., 2007). Such models have been used to map thermal landscapes and to derive null models for assessing the extent of thermoregulation (Hertz et al., 1993). Grey and black bulb temperature loggers are often used to study animal and human thermal stress and comfort (see Section 3.2.1; Gillerot, Landuyt, et al., 2024; Gillerot, Rozario, et al., 2024). Now 3D printing with a variety of techniques and materials creates new opportunities for creating operative temperature models (Alujević et al., 2024; Hertz et al., 1993; Leith et al., 2024). Small thermocouples can also be inserted into or pressed against the surface of animals (e.g. onto the thorax of butterflies) and plants (e.g. into leaves, bark, fruits) to measure internal and/or surface temperatures (e.g. Berwaerts & Van Dyck, 2004). Each of these approaches has specific advantages and drawbacks; for instance, 3D printing can be expensive if a large number of models is needed; yet, such models are suited for long-term microclimate monitoring without the continuous presence of researchers in the field. The measurements of surface temperatures of the thorax of butterflies (e.g. for forest species that follow sun flecks) is reflecting realistic species behaviour but impractical to maintain for long time periods and many individuals.

4.2 | Shielding air temperature loggers: To shield or not to shield?

In environments exposed to direct solar radiation (e.g. grasslands), unshielded air temperature loggers can cause significant temperature biases because of 'logger overheating'. In other words, the logger is heated by solar radiation and one records the temperature of the logger, not the air. This strongly depends on the type of logger used, and the issue is much smaller in forests (Maclean et al., 2021). In open habitats, we would generally recommend the use of ultra fine-wire thermocouples without a shield to accurately and precisely record air temperatures (e.g. type SurveyTag, ConceptShed; Maclean et al., 2021). Shielding can alter the microclimatic conditions of interest in environments exposed to direct solar radiation. For example, direct contact between the logger and shield can influence temperature measurements by affecting the shield's temperature through radiation absorption. Additionally, the shield creates its own microclimate (lowering wind and air mixing), leading to notable differences in thermal conditions compared to the surrounding environment. This issue is especially pronounced on hot middays with high solar radiation and little wind, and near the ground surface, where heat transfer through conduction and convection results in substantial variations in air temperature. This is the exact reason why synoptic weather stations use ventilated Stevenson screens at 2 m above the ground. On the contrary, when (often cheaper) temperature loggers not relying on ultra fine-wire thermocouples are used, we recommended to shield loggers using standardised shielding (to increase interoperability) to minimise the thermal influence of the logger. Shielding is of course not necessary for soil temperature measurements.

Waterproofing of loggers may increase reliability, yet also affect measurements by changing loggers' thermal properties. For example, Roznik and Alford (2012) demonstrated that coating loggers (Thermochron iButtons) is an affordable and reliable method of waterproofing. This approach prevents device failure and data loss, but can have considerable influence on temperature readings (Maclean et al., 2021).

It is also important to take the local fauna into consideration as animals can damage microclimate loggers or disrupt study settings by moving loggers. Therefore, it is advisable to consistently protect loggers (at all study sites including control plots to avoid confounding effects among sites) with nets, cages or other means, of course avoiding or minimising the potential effects of these structures on radiation, air movement and other factors that regulate local microclimates.

4.3 | Soil moisture, air humidity and other variables

In addition to temperature, measuring atmospheric humidity and soil moisture is often an important part of microclimate ecology. Currently, the most popular microclimatic loggers for measuring soil water content are based on dielectric permittivity—either measured through time domain reflectometry (TDR), capacitance technique, time domain transmission (TDT) or frequency domain reflectometry (FDR). For comprehensive reviews see, for example, Babaeian et al. (2019), Robinson et al. (2008) and Romano (2014). As all these sensors measure the propagation of electromagnetic signals through the soil, the raw measurements must be converted to soil water content through calibration, ideally specific for each measurement site or at least a specific soil type (Mane et al., 2024). Air humidity is usually measured as relative air humidity through specialised loggers, and several logger types are available (see examples in Table S1). Important to note is that air humidity loggers can suffer from saturation either due to water condensation or inappropriate shielding, which is difficult to correct afterwards (Ashcroft & Gollan, 2013a; Feld et al., 2013). Some microclimate variables (e.g. wind, long-wave radiation) have been measured much less often than temperatures in microclimate ecology. Yet, there are, for example, many recent developments of low-cost consumer-grade pyranometers and anemometers (e.g. Gillerot et al., 2022).

4.4 | Calibrating microclimate loggers

Temperature logger (inter)calibration is a crucial aspect in ensuring accurate temperature measurements, particularly for low-cost loggers which generally have lower accuracy and precision (Caissie & El-Jabi, 2020; Hunt & Stewart, 2008). These loggers may exhibit systematic deviations from true temperatures. While technical calibration may pose challenges, post-measurement correction to mitigate measurement errors can be feasible if specific procedures are conducted before deploying the loggers in the field. Calibration methods generally fall into two main categories: (1) establishing a correlation between logger readings and those of a research-grade accurate sensor (such as an ultra fine-wire thermocouple or accurate mercury thermometer) to evaluate reference temperatures, or (2) deploying a multitude of loggers in stable and uniform conditions to intercalibrate them (Mena et al., 2021). Ideally, the procedure should be repeated across a range of temperatures (the same range as the one that will likely be measured in the field) to assess potential shifts under varying environmental conditions (Anacona et al., 2023). Calibration for other logger types may involve different processes (e.g. wind sensors can be installed at the site of official synoptic weather stations to allow logger intercalibration; Gillerot et al., 2022). Additionally, loggers' internal clocks may experience time drift, necessitating further data preprocessing and frequent clock recalibration to synchronise with, for instance, the laptop computer clock during data retrieval from the logger.

5 | GUIDELINE 4: TEMPORAL RESOLUTION AND EXTENT

> Due to battery life and memory size limitations, data loggers usually store a limited number of records. This limitation determines the interval and duration that can be covered with a time series. Hence, users face a trade-off between generating shorter time series at very high temporal resolution or generating coarser time series over longer periods of time.

Setting the appropriate temporal resolution and extent of a data logger in the field should first depend on the study question and the microclimatic variable of interest (see Section 3), as well as on logger specifications (see Section 4) and site properties (e.g. accessibility and risk of theft: see Section 7). The most-often applied temporal resolutions (in minutes) and extents (in months) in the SoilTemp database are displayed in Figure 4. Microclimate datasets covering large temporal extents are still currently rare and there is a recent tendency towards increasing the temporal resolution. Below, we provide specific guidelines on how to define the appropriate temporal resolution and extent of a logger in the field, focusing on temperature (for the sake of brevity). Note that the same overall reasoning applies to other microclimatic variables perhaps with slightly different conclusions. For instance, if the focus is on wind speed, then one may put more emphasis on temporal resolution than extent.

5.1 | Guidelines on temporal resolution

In sunny environments, air temperatures can fluctuate in the order of 10–15 degrees over milliseconds (Maclean et al., 2021). For many applications, species and objects of interest, however, this fine-scale temporal variation would be integrated. If using a device that can detect these fluctuations—such as an ultra fine-wire thermocouple—this

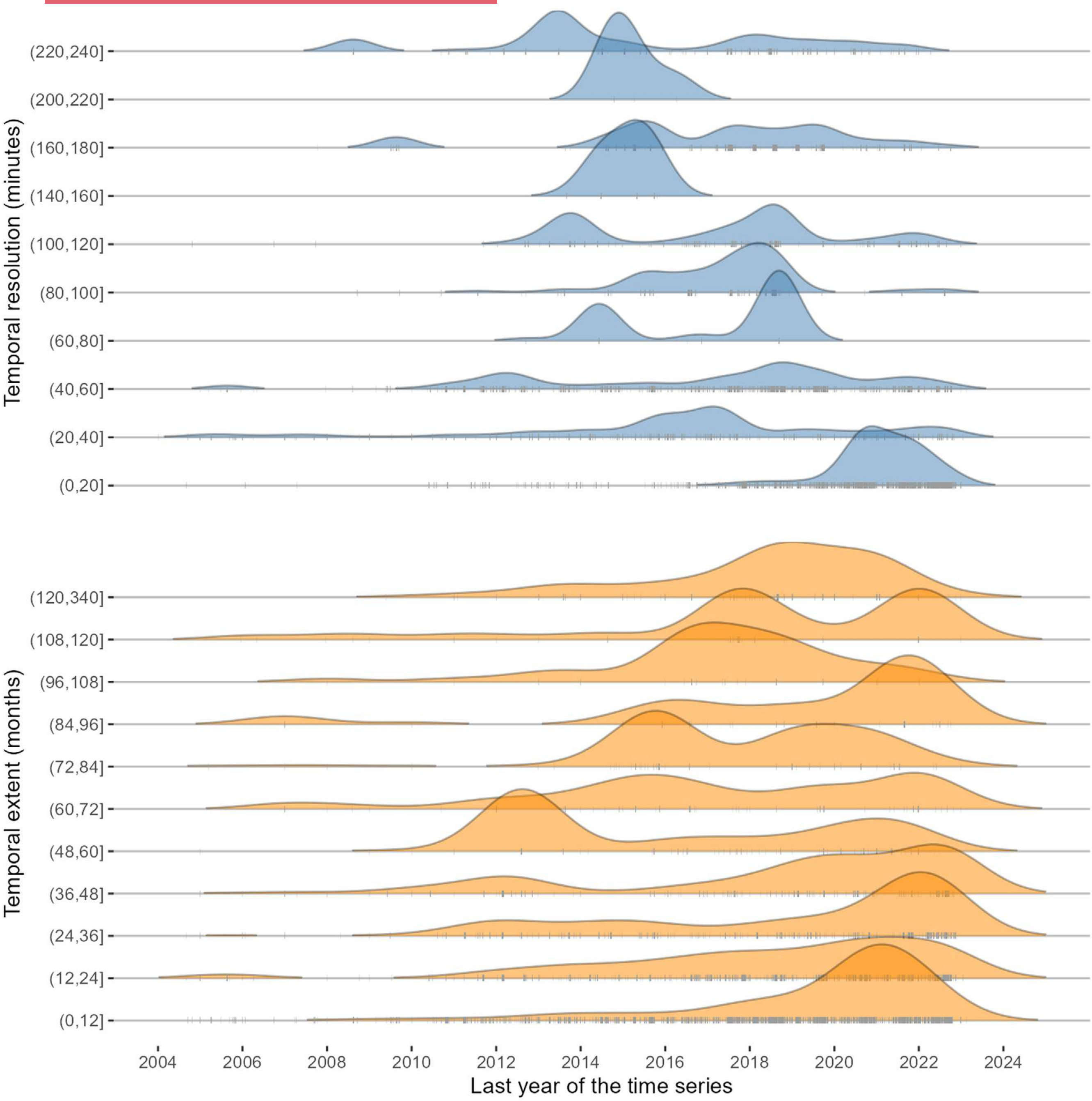

FIGURE 4 Temporal resolution and extent covered by microclimate time series. Shown here is the density distribution of the number of temperature time series registered in the SoilTemp database as of April 2024 (Lembrechts et al., 2020) depending on the temporal resolution (in minutes) and extent (in months) of the focal time series as a function of the end date (i.e. last year) of the focal time series.

issue should be addressed by taking rapid burst measurements with either on-chip or off-chip averaging. More fundamentally, however, to set the right temporal resolution to record microclimatic temperature over time, one should consider the following questions: What to measure (air, water, soil, surface or operative temperature)? What is the thermal conductance and capacitance of the mixture, substance or surface I want to measure? How much is it exposed to direct solar radiation and dominant winds?

First, the thermal conductivity and capacitance of the measured mixture, substance or surface affect the rate at which temperature rises or falls and thus the magnitude or amplitude of the temperature fluctuations (Figure 5). For example, the surface of dry inorganic soil on a sandy beach conducts heat much more quickly than a moist organic soil layer inside a peatland leading to greater amplitudes of surface temperature fluctuations over the same time period in the former than in the latter (Bramer et al., 2018; Campbell, 1985; Johansen, 1977). Second, whether the studied location or organism is fully exposed or sheltered from direct solar radiation and the dominant winds will modulate those fluctuations over time, through either buffering or amplifying effects (Gril, Spicher, et al., 2023). For

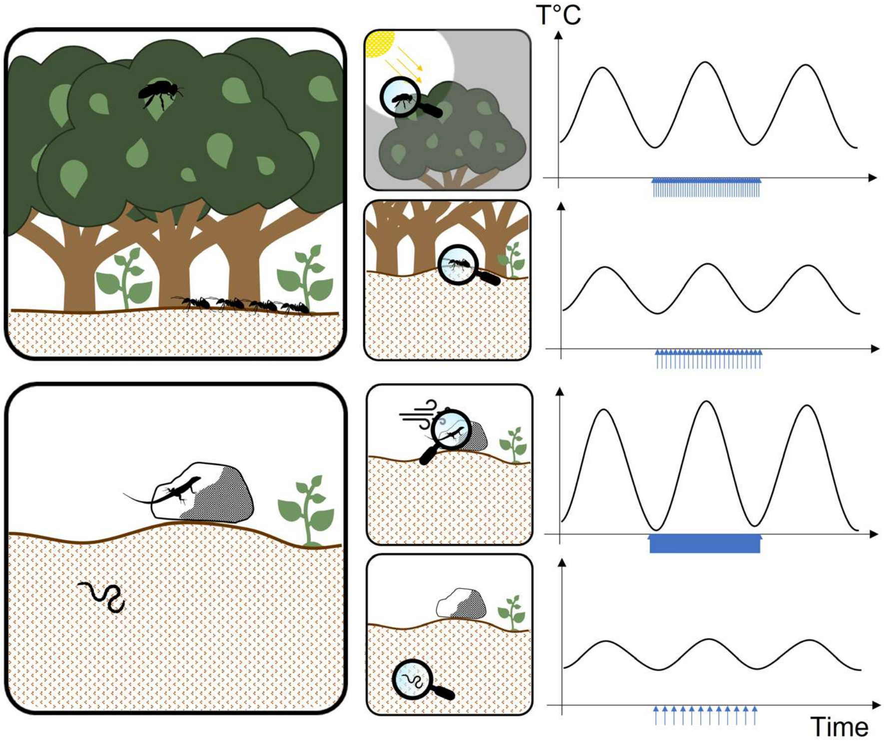

FIGURE 5 Setting the right temporal resolution for the right spatial location when installing microclimate data loggers in the field depends on the thermal conductance of the focal mixture, substance (e.g. ambient air or topsoil layer) or surface (e.g. leaf surface or rock surface) as well as its exposure to direct solar radiation and the dominant winds. The left panels depict two distinct habitats (i.e. a forest on top and a boulder field at the bottom) where different organisms (e.g. bees, ants, lizards, earthworms) share different microhabitats. The temporal axis of the plots in the right panels depicts diurnal temperature fluctuations over three consecutive days. The blue arrows, throughout the course of the second day, show the density of temperature readings, or the temporal resolution between consecutive measurements, that is adjusted relative to the daily range, with finer temporal resolutions for highly conductive surfaces that are highly exposed to direct solar radiation and the dominant winds. From the perspective of a bee, leaf surface temperature at the top of a tree canopy fluctuates more than air temperature near the ground in the understorey, where ants are foraging, which calls for finer temporal resolutions in the former (e.g. every 10 min) than in the latter (e.g. every hour). Similarly, for a lizard basking in a boulder field and exposed to direct solar radiation and dominant winds, rock surface temperature fluctuates more than subsurface soil temperature as perceived by earthworms, which also calls for finer temporal resolutions in the former (e.g. every minute) than in the latter (e.g. every 2 h). Animal silhouettes were downloaded from phylopic.org.

instance, a temperature logger installed near the soil surface in the understorey of a dense forest is far less exposed than a temperature logger installed on the surface of a rock or boulder located in an open area next to the forest (Figure 5; Fragnière et al., 2024). The underlying basic principle is that one should always record the temperature at a finer temporal resolution, to be able to capture both extremes of a diurnal cycle (i.e. daily maximum and minimum values), when the focal location or organism is climatically more exposed as well as if the thermal conductance of the measured mixture, substance or surface is higher and the capacitance lower.

It is also advised to record temperature at a temporal resolution that is finer than the frequency of the biological or ecological signal of interest to be able to capture this signal in temperature fluctuations. The frequency of a signal depends on the recurrence rate of the studied event over time, with a high frequency signal meaning that the focal event repeats many times over a fixed period. Ecophysiologists, studying how physiological processes scale with microclimate conditions, usually focus on biological signals at high frequency, such as body temperature and leaf surface temperature in response to diurnal cycles (Fauset et al., 2019; Tosini & Menaker, 1995), thus requiring time series at fine temporal resolutions. By contrast, foresters or biogeographers studying how environmental conditions affect lower frequency signals such as tree mortality or distribution of species, respectively, have historically emphasised aggregated microclimatic data such as annual or monthly summary statistics to capture seasonal cycles (Haesen, Lembrechts, et al., 2023). However, researchers should still exhibit caution to avoid being over-reliant on coarse temporal resolution climate time series. This is because temporally coarse data may not capture physiologically meaningful variables that can better explain even low-frequency signals, such as species' distributions (Gardner et al., 2019; Klinges, Baecher, et al., 2024), and temporally averaged climate is rarely indicative of average biological responses that tend to non-linearly vary with climate (see discussions of Jensen's Inequality; Bütikofer et al., 2020).

It should be noted that the measurement of temperature fluctuations in the high-frequency range may be limited by the thermal inertia of loggers, that is, a temporal lag of logger energy change after external energy change (Maclean et al., 2021; Mercier et al., 2019). For low-cost loggers and to improve measurement accuracy, it is thus advised to consider data aggregation of consecutive records resulting in more reliable mean estimates. For example, recording temperature every 5 min and aggregating every 12 consecutive measurements can yield hourly estimates, which are more robust than a single hourly record.

5.2 | Guidelines on temporal extent

The minimum duration to set for a logger to record temperature should span the full period during which key physiological processes and/or species interactions happen (e.g. the growing, mating or breeding season; Kim et al., 2022). However, since year-round conditions may still be important (e.g. winter temperatures may affect dormant plants and invertebrates or nutrient cycling; Niittynen et al., 2020), collecting data across seasons is recommended to detect unexpected impacts.

Due to inter-annual variation in macroclimate (including multi-year trends and cycles), there is considerable use in collecting microclimate data over multiple years (Kim et al., 2022). For example, data collected during contrasting El Niño and La Niña phases would provide insight into how strongly these long-term cycles (i.e. low-frequency signal) impact microclimate. Microclimate data from even longer durations (and particularly from multiple different habitats) are especially valuable to test whether microclimatic changes are decoupled from long-term macroclimate trends, certainly within the context of microrefugia (Lenoir et al., 2017). As a result, microclimate data sets with large temporal extent, which are currently rare (Figure 4), can provide a fuller understanding of microclimate and maximise the use of the data collected. Collecting microclimate data over long time periods is, however, challenging. For example, microclimate loggers have not often been designed for long-term field deployment (e.g. sensor drift, non-durable materials, frequent battery replacement necessary), and the current scientific funding model typically does not support long-term monitoring.

6 | GUIDELINE 5: SPATIAL RESOLUTION AND LOGGER REPLICATION

> Where to install microclimate loggers? The density and distance between loggers determine how environmental variation is captured. Loggers inherently measure highly localised conditions that are influenced by hierarchical biometeorology across spatial scales.

Regional macroclimate is modulated by landscape-scale topography to shape mesoclimate, within which there can be multiple nested sets of microclimates (Figure 6; Pincebourde & Woods, 2020). Even a single spatial point (horizontally) may express different amounts of thermal variability above- or below-ground (vertically). For instance, soil or substrate surface temperature tends to vary more in space but less in time than air temperature (see examples given in Figure 5; Campbell & Norman, 2012). How much the climate varies across scales within a landscape is thus core knowledge for determining the number and placement of microclimate loggers, further determined by the specific study aims (e.g. which spatial or environmental gradients are of interest). Given this, there is no fixed spatial resolution for monitoring microclimate across all contexts. Yet, recognising such hierarchies of

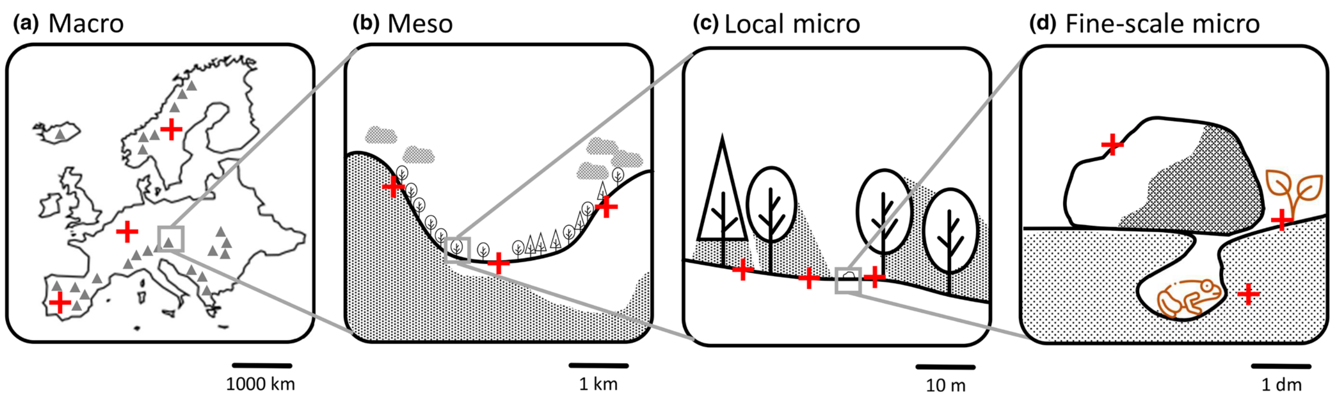

FIGURE 6 The nested nature of microclimates. Locally measured microclimate (e.g. temperature, moisture, wind) always represents a combination of local, regional and global climate signals. At each scale from macro to micro, climatic gradients can be unfolded, just like replicated geometric shapes in a fractal. (a) At macro-scales, latitudinal gradients, continentality and global circulation patterns control macroclimate. (b) At meso-scales, topography is the dominant driver and this can reverse macro-scale temperature trends (e.g. via lapse rates, cold air pooling, solar radiation exposure). Indeed, a high-elevation location in the tropics can be cooler, on average, than a high-latitude location at sea level (c and d). At micro-scales, vegetation patterns, such as canopy cover, but also microtopographic gradients become the most dominant drivers. For instance, a forested location at low elevations may be cooler than an open grassland at high elevations. Depending on the spatial resolution and extent of the measurements, the micro-scale signals can be filtered out more easily than the macro- and meso-scale variation. Frog and seedling icons downloaded from flaticon.com.

environmental variation known to drive microclimate conditions can substantially inform microclimate logger placement (see discussions of Jensen's Inequality, Bütikofer et al., 2020). To achieve this, we recommend first identifying proximal microclimates of interest for the research questions (Klinges, Baecher, et al., 2024), and then using stratified random sampling to place loggers within such proximal microclimates. If spatial patterns of species' presences and absences are of interest, an alternative is to deploy sensors in both occupied and unoccupied (or avoided) microhabitats to better understand species distributions.

6.1 | Identifying proximal microclimates

Relevant microclimates, and the associated biophysical forcing, are determined by a study's fundamental goals. If microclimate measurements are to be used to understand the ecology of a particular organism or process, then logger replication and placement should maximise microclimate proximity: the degree to which microclimate data represent the actual conditions that an organism or system is exposed to, distinct from the spatiotemporal resolution of the climate data (Klinges, Baecher, et al., 2024). Well-placed loggers in an animal's habitat can be used, for example, to infer its behaviour (Briscoe et al., 2022; Moore et al., 2018). Known mechanistic links between the ecological response of interest and particular microclimates, or specific hypotheses that are to be tested concerning such links, can then further constrain logger placement. For example, studies of the tolerance of amphibians and insects to heat extremes required placing temperature loggers in tree holes and phytotelmata within forest canopies (Scheffers et al., 2014) or inside pitcher plants (Kingsolver, 1979). Having an understanding of the spatial frequency distribution of microclimate suitability is often adequate to know the spatial configuration. This avoids the task of exhaustively sampling disparate microclimates within a landscape, as not all may be relevant to the study of a focal organism or process. Yet, if microclimate is considered a correlate to ecological responses across broader taxonomy, for instance, with a focus on general forest biodiversity responses, or without an a priori understanding of its mechanistic role, then greater environmental representation may be necessary. For example, it may be important to sample microclimates of many habitats within a landscape or region to understand habitat suitability for an entire bird or amphibian community (Frey et al., 2016; Nowakowski et al., 2015).

6.2 | Deploying loggers via stratified random sampling

After identifying which environmental gradients dictate relevant microclimates for a given research study, it is time to establish an optimal network of loggers to adequately sample these gradients (Lembrechts et al., 2021). Pragmatically, the number of loggers for a study is often set by budgetary constraints. To maximise variation sampled with a limited set of resources and loggers, we encourage the use of stratified random sampling via multivariate ordination of environmental data to place loggers across the target landscape (Klinges, Lembrechts, et al., 2024). This approach entails the use of spatial gridded layers that quantify the environmental drivers of microclimate most important to one's landscape and study (e.g. ambient macroclimate, elevation, plant area index, human land use, distances from water bodies, soil characteristics, etc.). While such gridded layers may be fine-resolution for some inputs such as digital elevation models, the coarse resolution of other layers may constrain logger site selection; to address this, statistical or mechanistic downscaling of some variables may be needed (Klinges et al., 2022; Kusch & Davy, 2022; Ovakoglou et al., 2022). Then with such gridded layers in hand, multivariate ordination can be used to quantify 'bins' of possible logger locations, each representing a different stratum of the available environmental space. A given number of spatial points are then randomly chosen from each bin to serve as deployment locations. It is advisable to include some redundancy in logger representation, so that sampling is not overly reliant on any single logger given the likelihood of logger malfunction or failure. Loggers at multiple heights/depths may need to be deployed at some or all locations, depending on vegetation height/complexity and soil composition as well as target applications. We point the reader to specific recommendations and software (see Klinges, Lembrechts, et al., 2024; Lembrechts et al., 2021) that facilitate stratified random sampling given a study area and a predetermined budget or logger count.

The density and representation of loggers across a region in turn determine the transferability of data or insights to future studies. Microclimate logger measurements can be augmented with spatial interpolation (Ashcroft & Gollan, 2013b; Stark & Fridley, 2022) or mechanistic microclimate modelling (Kearney & Porter, 2017; Maclean et al., 2019) to map microclimate across broader spatiotemporal representation (see also Section 10).

7 | GUIDELINE 6: THE STUDY SITES

Deploying microclimate loggers in the field across many sites requires planning. We discuss natural and anthropogenic events, logistics, as well as health and safety. In general, we advise researchers to collaborate with local researchers to gain in-depth knowledge in site-specific characteristics for planning successful fieldwork.

7.1 | Landscape features at the study site

Landscape features of the site (e.g. topography, elevation, land cover, water bodies) are drivers of microclimates but can also strongly affect the practicalities of logger installation. For example, different logger types and installation methods may be required to securely install loggers in rocks, sand or substrates rich in clay, organic material or water. Depending on the site, there are also additional risks of logger and data loss from, for instance, animals, fires, flooding, avalanches, sandstorms or people. Distances from roads and trails, if present within the landscape, should be considered during study planning and deployment, both to facilitate access to deployment locations and to identify the areas of frequent human visitation.

7.2 | Humans at the study site

Human presence can increase the risk of losing loggers and data, particularly in urban areas, managed lands or natural areas with tourism activities (Dyson et al., 2019). Yet, it can be important to consider microclimates on land impacted by human activities, such as controlled fires, tree logging and mowing, or close to roads, buildings and forest edges. Visible loggers may attract unwanted attention, but labelling loggers with personalised and polite messages informing about the ongoing research reduces theft and vandalism (Clarin et al., 2014). Labels can contain contact information to help retrieve lost loggers. Alternatively, loggers can be hidden from sight to reduce theft and then retrieved using an attached Bluetooth signalling device (e.g. an Apple AirTag), a metal detector or a piece of wire or cable tie connecting the sensor to the soil surface. For researchers working abroad, we recommend consulting local collaborators and other partners to navigate relevant legislation, permission protocols and sensitivities as these are site-specific and may be a fundamental constraint on research (e.g. INTERACT, 2019a, 2019b). Obtaining permissions and consent from local landowners or managers is necessary, and they should be given appropriate credit or an opportunity to participate in the research to avoid helicopter research (Adame, 2021; Nuñez et al., 2021). Research ethics (Adame, 2021) and cultural sensitivity (Ramos, 2018) are an inseparable part of developing sustainable microclimate research.

7.3 | Logistics at the study site

Logistics require planning ahead to minimise logger and data loss. We recommend visiting sites frequently even if the memory and battery of the loggers do not require this. Increasing visit frequency decreases potential data loss from logger loss or failure and allows monitoring of any changes at the site. However, accessibility and funding set limits and remote sites require more planning and resources for access. Having more loggers results also in more time to get around them, meaning each one is visited less frequently. In general, increasing the visiting frequency for remote locations can be nearly impossible (e.g. remote islands, mountains). Therefore, we recommend collaborating with local researchers or other local partners to monitor loggers and retrieve data when necessary. Another solution is using smart IoT (Internet of Things) devices (Andreadis et al., 2023; Pieters et al., 2021; Rebaudo et al., 2023), which is especially promising for remote locations or study sites where one wants to reduce visitor frequency to protect vulnerable biodiversity. However, IoT cannot (yet) always be deployed due to costs and lack of internet or power supply, although new solutions are rapidly being developed (see Conclusions). Lastly, site-specific characteristics should also be considered when locating loggers, particularly in dense vegetation and soft or unstable substrates such as sand dunes, where loggers may be lost even in the presence of centimetre-accuracy GPS documentation. Thus, we recommend exploring different practical solutions, such as markers, flags and metal tags detectable with metal detectors.

7.4 | Health and safety at the study site and the leave-no-trace

As in any ecological study, health and safety precautions are inherently part of planning successful microclimate fieldwork and fruitful collaborations. Thus, we recommend investing in in-depth education in fieldwork safety and considering site-specific practices (Araya et al., 2023; Daniels & Lavallee, 2014). Sufficient planning can prevent many natural and anthropogenic risks. Importantly, health and safety of researchers, especially early-career researchers (Clancy et al., 2014) and at-risk individuals (Coon et al., 2023; Demery & Pipkin, 2021; Rudzki et al., 2022) as well as the leave-no-trace and no-significant-harm principle in terms of environmental impacts (e.g. lost loggers and batteries; Frendrup et al., 2021) should be priorities.

8 | GUIDELINE 7: REFERENCE DATA

Reference data are standardised data against which one's own collected microclimate data can be compared and interpreted (Figure 2). Those data can come, for instance, from nearby standardised weather stations and/or modelled or interpolated gridded products for the same study sites. Reference data are useful, or even necessary to quantify, contextualise and predict microclimate. Yet, reference data can come from a multitude of sources.

8.1 | Choosing a reference

Climatic conditions at fine spatiotemporal resolution can be highly variable and idiosyncratic, and may need a comparison to a suitable and standardised reference. There are many types of reference data (listed in Table S2), and the choice depends on the research aims and the specific characteristics of the reference. For instance, reference data can represent macroclimate dynamics that set microclimate data as local anomalies in a broader context. Global macroclimate data quantify temperature trends over time (hours to centuries) and space (such as those brought about by large-scale variations in latitude and elevation). Alternatively, reference data might represent climate at a relatively fine spatiotemporal scale, yet, characterise the ambient conditions in open, unshaded areas, well away from trees and buildings, and as such are the relevant standardised comparator for highly localised microclimates. Reference data are important when the goal is to predict microclimate in space or time (Gril, Laslier, et al., 2023; Zellweger et al., 2024) or to compare microclimatic anomalies, relative to macroclimate, across large spatiotemporal extents. References should be matched sensibly to the target microclimate variable, accounting for temporal resolution and extent, which may determine the best source to use. Entirely different conclusions can be reached depending on the reference (Figure 7), highlighting the importance of a well-considered choice of reference.

8.2 | Three categories of reference data

Reference data can be obtained from (i) single, existing weather stations; (ii) own, custom loggers in a reference location; and (iii) gridded products.

First, synoptic weather stations are distributed across the world and are highly standardised (WMO, 2020). They are operated by national meteorological institutes and coordinated by regional/global organisations (e.g. WMO), with data collection following established guidelines and rigorous quality-control schemes to ensure the accuracy and comparability of measurements. However, national networks of synoptic weather stations are not evenly distributed across the globe, are in open areas and their time series can be subject to inhomogeneities, such as station relocation.

Second, researchers may instead opt to use their own reference, which could be a weather station operated by the researchers themselves, or it could be the same logger type as the one used to measure microclimate in different microhabitats. However, the reference logger should follow strict rules to allow fair comparisons across microhabitats. If all studied microclimates are in the shade (e.g. below trees or shrubs), and the reference is in open habitat, direct solar radiation on the logger should be treated carefully (see Section 4.2). A benefit of using one's own reference is the ability to customise the location and operation of the reference, such that what is measured is the appropriate reference tailored for the research question.

Climatic grids are a third source of reference data. We list specific examples of such reference data and their associated strengths and limitations in Table S2. These refer to a spatial representation of climate variables in a regularly spaced grid system in two or more dimensions (when time and/or multiple horizontal layers are included). In many cases, they represent conditions at 1.5–2 m above-ground, the same as synoptic weather stations. Gridded macroclimate data typically derive from statistical interpolation (e.g. using methods such as kriging or splines) of empirical observations, using

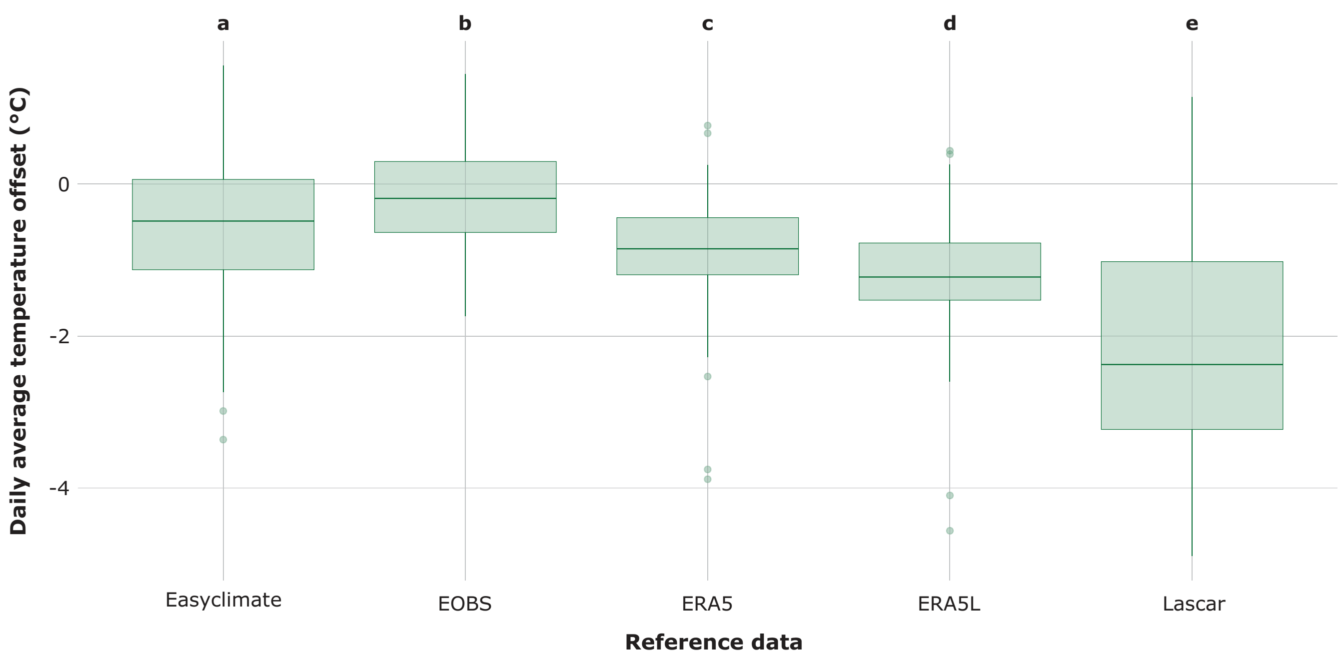

FIGURE 7 The importance of the choice of reference data. Shown are daily mean forest temperature offset values (below-canopy forest minus a reference temperature, such that negative values denote cooler forest temperatures) calculated from June 2018 to October 2018 for a single forest plot in Poland, calculated using different sources of reference data (easyclimate, EOBS, ERA5, ERA5Land and custom Lascar loggers located outside the forest in a passively ventilated radiation shield). For more information regarding the reference data and their characteristics, we refer to Table S2. Different letters denote statistically significant differences according to a Kruskal–Wallis test with post hoc Dunn's test. Data from Meeussen et al. (2021).

external predictors such as topography, land cover and/or proximity of water bodies (Cressie, 1990; Goovaerts, 1997). When based on a representative observation network, interpolated climate grids can provide a highly accurate picture of regional climatologies (Aalto et al., 2016). Several factors can introduce uncertainties, however, from insufficient coverage of observations (e.g. uneven distribution of synoptic weather stations) to the choice of interpolation method (Hofstra et al., 2010; Li & Heap, 2011). Additional sources of gridded climate data include atmospheric reanalysis data that assimilate observational data (e.g. weather stations, meteorological soundings, remote sensing) into a numerical weather prediction model, to provide a comprehensive, physically consistent spatiotemporal depiction of the atmospheric state (Dee et al., 2011). The result is a high temporal resolution array of meteorological variables, over multiple vertical layers (from soil to surface to stratosphere). Spatial resolution is often coarse (>25 km), though higher spatial resolution products exist (e.g. ERA5-Land; Muñoz-Sabater et al., 2021). Non-temperature variables (e.g. rainfall, snow) can be more challenging to derive. In general, careful consideration of the data set and its underlying uncertainties is advised, and some advantages and drawbacks of specific reference data are available in Table S2. Finally, for temperature specifically, gridded reference data should be corrected by an adiabatic lapse rate if recorded at a different elevation than the study site. Lapse rates themselves can vary and should ideally be adapted to the region and season (Greiser et al., 2024). There are tools available to do this in the mechanistic model *microclimf* (Maclean, 2022).

9 | GUIDELINE 8: DATA COMPILATION

The recent surge in microclimate data availability necessitates standardisation of data preparation and compilation prior to analyses. We here propose a four-tier guideline starting from data sourcing, quality control, alignment, to database finalisation ready for analyses (Figure 8).

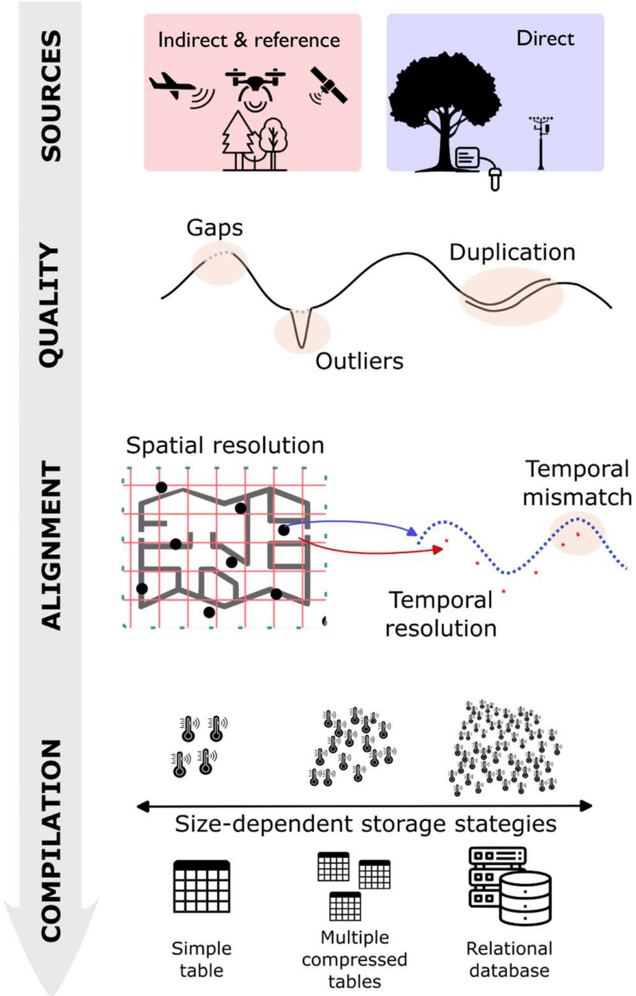

FIGURE 8 The four steps in the data compilation process: From sourcing to database finalisation. In the alignment step, the red arrow refers to the climatic grid used as reference data, the blue arrow denotes the logger location.

9.1 | Data sources

Microclimate and reference data can thus come from a multitude of logger types and data sources. Direct in situ measurements (e.g. from loggers) offer measurements at specific locations. However, these measurements are often purpose-driven, complicating comparisons across different data sets (Kemppinen et al., 2024). Indirect sources of microclimate data can be added to the direct measurements, and can include, for instance, remote-sensing data (e.g. thermal imagery from unoccupied aerial vehicles; Zellweger et al., 2019) or come from mechanistic and/or statistical models. In addition to the microclimate data, reference data (Guideline 7) can also be added in the data compilation step.

9.2 | Data quality control

To ensure the reliability of microclimate time series, measurement errors, outliers, temporal gaps, duplications and time-series inversions need to be addressed. First and foremost, one should plot the time series to visually detect potential anomalies, focusing on gaps or unexpected outliers (e.g. flat temperature lines and sharp peaks). Additionally, comparing multiple related time series (e.g. from nearby locations) against reference data (Guideline 7) helps to identify potential outliers or divergences due to malfunctioning loggers. Non-relevant recordings may result from, for instance, soil moisture recordings from frozen soils or wind measurements from periods when the anemometer was covered by snow. Beyond visual inspection, automated time-series control can identify finer issues like missing data, irregular time steps, incorrect chronological order or duplicated records. For automated data control, algorithms such as those available in the *myClim* and *lubridate* packages in R (Grolemund & Wickham, 2011; Man et al., 2023) or the *darts*,*etna* and *MetObs* packages in Python (Herzen et al., 2022; Vergauwen et al., 2024) have been developed. Data cleaning and outlier removal can increase the number of missing values, thus creating gaps in the time series. Small gaps can be filled using simple linear approximation, while longer gaps might be filled using more sophisticated interpolation methods (von Schmalensee, 2023), or similar time series to reconstruct the temporal dynamics, such as data from another study plot or reference data (Tonini et al., 2016). However, gap-filling methods should be used carefully, as they can impact the results of subsequent analyses.

9.3 | Data alignment

Microclimate and reference data, sourced from diverse origins, are formatted in various standards concerning the coordinate system, resolution and file format. To achieve alignment, common standards must be defined. Temporal reference alignment is crucial, especially on larger scales or when dealing with seasonal time shifts that can cause local time disparities. Two viable approaches are aligning all dates to the UTC time zone or to solar time, determined by setting noon when the sun reaches its zenith (see the *lubridate* and *myClim* packages in R). Similarly, aligning spatial coordinate systems, such as EPSG codes, is essential before data compilation. The second critical aspect involves navigating spatiotemporal resolutions. Various measurement intervals require temporal thinning, interpolation or aggregation before data set compilation. The optimal approach depends on the study questions and intended variables. Likewise, aligning spatial raster with point data necessitates considerations of data upscaling and downscaling before alignment. Caution must be considered when downscaling, as it tends to overlook local processes and drivers like microtopography and vegetation spatial heterogeneity, while upscaling sacrifices spatial resolution (Lembrechts et al., 2020). This spatial alignment issue should also consider the vertical dimension, as microclimate shifts with height (Geiger et al., 2009). Once aligned in space, the final step entails cropping time series to align them temporally, ensuring comparability between data sets.

9.4 | Data compilation and storage

The compilation and storage of 'ready-to-use' data can vary depending on the dataset size. Small data sets, comprising a few dozen time series, may not require any specific treatment and can be stored locally in a simple table format. Larger data sets, containing hundreds of time series, might need to be split into multiple files and compressed (e.g. using .gzip) to prevent overloading local memory. Extra-large data sets, with thousands of time series, will require appropriate database toolkits, such as SQL databases, to facilitate easy data navigation (Figure 8).

10 | GUIDELINE 9: DATA ANALYSES

Once the microclimate data have been compiled and curated, it is time to analyse the data, starting with techniques for summarising and visualising the multidimensional information stored in multiple microclimatic time series. Understanding key drivers of microclimate variations is essential before data analyses using either correlative or mechanistic models. Finally, we discuss the importance of incorporating microclimatic conditions into ecological models to improve predictions of ecosystem responses to climate change.

10.1 | Summarise and visualise microclimate data

Prior to data analyses, it can help to explore some summary statistics using aggregation and visualisation tools (Man et al., 2023). Data aggregation condenses temporal data sets into easily interpretable units, typically by computing summary statistics. Visualisation approaches can involve plotting, for instance, raw temperature data or temperature offsets in comparison to reference data, such as macroclimate, which provides insights into potential drivers of these temperature differences. Microclimatic extremes (minimum and maximum) warrant careful consideration due to their high sensitivity to outliers (see also Section 9). Common approaches include assessing instead the 5th and 95th percentile of the entire distribution.

Visualising temporal microclimate data can become complex as the number of loggers and length of time series increases. While a simple visualisation over time offers a broad understanding of temporal dynamics, it may obscure finer scale patterns like diurnal cycles amidst interannual variations (see Text S1). Thermal isocline heat maps, which display microclimatic variables across two temporal scales, offer a solution by showing, for example, months on the *x*-axis, hours on the y-axis and colour-coding by average temperature across loggers (see Text S1 for some examples including R code). Plotting logger locations in space aids in understanding spatial autocorrelation, and plotting logger locations on a 'Mean Annual Precipitation' versus 'Mean Annual Temperature' graph allows exploration of macroclimatic context (Lembrechts et al., 2020). For spatially oriented data like wind, light or rainfall direction, a circular plot representing event density provides an initial understanding of data distribution.

10.2 | Make inferences about microclimate in space and time

Most models used by microclimate ecologists to make inferences about microclimates in space and time are empirical in nature, directly describing the observed patterns or relationships between predictors and the microclimate variable of interest (Haesen, Lembrechts, et al., 2023). They are often simpler to develop and require less computational resources compared to mechanistic models. The flexibility of statistical approaches means that they can be applied to a broad range of problems without explicit knowledge of the constraints on the system (Dormann et al., 2012). However, they may oversimplify the underlying processes and lack generalizability beyond the range of observed conditions. Moreover, simpler methods like linear regression or spatial interpolation techniques (e.g. kriging) may fail to capture nonlinear relationships or interactions among microclimate drivers accurately (Gril, Spicher, et al., 2023). Machine learning models like boosted regression trees, random forests and neural networks enhance predictive accuracy by easily fitting complex patterns, interactions and nonlinear relationships frequently found in natural systems (Haesen et al., 2021; Haesen, Lembrechts, et al., 2023; Haesen, Lenoir, et al., 2023; Lembrechts et al., 2020). Nevertheless, these models may operate as black boxes and require substantial training data to prevent overfitting. Importantly, analysing microclimate time-series data with empirical models often necessitates accounting for both spatial and temporal autocorrelation (Dormann et al., 2007; Mitchell et al., 2019).

Mechanistic models, based on physical principles, are grounded in a deeper understanding of the underlying processes governing microclimates, allowing for more accurate predictions in diverse scenarios. These models can incorporate interactions between various factors such as solar radiation, topography and vegetation, providing detailed insights into microclimate dynamics (Kearney, Briscoe, et al., 2021; Kearney, Jusup, et al., 2021; Maclean et al., 2019). Additionally, mechanistic models can extrapolate beyond observed data, enabling predictions in locations or times where empirical data may be lacking. However, mechanistic models require extensive data and knowledge of input parameters and often involve complex mathematical formulations, which can be challenging to implement and interpret without specialised expertise. Furthermore, uncertainties in model parameters or assumptions may affect the reliability of predictions. Mechanistic and statistical approaches represent either end of a continuum (Dormann et al., 2012). The integration of statistical and mechanistic techniques and model emulation hold potential for creating computationally efficient microclimate models that are grounded in mechanistic understanding (Kemppinen et al., 2024; Perry et al., 2022; Reichstein et al., 2019).

10.3 | Biotic responses to microclimates

Ecophysiological processes, species distributions and ecosystem functions, in general, do not directly respond to macroclimate conditions but rather to microclimatic dynamics that are altered by local habitat conditions (Beugnon et al., 2024). Therefore, we recommend that models of ecological responses to macroclimate change incorporate those microclimatic variables as covariates in addition to the traditional set of bioclimatic variables used in most modelling studies. Such models do not necessarily need to replace the traditional set of bioclimatic variables with microclimatic equivalents, as this may not necessarily improve the predictive power of the models. In fact, microclimatic variables may even have a lower explanatory power if not carefully matched with the response variable of interest in terms of spatiotemporal resolution. For instance, the response variable of interest, a binary variable of the spatial distribution of an understorey plant species, might not be available at a sufficiently fine spatial resolution (e.g. presence–absence data at 1 km resolution) to match the fine spatial resolution of the microclimatic predictor variables that are available for use in a species distribution model tailored for understorey forest species (e.g. ForestClim variables available at 25-m resolution; Haesen, Lembrechts, et al., 2023). This mismatch in spatial resolution between the response and predictor variables prevents predicting a meaningful distribution of the focal species of interest at the right spatial resolution. Although it is still possible to aggregate the raw microclimate predictor variables at a coarser resolution matching the response variable, this may lead to a loss of predictive accuracy compared to a model for which both the response variable and the microclimate predictor variables are available at finer and matching resolutions (Haesen, Lenoir, et al., 2023). Besides, aggregated microclimatic conditions are likely to be highly correlated with their traditional bioclimatic counterparts, which can be problematic for some correlative-based models (Klinges, Baecher, et al., 2024). Instead, a more pragmatic solution would be to generate carefully considered variables grounded in mechanistic understanding and capturing microclimate conditions in space and time by relying on the raw microclimatic time series. For instance, one can compute the offset between macroclimate and microclimate, which can later be aggregated at the spatiotemporal resolution that matches with the traditional set of bioclimatic variables, to capture microclimatic conditions (Haesen et al., 2021). Alternatively, as a proxy of microclimatic modulations, the slope coefficient of the linear relationship between microclimate and macroclimate data can be extracted at a temporal resolution, for example, monthly, seasonally or yearly, that matches with the temporal resolution of traditional bioclimatic variables used in ecological modelling (Gril, Spicher, et al., 2023). Once calculated, these microclimatic variables can be integrated into ecological models, unlocking new research pathways for mechanistically understanding biological responses to global change.

11 | GUIDELINE 10: DATA AND CODE DEPOSITION

We support open access to microclimate data and code. To enable this efficiently and ethically, special attention must be paid to the structure of the database, data and metadata formats, but also to preserving sensitive data, as well as obtaining consent by stakeholders, and deciding on ownership rights in an inclusive way.

Open access to microclimate data facilitates easy access for researchers working within the same study system, supports larger-scale collaborative analyses for understanding the role of microclimatic processes in ecology (e.g. Risch et al., 2023) and enables regional or global microclimate mapping, which all in all enhances baseline data availability (Haesen, Lembrechts, et al., 2023; Haesen, Lenoir, et al., 2023; Lembrechts et al., 2022). Openly sharing such data also contributes to the creation of long-term data sets, essential for assessing microclimate changes over recent decades (Lembrechts & Nijs, 2020) (see Section 5), and stimulates interdisciplinary or transdisciplinary research. Obviously, reaching a consensus on data ownership rights is needed beforehand and any potentially sensitive information, such as exact coordinates of private or ecologically vulnerable locations, are anonymised or aggregated before data sharing.

For reproducibility, microclimate data should always be published open access alongside their associated scientific articles, according to the 'FAIR' principle, that is, that data are Findable, Accessible, Interoperable and Reusable (Wilkinson et al., 2016). Submitting microclimate data to SoilTemp, the (soon) open-access, global, integrated microclimate database can facilitate all of the points made above (Lembrechts et al., 2020). Additionally, targeted alternatives exist for specific data types, like the International Soil Moisture Network (ISMN; Dorigo et al., 2021).

When sharing microclimate data, we recommend using standard or well-documented, non-proprietary formats (e.g. csv, txt and/or *myClim* R objects) (Man et al., 2023) with distinct separators of columns (tabulators, commas, semicolons), dates (ISO formats) and decimals (dots). Unfortunately, commercial software (that can be necessary for downloading data from loggers) may not always follow such rules and reshaping original files may thus be necessary (e.g. via the *myClim* package, see Section 9). For larger microclimate data sets, specialised formats such as the open-source *TubeDB* might be useful (Wöllauer et al., 2021). Microclimate files dedicated to data sharing should be cleaned, error-free and trustworthy, and merged into a single data file in cases of repeated data downloads from the exact same logger at a given locality through time.

Metadata should also be considered an integral part of microclimate time series, especially so for data sharing. To facilitate re-use, self-explanatory headers or clear indication of column identity is key. When sharing data through existing databases such as SoilTemp, TubeDB, ISMN or others, it is expected that metadata is filled out in predefined fields with limited flexibility. It is also important to ensure compatibility (i.e. keep unique ID keys to enable spatiotemporal pairing), and if possible, to include additional associated proximal biodiversity or environmental information. Relevant metadata indeed includes information on soil and substrate properties, canopy cover (e.g. with camera traps, Chianucci et al., 2021) and the biophysical properties of the loggers themselves.

Finally, sharing data is a major step towards efficient scientific collaboration, but the same argument can be made for any microclimate-related code or script to handle and analyse the data. To share such code in a useful way, time should be invested to structure and label codes as much as possible. Sharing codes can be done via data repositories (e.g. Figshare) or on dedicated public platforms (e.g. GitHub). Ultimately, broadly applicable code should be compiled into dedicated packages with custom functions to warrant interoperability. In terms of microclimate data, the recent packages *myClim* in R (Man et al., 2023) and *MetObs* in Python (Vergauwen et al., 2024) are useful examples to follow.

12 | CONCLUSIONS: THE WAY FORWARD

Microclimate monitoring has rapidly gained popularity over recent decades because of the increasing availability of low-cost microclimate loggers and because it is increasingly accepted that microclimate plays a critical role in ecology, biogeography, evolution and related fields (Kemppinen et al., 2024). While our 10 practical guidelines highlight that each microclimate-related research question is unique and, consequently, will require tailored sampling designs and measurement solutions, we aimed to provide not only a conceptual framework but also the hands-on tools necessary to make these tailored decisions as standardised and quantitative as possible. We therefore aim for this paper to represent a step towards increased global standardisation of microclimate studies. However, this is just one step towards harmonising microclimate research. There are still important areas for scientific advancements in this field.

First of all, real-time data collection through the Internet of Things (IoT) or related technologies is becoming more accessible and available in more remote environments (Pieters et al., 2021; Rebaudo et al., 2023). Such remote data transfer would facilitate monitoring, reduce resources necessary for fieldwork, limit data loss and provide immediate data for analysing microweather events as they happen in real time. We also urgently need more high-quality, affordable microclimate loggers for various microclimatic parameters beyond temperature (e.g. for wind and solar radiation, affordable sensors are not yet widely available; Gillerot, Landuyt, et al., 2024; Gillerot, Rozario et al., 2024). Similarly, there is an increasing need to measure a more diverse array of microclimatic parameters, including soil water potential, dew, vertical profiles of air temperature and wind speed, solar radiation and organism-specific microclimate data, for example, data relevant to animal and human health (Guideline 3). For all these, the development of reliable, low-cost loggers will be key for big data and scaling microclimate-related phenomena from organism level to global levels.

Although microclimate ecology is a well-established field of research, the relatively recent compilation of autonomous data loggers across many locations on Earth (Lembrechts et al., 2020) has led to an explosion of microclimate time-series availability at fine temporal resolutions, usually focusing on relatively short-term periods and chiefly concentrated during the last decade (Figure 4; Section 5). However, long-term microclimatic time-series spanning several decades, in a wider range of habitats (current bias to temperate forests) and throughout the world (current bias to the northern hemisphere) (see Section 6) are deeply needed to understand long-term dynamics in microclimate changes and to address key questions related to the impact of global warming on biodiversity redistribution. Therefore, the establishment of long-term microclimate monitoring networks, similar to national networks of weather stations, should become a research priority.

Microclimate can also feedback to the macroclimate (De Frenne et al., 2021). For instance, microclimate can drive local vegetation patterns and ecosystem processes, which affect surface conditions (e.g. surface albedo and roughness), heat fluxes and carbon cycling over a larger extent. The dynamics of these relationships could be especially important for moderate to long-term studies focusing on, e.g. species range dynamics and future scenarios of ecosystem functioning and services. Many microclimate processes (e.g. canopy or soil surface processes, such as feedbacks of below-canopy microclimates in forests) are not yet being represented in macroclimate models. However, understanding microclimate variability is important when investigating sub-pixel variability, at least to constrain the uncertainty levels in macroclimate grids or remotely sensed data of surface temperature and moisture. Such microclimate variability has useful applications in highlighting regions with particularly high uncertainty in the macroscale product, thus providing guidance on which variables to focus for further model development (see Section 10).

Finally, harmonised data monitoring will facilitate integration into global databases (see Guideline 10), such as the SoilTemp database (Lembrechts et al., 2020), which has recently expanded beyond temperature and soil moisture to include all in situ measured microclimate parameters. To optimise ecological research and beyond, however, it remains crucial to improve the integration of the SoilTemp database with other ecological databases focused on species distributions and ecological patterns. Standardisation could further pave the way for a harmonised global network—or network of networks—of standardised microclimate loggers, in line with the existing global weather station network (WMO, 2023). This further unification is urgently needed in ecology and evolution, which increasingly depend on large-scale, high-resolution and long-term data on microclimates and their changes in response to global changes, such as climate warming, land use change and biodiversity loss.

AUTHOR CONTRIBUTIONS

Pieter De Frenne, Julia Kemppinen, Jonas J. Lembrechts, Karen De Pauw & Koenraad Van Meerbeek were the core team of this review and conceived the initial ideas. Rémy Beugnon, David Klinges, Jonathan Lenoir, Pekka Niittynen, Sylvain Pincebourde, Rebecca A. Senior and the core team were section leaders. All authors wrote the manuscript. The workflow of how this manuscript was written and some author demographics are available in Supporting Information Figures S1 and S2.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interests to declare.

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DATA AVAILABILITY STATEMENT

This is a review and no new data were used in this paper.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. The workflow of this manuscript, providing a detailed description of how this manuscript was developed, how work tasks were divided and the general flow of the process.

Figure S2. Demographics of the authors of this manuscript. We provide background information on all 27 authors of the manuscript.

Note that authors could indicate all options regarding their discipline, most often studied biome and study object.

Text S1. R-code and visuals for the four steps in the data compilation process (see Figure 8) in Guideline 8.

Table S1. Overview of a selection of currently available and most often used (according to the SoilTemp database) microclimate logger types, powered by batteries and suitable for field studies in ecology and evolution.

Table S2. Overview of available reference data, and their characteristics such as spatiotemporal resolution and extent, and some advantages and drawbacks of each type of reference.

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