

ARTICLE

Methods, Tools, and Technologies

# A guide and tools for selecting and accessing microclimate data for mechanistic niche modeling

Abigail V. Meyer<sup>1</sup> | Yutaro Sakairi<sup>1</sup> | Michael R. Kearney<sup>2</sup>  | Lauren B. Buckley<sup>1</sup> 

<sup>1</sup>Department of Biology, University of Washington, Seattle, Washington, USA

<sup>2</sup>School of BioSciences, The University of Melbourne, Melbourne, Victoria, Australia

**Correspondence**

Lauren B. Buckley  
Email: [lbuckley@uw.edu](mailto:lbuckley@uw.edu)

**Funding information**

National Science Foundation,  
Grant/Award Number: DBI-1349865

**Handling Editor:** Robert A. Washington-Allen

## Abstract

Most ecological analyses and forecasts use weather station data or coarse interpolated, gridded air temperature data. Yet, these products often poorly capture the microclimates experienced by organisms that respond to fine-scale spatial and temporal environmental variation near the surface. Sources of historic and projected future data with finer spatial and temporal resolution are proliferating. We qualitatively and quantitatively review and evaluate the available data on three core issues central to microclimate modeling: the quality of the input environmental data, the ability of algorithms to capture microclimatic processes given environmental forcing data, and how best to access microclimatic data. We show how differences between observed environmental conditions and those estimated using environmental forcing data, microclimate algorithms, and precomputed microclimate datasets can be substantial depending on the variable, location, and season. The choice of environmental dataset to parameterize biophysical models has ramifications for biological estimates, such as the duration of potential activity and incidence of thermal stress. New data sources offering high temporal and spatial resolution correspond well to observational data and have the potential to revolutionize understanding of the ecological implications of microclimate variability. We provide resources to help users select and access appropriate environmental data for biological applications, including users' guides and interactive visualization, to better infer how organisms experience climate variability and change.

## KEY WORDS

biophysical, climate change, data comparison, energy budget, forecast, hindcast, microclimate, radiation, temperature

## INTRODUCTION

Interactions of organisms with their environment determine their physiology, behavior, energetics, and ultimate

demography and distribution (Helmuth et al., 2010; Sears et al., 2019). A central challenge in ecological and evolutionary studies is matching the scale and nature of environmental data to the biological questions being asked.

This is an open access article under the terms of the [Creative Commons Attribution License](#), which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2023 The Authors. *Ecosphere* published by Wiley Periodicals LLC on behalf of The Ecological Society of America.

These interactions are often at the scale of minutes and meters, but most ecological and evolutionary studies rely on much coarser environmental data to infer responses (Helmuth et al., 2010; Nadeau et al., 2017; Potter et al., 2013). For example, studies tend to use temperature data with spatial resolutions 10,000-fold coarser than the size of focal animals and 1000-fold coarser than the size of focal plants (Potter et al., 2013). Spatially fine-resolution datasets are often temporally coarse, like WorldClim (Fick & Hijmans, 2017), which provides monthly long-term averages at a spatial resolution of 1 km. Yet diurnal and seasonal climate variations experienced by organisms can differ from coarse-resolution data by up to 20°C (Scherrer & Koerner, 2010) and are crucial determinants of an organism's activity and energetics (Dillon et al., 2016; Wang & Dillon, 2014). Moreover, environmental extremes can be more important than means in determining patterns of environmental stress (Buckley & Huey, 2016), and the nonlinear temperature responses of many biological processes result in further inaccuracies when temporally averaged data are used (Bütkofer et al., 2020; Denny, 2017; Kearney et al., 2012). Finally, throughout the day, many organisms move through landscapes to select suitable microclimates (Sears et al., 2016; Woods et al., 2015), highlighting the need for climate data with fine spatial and temporal resolutions.

Many studies of species-environment responses use correlative models, where behavioral, demographic, or distributional patterns are statistically related to environmental conditions. For correlative modeling, it is not so important to get the absolute values right; if the data capture spatial/temporal patterns, they will be useful for prediction (Elith et al., 2010). There are many useful resources in the literature on how to choose, obtain, and use environmental data for correlative methods (Araújo et al., 2019; Cobos et al., 2019; Warren & Seifert, 2011). In this article, we are concerned with mechanistic models of species' environmental responses, where accurate estimates of environmental conditions experienced by the organism—that is microclimates or “functional environments”—are needed to calculate how the conditions influence the organism's energy and mass balances and subsequently its performance. Mechanistic niche models were recently reviewed (Briscoe et al., 2023), but there are no general overviews of the environmental datasets available for parameterizing the models. The aim of this article is to provide analyses, tools, and guidance for this kind of modeling.

Recent reviews (Bramer et al., 2018; Bütkofer et al., 2020) have examined how mismatches between the environmental data used in analysis and the environmental conditions experienced by organisms can alter predictions of biological responses to climate change. Microclimate

variability, often associated with topographic heterogeneity, can buffer organisms from thermal stress associated with climate change (De Frenne et al., 2013; Suggitt et al., 2018). The reviews provide strong motivation for further incorporating the spatial and temporal variation experienced by organisms into biological analyses. The recent reviews tend to focus on air temperature and the direct use of environmental data for biological applications (Bramer et al., 2018; Lembrechts et al., 2019). Many studies approximate the body temperatures of organisms as air temperature (Huey et al., 2012), but radiation and evaporation effects can cause strong offsets. For example, the difference in body temperature between the sun and the shade within a habitat can be much greater than body temperature differences between geographically distinct habitats (Sunday et al., 2014).

Here we review the available environmental data for use as inputs into microclimate and biophysical models. We introduce an interactive application ([https://map.trenchproject.com/RShiny\\_Microclim/](https://map.trenchproject.com/RShiny_Microclim/)) and user guides ([https://bookdown.org/huckley/microclimate\\_users\\_guide/](https://bookdown.org/huckley/microclimate_users_guide/)) to accompany this review and aim to assist in selecting and accessing environmental data for biophysical applications. We illustrate the application's functionality by comparing the performance of a subset of environmental data sources in capturing temporal and spatial patterns of environmental variation and in predicting patterns of body temperature variation. Overall, we seek to expand the use of microclimate data to understand responses to environmental variability by providing visualizations and user guides for the available data resources.

## Approaches for biophysical modeling

Estimating body temperatures generally requires two classes of models: microclimate and biophysical. Microclimate models characterize the processes of heat transport through air and soil to estimate vertical temperature and wind profiles. These profiles can be used to scale conditions from sensor to organism height. Microclimate models also characterize radiative environments, including direct and diffuse solar radiation and longwave radiation emanating from the sky, ground, and surrounding objects like vegetation. Conditions can be much warmer or colder in organisms' habitats near the ground than at the standard 2 m height of climate measurements (Bütkofer et al., 2020). The extent of the climatic gradient between the ground and 2 m aboveground depends on the extent of air mixing, which in turn depends on the roughness of the surface (e.g., vegetation creates more turbulent airflow than does bare ground). Fortunately, relationships for estimating wind and air

temperature profiles are well established (Campbell & Norman, 2000; Gates, 1980) and can be readily estimated with environmental information from at least one point (and ideally multiple points) along the gradient from the free atmosphere to the ground along with substrate temperature. Microclimate models can also predict thermal and hydric conditions below ground, in soil, or in burrows (Briscoe et al., 2022).

Biophysical models estimate body temperatures using an energy budget to balance heat exchanges between organisms and their environment (Campbell & Norman, 2000; Gates, 1980). Heat exchange is often dominated by the exchange of longwave radiation emitted from the organism and received from the surfaces (including the sky) of its environment. During the day, heat exchange is also strongly affected by solar radiation. Much of the remainder of heat exchange is driven by mass transfer of heat between the air and the organism, depending on the temperature difference between the organism and its environment, the wind speed, and the thickness of the boundary layer of air surrounding the organism (Bramer et al., 2018). Organisms also exchange heat with surfaces they are directly in contact with via conduction.

Microclimate and biophysical models have long been available (Campbell & Norman, 2000; Gates, 1980), but their application is expanding with increased availability of computation tools. The NicheMapR R package provides detailed and comprehensive microclimate and biophysical models that compute body temperature, water loss rates, and energy budgets for ectotherms and endotherms (Kearney & Porter, 2017, 2020). The complementary TrenchR R package offers modular and accessible functions to implement microclimate and biophysical models as well as specialized biophysical models for particular taxa ([trenchproject.github.io/TrenchR/](https://trenchproject.github.io/TrenchR/)). NicheMapR and TrenchR both offer user interfaces for microclimate and biophysical modeling (<https://camel.science.unimelb.edu.au/biological-forecasting-and-hindcasting-tools/>, [www.trenchproject.com/tools](http://www.trenchproject.com/tools)). Plant-specific biophysical models are the focus of several R packages (tealeaves: Muir, 2019; plantecophys: Duursma, 2015). Some energy budget calculation components of biophysical models are also available in the ThermImage package (Tattersall, 2017). Microclimate models, with an emphasis on describing spatial variation, are available in the microclima (Maclean et al., 2019) and microclimc (Maclean & Klings, 2021) packages.

## Data need for biophysical modeling

Biophysical calculations for dry-skinned ectotherms require, at a minimum, joint estimates of air temperature,

wind speed, solar radiation, and ground temperature (Buckley et al., 2018; Kearney & Porter, 2020; Kearney et al., 2010). For modeling organisms of various sizes, it is vitally important to adjust these variables to the height of the organism above the ground (Kearney et al., 2021). Humidity is required for endotherms and wet-skinned ectotherms. Additional microclimate variables, including precipitation, surface albedo, vegetation, cloud cover, and shade level, can be added to increase the realism of describing how organisms experience their environment. This constellation of variables is rarely available in empirical data sets at broad temporal or spatial scales, but they can be modeled with macroclimatic algorithms. Material properties such as propensity to absorb solar radiation or conduct heat can either be empirically measured or approximated based on available data compilations (e.g., Gates, 1980).

We consider three core issues central to microclimate modeling: (1) the quality of the input environmental data; (2) the ability of algorithms to capture microclimatic processes given environmental forcing data; and (3) how best to access microclimatic data. Environmental data can sometimes be used directly in biophysical models but often needs to be further processed using microclimate models to, for example, scale conditions to the height of organisms. We focus on the weather/climatic variables needed for the NicheMapR and TrenchR microclimate models, but note that additional factors such as vegetation characteristics, soil properties, and topography can also shape microclimate (Sears et al., 2019) and can be incorporated into these models. For example, soil databases such as SoilGrids (<https://www.isric.org/explore/soilgrids>) can provide quantitative textural data that can be converted with pedotransfer functions to obtain hydraulic parameters for soil moisture modeling (Kearney & Maino, 2018).

Some environmental conditions can be estimated from physical first principles. For example, solar radiation can be approximated by discounting incoming solar radiation at the top of the atmosphere by atmospheric absorption, which varies with elevation, solar angle, and atmospheric composition. Total radiation can be partitioned into direct, reflected, and diffuse radiation based on cloud cover (Campbell & Norman, 2000; Gates, 1980). However, cloud cover is exceptionally difficult to model, making it generally preferable to use observations of solar radiation.

An additional complexity is that many organisms select microhabitats to minimize or maximize absorption of solar radiation depending on their body temperature. Explicitly modeling microhabitat selection through space and time is a substantial undertaking (Malishev et al., 2018; Sears et al., 2011). However, knowledge

of the organism's thermoregulatory strategies and goals (e.g., preferred body temperature) can simplify biophysical modeling and lessen the need for detailed environmental data. One strategy is to assume organisms will select the body temperature closest to their preferred body temperature, assuming available body temperatures range from that in full shade to that in full sun, and allowing postural adjustments (Buckley & Kingsolver, 2019; Kearney & Porter, 2009). NicheMapR allows for additional behavioral adjustments, including climbing and retreating below ground.

The third core issue is particularly challenging because microclimatic calculations need to be made at the organismal scale, typically hourly or finer in time and meters or finer in space (Dillon et al., 2016; Woods et al., 2015). The fine-scale nature of microclimatic forcing data means that computational and storage requirements are high. This leads to a trade-off between using microclimate models "on-the-fly" on a point-by-point basis when making biophysical calculations and producing pre-computed microclimatic products for general use in the same way that macroclimatic data are provided for correlative species distribution modeling (e.g., WorldClim v2; Fick & Hijmans, 2017).

Our comparison progresses through the three core issues central to microclimate modeling. We start with spatial and temporal comparisons of environmental forcing data. We then use a biophysical model to estimate lizard body temperatures from (1) the environmental forcing data; (2) the output of applying microclimate algorithms to the environmental forcing data; and (3) microclimate datasets and environmental forcing data vertically scaled to organism height. We intend these comparisons to illuminate the differences in available microclimate data for use in biophysical research and to help researchers find and access the most applicable data for their needs.

## METHODS

### Environmental forcing data

Three main approaches used to generate gridded environmental data are reviewed in Appendix S2: statistical data interpolation, remote sensing, and dynamic systems models (Bramer et al., 2018; Daly, 2006). Sources of historical and forecasted microclimate data are summarized in Table 1 and Appendix S1: Table S1 and further described in Appendix S3. We focus our comparison and data resources on the United States due to the wide range and free availability of datasets and of diverse climates represented. We offer user guides for accessing the environmental data

directly or via Application Programming Interface (APIs) in statistical programs such as R ([https://bookdown.org/huckley/microclimate\\_users\\_guide/](https://bookdown.org/huckley/microclimate_users_guide/)).

We focus our example comparison on five environmental forcing datasets. We include two datasets generated by statistically interpolating data values from irregularly spaced station locations (Daly, 2006). gridMET is a high-resolution dataset of daily surface meteorological data for the contiguous United States that blends spatial attributes of gridded climate data from PRISM—the USDA's climatological data—with temporal attributes from regional reanalysis using climatically aided interpolation (Abatzoglou, 2013). The Natural Environment Research Council's (NERC) NEW01 dataset offers a gridded (10' resolution) hourly climatology for an average day each month over a reference period (1961–1990) (New et al., 2002). We include three datasets generated by assimilating of observational data in dynamic systems models. ERA-5 Land is a global dataset incorporating observation-based atmospheric forcing into dynamic models with coverage from 1981 to present. The data are high-resolution both spatially ( $0.1^\circ \times 0.1^\circ$  or  $9 \times 9$  km) and temporally (hourly), and ERA-5 Land provides a large range of variables at various depths above- and belowground. The Global Land Data Assimilation System (GLDAS) provides global data for 1948 to the present and for many variables at lower resolution spatially ( $0.25^\circ \times 0.25^\circ$ ) and temporally (3-hourly) than ERA-5. National Centers for Environmental Prediction provide the NCEP/NCAR Reanalysis (NCEP), a global data product offering surface and surface flux conditions from 1948 to the present at relatively coarse spatial ( $2.5^\circ \times 2.5^\circ$ ) and temporal (6-hourly) resolution.

We compared the gridded data products to US Climate Reference Network (USCRN) weather station data at hourly resolution. Each USCRN station used in the analysis was compared to the closest spatial data product point. For an initial comparison of data product time series, we focused on three USCRN stations in different regions: OR John Day 35 WNW ( $-119.65^\circ$ ,  $44.55^\circ$ ), Oregon, 691 m; CO Nunn 7 NNE ( $-104.73^\circ$ ,  $40.87^\circ$ ), Colorado, 1798 m; and HI Hilo 5 S ( $-155.07^\circ$ ,  $19.7^\circ$ ), Hawaii, 19 m. For the subsequent spatial analysis, we analyzed all 155 USCRN stations. We analyzed data for January and July 2017, the most recent year consistently available across datasets. January and July were selected to represent winter and summer months to understand seasonal discrepancies.

### Microclimate algorithms

NicheMapR includes functions that use several of the environmental datasets above as inputs to force

**TABLE 1** Overview of environmental forcing data and precomputed microclimate datasets. We indicate microclimate algorithms applied to the forcing data as well as the data used to force precomputed microclimate datasets. Data are linked to the R Shiny app ([https://map.trenchproject.com/RShiny\\_Microclim/](https://map.trenchproject.com/RShiny_Microclim/)) and our user guide ([https://bookdown.org/huckley/microclimate\\_users\\_guide/](https://bookdown.org/huckley/microclimate_users_guide/)) provides details on accessing each database.

Name	Horizontal coverage	Horizontal resolution	Vertical coverage	Vertical resolution	Temporal coverage	Temporal resolution	Microclimate variables
Environmental forcing data							
Station data							
USCRN	US only	Stations	1.5 m above to 5 cm below	Surface and 5 cm belowground	2000 to current	Sub-hourly	Air temperature, wind speed, humidity, solar radiation, and substrate temperature
Interpolated data							
gridMET	US only	0.04° × 0.04°	Surface	Surface	1979 to yesterday	Daily	Air temperature, wind speed, radiation, and humidity
NEW01	Global	10' × 10'	Surface	Surface	1961 to 1990 normals	Hourly for 1 day monthly	Mean air temperature, mean air temperature range, relative humidity, wind speed, and cloud cover
Dynamically modeled and mixed source data							
ERA-5 Land	Global	0.1° × 0.1° (9 × 9 km)	2 m above to 289 cm below	0–7 cm, 7–28 cm, 28–100 cm, 100–289 cm belowground	1981 to 3 month behind current	Hourly	Air temperature, wind speed, solar radiation, substrate temperatures, and substrate moisture
GLDAS	Global	0.25° × 0.25°	Surface to 200 cm below	10, 40, 100, 200 cm belowground	1948-01-01 to 3 months behind current	3-Hourly	Air temperature, wind speed, radiation fluxes, specific humidity, substrate temperatures, and substrate moisture
NCEP	Global	2.5° × 2.5°	Surface to 200 cm below	2 m and surface above; 0–10 cm and 10–200 cm below	1948-01-01 to current	6-Hourly	Air temperature, wind speed, radiation fluxes, humidity, substrate temperatures, and substrate moisture
Precomputed microclimate datasets							
microclim	Global	15 × 15 km	Surface to 1 m depth	0, 2.5, 5, 10, 15, 20, 30, 50, 100, 200 cm	1961 to 1990 normals	Hourly for 1 day monthly	Air temperature, wind speed, relative humidity, solar radiation, sky radiation, and substrate temperatures

(Continues)

**TABLE 1** (Continued)

Name	Horizontal coverage	Horizontal resolution	Vertical coverage	Vertical resolution	Temporal coverage	Temporal resolution	Microclimate variables
microclimUS	US only	4 × 4 km	200 cm belowground to 200 cm aboveground	Below at (0, 2.5, 5, 10, 15, 20, 30, 50, 100, 200 cm) at (0%, 50%, 75% and 90%) shade. Above at 1 cm and 200 cm	1979 to 2017	Hourly	Air temperature, wind speed, relative humidity, solar radiation, sky radiation, substrate temperatures, and substrate moisture

Abbreviations: GLDAS, Global Land Data Assimilation System; NCEP, National Centers for Environmental Prediction; USCRN, US Climate Reference Network.

microclimate algorithms. The functions' output variables include air and soil temperatures, soil moisture, snow and wind speeds at multiple heights, and shade levels (Kearney & Porter, 2017). We illustrate the application of NicheMapR functions `micro_era5`, `micro_usa`, `micro_global`, and `micro_ncep` that are forced with ERA-5 (via the `mcera5` package; Klings et al., 2022), gridMET, NEW01, and NCEP data, respectively. The functions are designed for point locations. The microclimate model in NicheMapR can be adapted to a variety of other environmental forcing data and functions in TrenchR can be used to generate microclimate data.

## Microclimate datasets

The microclimate algorithms have been forced, with several of the environmental datasets discussed above, to generate datasets specifically intended for microclimate applications with multiple heights, shade levels, and substrates. These "pre-computed" datasets are convenient and save computational effort, but they often have tradeoffs associated with storage limitations. Several datasets were generated using NicheMapR microclimate models (Kearney & Porter, 2017). The microclim dataset used the NEW01 climate normals (New et al., 2002) to provide gridded global (~15 × ~15 km) hourly estimates of microclimate conditions for an average day of each month averaged across the climate normal period (1961–1990) (Kearney et al., 2014). The microclimUS dataset used gridMET to estimate microclimates hourly between 1979 and 2017 for gridded points approximately 60 km apart across the United States (Kearney, 2019a), and a parallel dataset exists for Australia (Kearney, 2019b). The datasets reveal tradeoffs: microclim offers fine spatial resolution, but the hourly estimates are for the typical day in a month, whereas microclimUS hourly predictions are for

actual days but with reduced spatial coverage. The MIC\_CLIM\_36 dataset provides hourly 36 km resolution microclimate data for 1980–1999 and 2080–2099 for North America (Levy et al., 2016). The Weather Research and Forecasting model was forced, with the output from a general circulation model (GCM), to generate microclimate variables at various heights, substrates, and shade levels. The dataset is optimized for extracting time series for single locations (see *Discussion*).

Environmental forcing datasets generated by reanalysis using land surface models (e.g., NCEP, ERA-5, and GLDAS) are increasingly disseminating microclimate variables close to what is needed for biophysical models. Simple microclimate models can be used to scale the variables to organism height if surface temperatures are available in the dataset. We include vertically scaled reanalysis datasets in our data comparison. We use the TrenchR function `air_temp_profile_neutral()` to scale NCEP, ERA-5, GLDAS, and USCRN to organismal height (1 cm).

## Data comparison

We developed an interactive data visualization built in R Shiny that aids dataset selection via interactive exploration of dataset features ([https://map.trenchproject.com/RShiny\\_Microclim/](https://map.trenchproject.com/RShiny_Microclim/)), code for visualization: <https://doi.org/10.5281/zenodo.7690026>). The temporal comparison allows the selection of environmental variables to compare time series across datasets, seasons, and locations. The spatial comparison maps estimated errors between a selected environmental variable and weather station data. The application also compares time series of operative environmental temperatures for selected datasets, seasons, locations, and organisms and assesses the ecological consequences of dataset selection. We provide highlights

of the data comparisons in this review and refer readers to the R Shiny app for additional datasets and variables (e.g., soil temperature, precipitation, and relative humidity).

We included the following variables for the environmental forcing data comparison: air temperature (in degrees Celsius) at reference height (2 m for ERA-5, gridMET, NCEP, and GLDAS; 1.5 m for USCRN; and 1.2 m for NEW01), surface temperature (in degrees Celsius), and solar radiation (in watts per square meter). In accordance with other comparison papers (Abatzoglou, 2013; Gleixner et al., 2020), we employed root mean squared error (RMSE), absolute bias, and Pearson's correlation coefficients to compare selected datasets with station data. For the spatial analysis, these performance metrics were mapped onto the continental United States to understand spatial discrepancies in dataset accuracy.

Finally, we examined the biological implications of discrepancies between data products using a biophysical model. The model predicts operative environmental temperatures ( $T_b$ ), which are the steady-state body temperatures predicted for an organism with given physical properties in a specific microenvironment, assuming no metabolic heat increment or evaporative cooling (Bakken, 1992). We estimated operative temperatures using parameters for *Sceloporus* lizards (Buckley, 2008; Levy et al., 2017), since they have been a frequent subject of thermal biology studies (Adolph & Porter, 1993). We estimated operative temperatures in full sunlight to highlight discrepancies from air temperature, but noted that the approach predicts thermally stressful or lethal temperatures (Sunday et al., 2014). The R Shiny application provides a choice of several biophysical models from the TrenchR package (<https://trenchproject.github.io/TrenchR/>). Here we examine a generic and simple heat budget model from Gates (1980) using functions from the TrenchR package [Tb\_Gates()].

We assumed a *Sceloporus* lizard with a mass of 8.9 g and a snout-vent length of 0.063 m (Levy et al., 2017) standing at a height of 0.01 m. We assumed the lizard's skin had a longwave infrared emissivity of 0.95 and a thermal conductivity of  $0.15 \text{ WK}^{-1} \text{ m}^{-1}$ . We partitioned solar radiation by assuming that half of the surface area was exposed to each of direct and reflected solar radiation. We estimated the diffuse fraction of solar radiation with the partition\_solar\_radiation() function using the "Liu\_Jordan" method and assumed a clearness index of 0.6. We assumed a substrate solar reflectivity of 0.3 and lizard solar absorptivity of 0.9 (Gates, 1980). We assumed that 5% of surface area was in contact with the ground. We estimated the convective heat transfer coefficient using the heat\_transfer\_coefficient\_approximation() function, assuming a wind speed of  $0.1 \text{ m s}^{-1}$ , which is appropriate

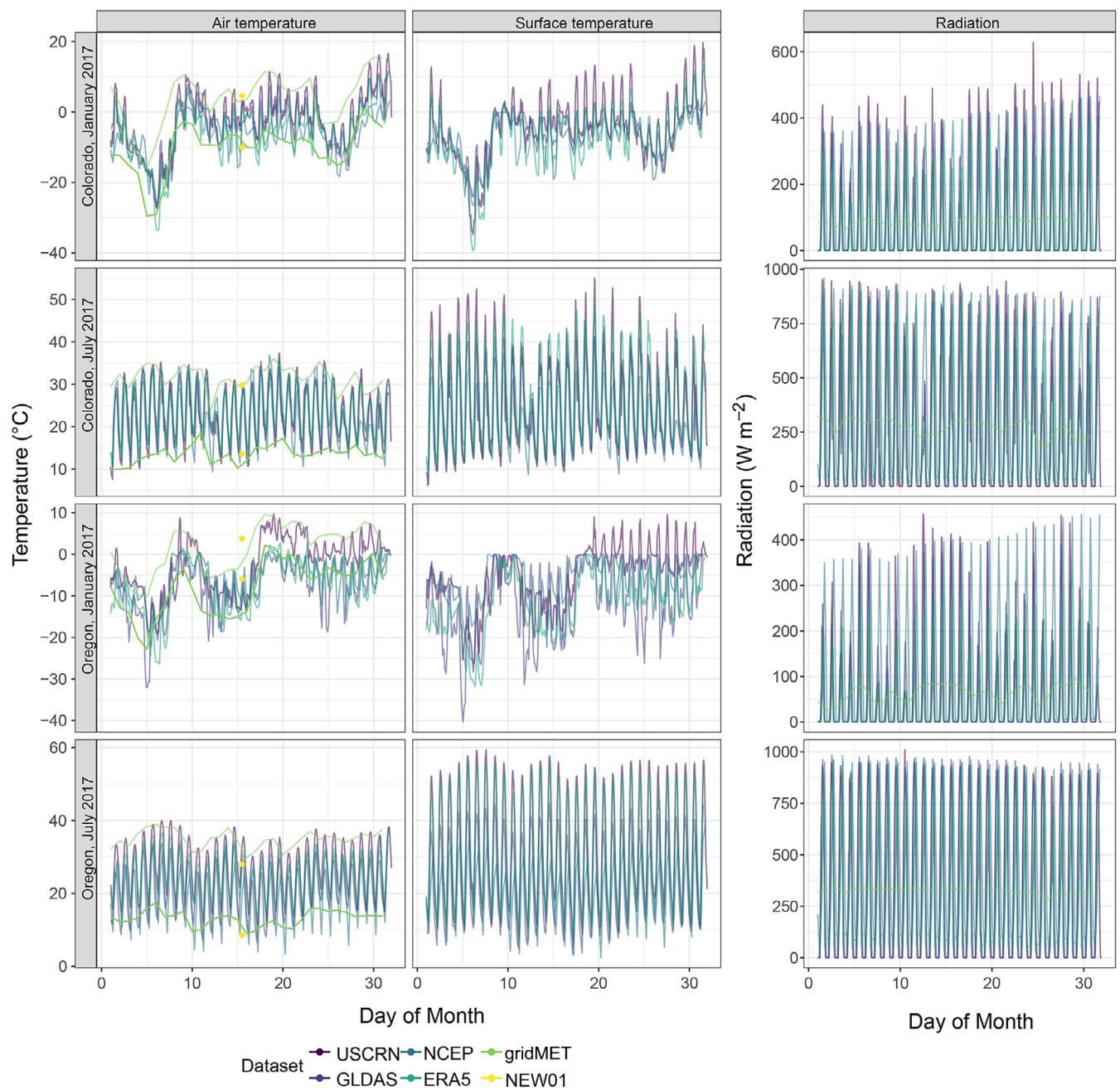
for a lizard near the ground, and default values for the thermal conductivity ( $25.7 \times 10^{-3} \text{ W m}^{-1} \text{ K}^{-1}$ ) and kinematic viscosity ( $15.3 \times 10^{-6} \text{ m}^2 \text{ s}^{-1}$ ) of air for simplicity.

For each comparative group, we drove the biophysical model with air temperature, surface temperature, and solar radiation. We first simulated with the data from reference height. We next simulated with the data outputs of the microclimate algorithms at organismal heights. Finally, we simulated with pre-computed microclimate datasets or vertically scaled data at organismal heights.

We used four biological metrics to compare the biophysical model output: average  $T_o$ ; hours during which  $T_o$  exceeded a critical thermal maximum of  $43^\circ\text{C}$ , which corresponds to the loss of performance (Levy et al., 2017); hours of activity, defined as hours when  $T_o$  is between  $32$  and  $37^\circ\text{C}$ , which corresponds to the range of observed body temperatures for field active *Sceloporus* (Levy et al., 2017); and average basal metabolism rate (in watts), calculated with the Qmetabolism\_from\_mass\_temp() function in TrenchR with 8.9 g mass (Levy et al., 2017) and lizard taxa.

## RESULTS

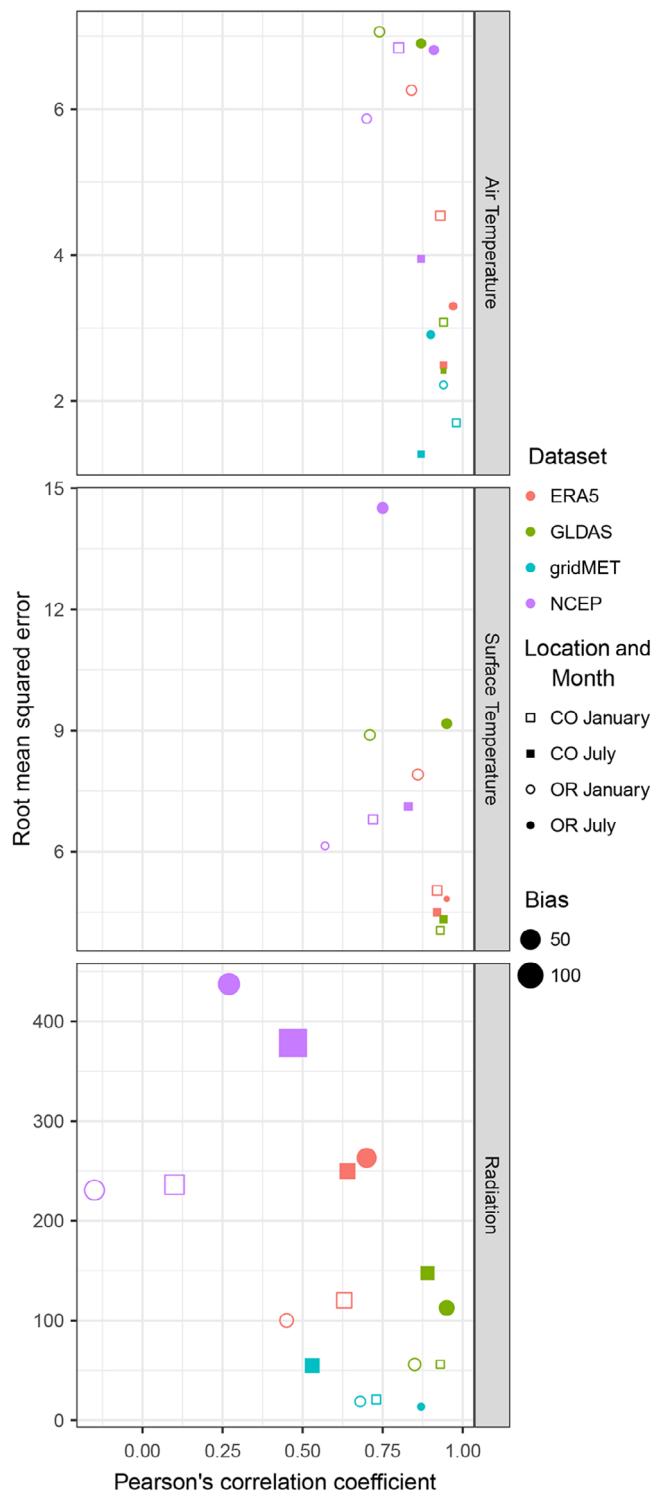
Our exploration of environmental data products, their agreement with USCRN weather station data, and the implications of environmental data selection for ecological metrics are restricted to select data products and environmental variables. Our R Shiny application ([https://map.trenchproject.com/RShiny\\_Microclim/](https://map.trenchproject.com/RShiny_Microclim/)) allows interactive explorations of additional datasets, variables, and locations. Temperatures from environmental forcing datasets generally agreed with USCRN weather station temperatures, but divergences occurred particularly for surface temperatures and during winter (Figure 1; see Appendix S1: Figure S1 for a two-week subset). ERA-5 air and surface temperatures diverged significantly from USCRN weather station data for Oregon in January 2017. GLDAS diverged low from USCRN in Oregon for both air and surface temperatures. This was not as prominent in the Colorado time series. NCEP also missed air and surface temperature highs in Oregon summer, likely due to its 6-hourly resolution. We included the gridMET data product to enable visualization of the difference between hourly and daily min/max data products and to highlight that data products differ in the environmental variables they provide. gridMET more closely followed USCRN weather station air temperature data in July as opposed to January. NEW01, a monthly climate normal, was included as a min/max air temperature. The NEW01 climate normals were representative for Colorado but



**FIGURE 1** Time series of (columns) air temperature at reference height, surface temperature, and solar radiation for (rows) January and July in Colorado and Oregon reveal how environmental forcing datasets (hourly: ERA-5 Land, 3-hourly: Global Land Data Assimilation System [GLDAS], 6-hourly: National Centers for Environmental Prediction [NCEP], daily [minimum and maximum]: gridMET, monthly: NEW01) differ from conditions at US Climate Reference Network (USCRN) weather stations (hourly).

diverged above in Oregon January and below in Oregon July. Summer radiation estimates corresponded quite well to the USCRN observations, likely due to relatively clear skies. Some extreme observations, particularly for summer in Colorado, were missed by the data products. USCRN observations frequently exceeded the estimated radiation for Colorado in January. NCEP tended to diverge above with solar radiation, particularly for Oregon in January.

We quantified the differences in Figure 1 for all data products using Pearson correlation coefficients, the average difference between data values (bias), and the RMSE (Figure 2; Appendix S1: Table S2). Performance tended to be directly correlated for bias and RMSE, but correlation coefficients sometimes exhibited divergent performance. ERA-5 exhibited relatively high performance across metrics for air temperature, with performance declining



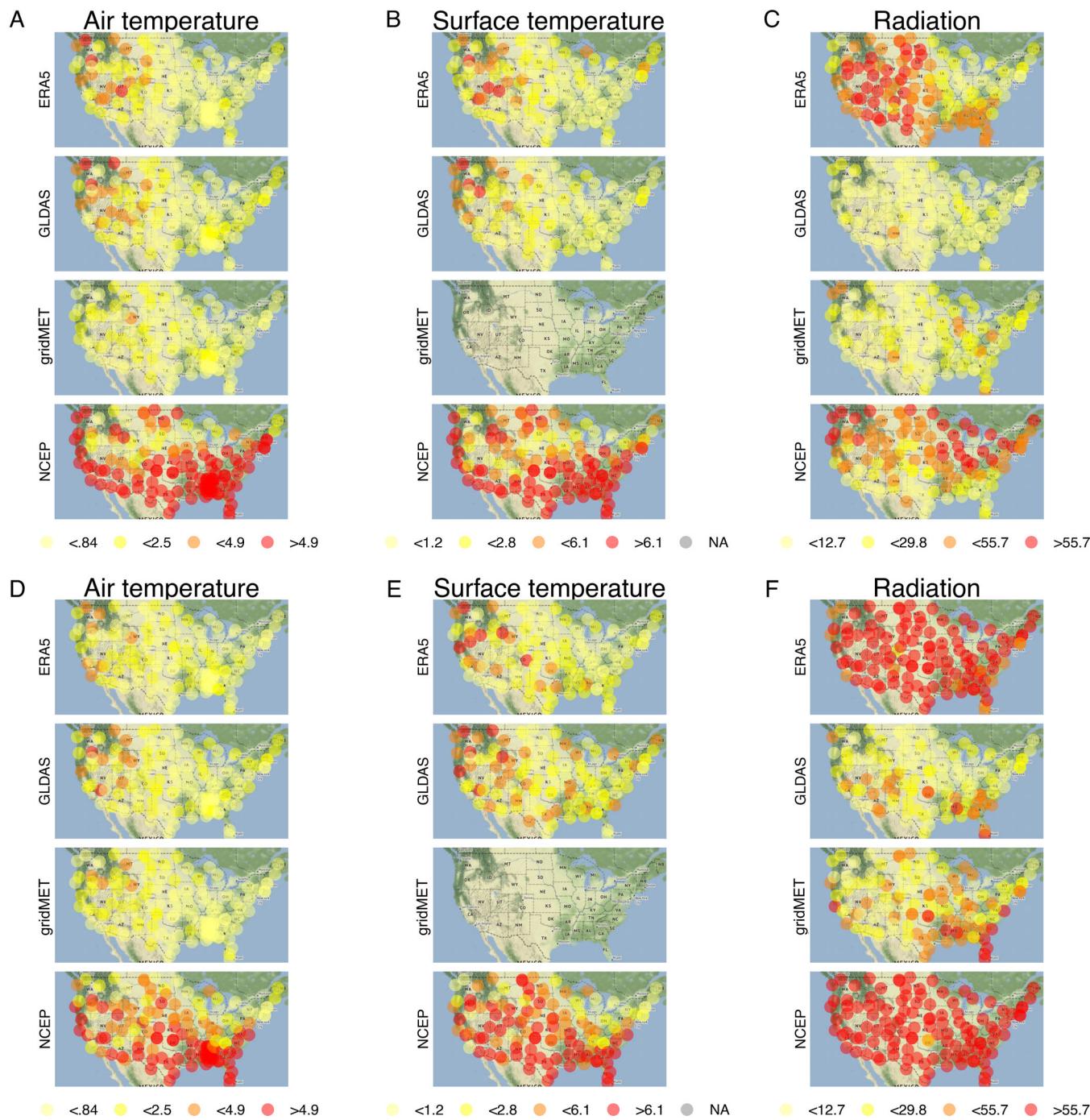
**FIGURE 2** Environmental forcing datasets differ in their relationship to US Climate Reference Network (USCRN) weather station data across environmental metrics (rows), locations (symbols), and months (fill). We compare the data across time periods using Pearson's correlation coefficients (x-axis), root mean squared error (y-axis), and bias (symbol size). GLDAS, Global Land Data Assimilation System; NCEP, National Centers for Environmental Prediction.

somewhat in winter. GLDAS air temperature estimates corresponded well to observations in Colorado but not in Oregon. gridMET was the strongest performer for daily average air temperature, but the high performance was likely due to the omission of diurnal variation. NCEP often exhibited weaker performance than the other datasets for air temperature. Correspondence with weather station data for surface temperature was more variable but still reliable for ERA-5 and GLDAS. ERA-5 performed better in summer than winter, while GLDAS performed better in Colorado than in Oregon. gridMET lacks surface temperature data altogether. NCEP exhibited moderate performance with errors for Oregon in July. ERA-5 exhibited weaker performance than some other datasets for this variable. GLDAS and gridMET tended to be among the top-performing datasets for radiation data, followed closely by ERA-5 and then NCEP.

We next quantified differences across all continental US weather stations in the USCRN network to examine spatial patterns, which differ among data products and environmental variables (Figure 3, see online visualization for Alaska and Hawaii stations). ERA-5 exhibited high agreement overall but greater bias for western stations and for solar radiation. GLDAS exhibited high agreement with a higher bias in the northwest for surface and air temperatures and a higher bias in the southeast for summer solar radiation. gridMET showed high agreement with a greater bias in the west for air temperature and a greater bias in the southeast for summer solar radiation. NCEP, exhibiting the lowest alignment, showed a higher bias in the south for air and surface temperatures, a higher bias in the north for winter solar radiation, and an overall high bias in summer solar radiation.

Body temperatures predicted for a *Sceloporus* lizard based on the environmental forcing data were substantially above environmental temperatures during the day due to heating by radiation (Figure 4; see Appendix S1: Figure S2 for a two-week subset, environmental forcing data in Figure 1; see Appendix S1: Figures S3 and S4 for microclimate model output and microclimate datasets used to parameterize the model). We assumed the lizard was unable to seek shade to highlight divergence from air temperature, but this assumption resulted in stressfully high body temperatures. Activity hours may increase and hours above critical temperature decrease by moving into shaded environments. Body temperatures predicted for a lizard at reference height (1–2 m) were substantially lower (Figure 4, left column) than those predicted in the habitats near the ground (1 cm) that small animals often occupy.

The output of environmental forcing data processed using microclimate models can be substantially higher, particularly for the micro\_era5 and micro\_ncep algorithms

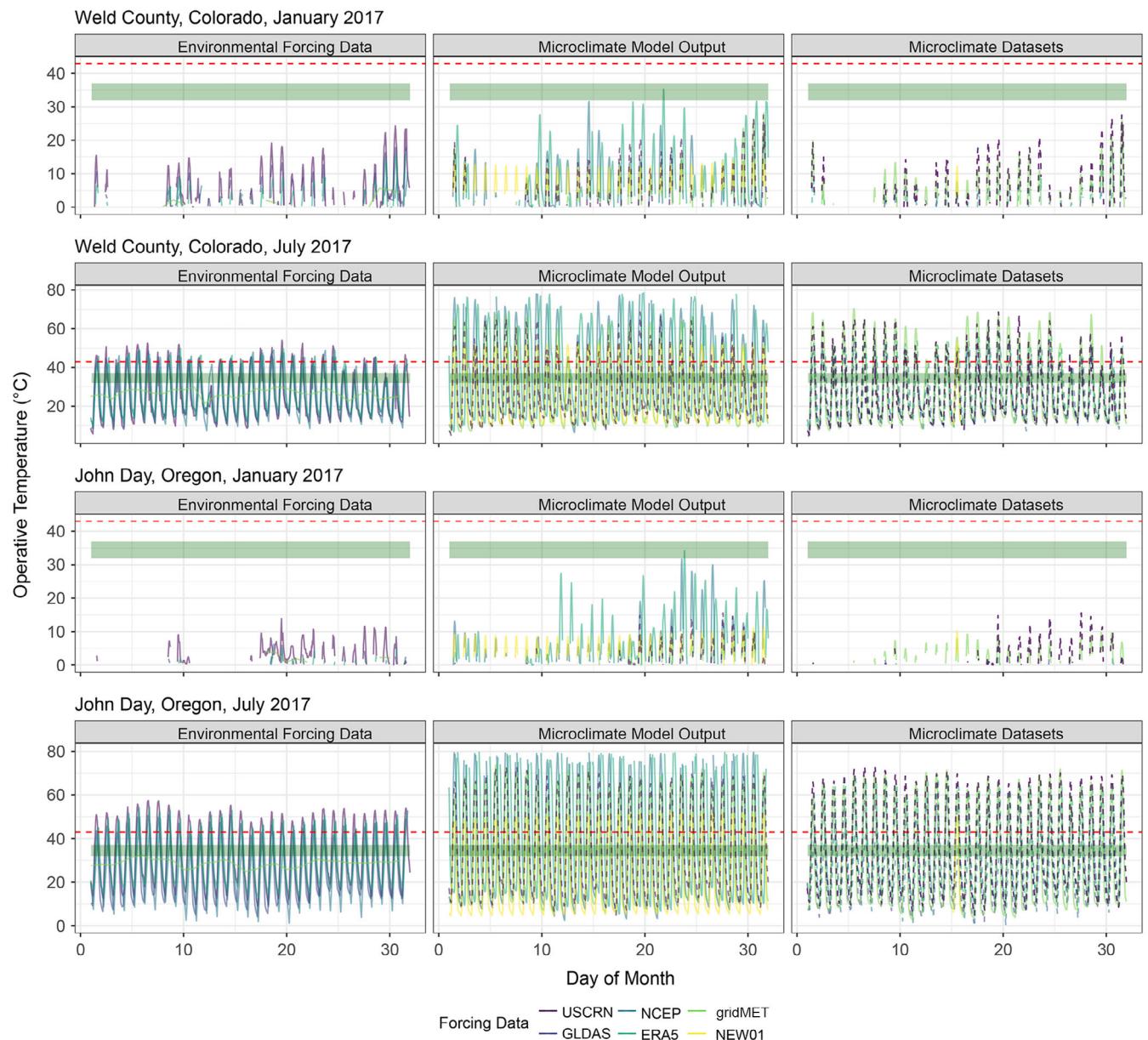


**FIGURE 3** Spatial patterns of agreement (darker colors: more bias) with US Climate Reference Network (USCRN) weather stations differ between environmental forcing data sets (rows), environmental variables (columns), and seasons (A-C: January, D-F: July). Each point indicates the absolute bias between a USCRN station and the respective dataset. The blank map for gridMET indicates the variable is missing from a dataset. GLDAS, Global Land Data Assimilation System; NCEP, National Centers for Environmental Prediction.

and particularly in winter (Figure 4, middle column), than precomputed microclimate datasets or environmental forcing data scaled to 1 cm (Figure 4, right column). The microclimate model output can also exceed body temperatures predicted based on observational data scaled to animal height (1 cm). Operative temperature estimates produced using output from the *micro\_global* algorithm

(using NEW01) tended to be low due to omitting daily variation. Estimates produced using the *micro\_usa* algorithm (using gridMET) aligned well with operative temperature estimates based on observations.

The precomputed microclimate datasets and environmental forcing data scaled to 1 cm all generally performed well in predicting operative temperatures (Figure 4, right



**FIGURE 4** Lizard body temperatures predicted using an energy budget model (operative temperatures) differ depending on the air and surface temperature and solar radiation data used to parameterize the model. Colors indicate the environmental forcing dataset. The columns depict parameterization with environmental forcing data at reference height (left); the output from microclimate models parameterized with the forcing data (middle); and pre-computed microclimate datasets (solid lines) and forcing data scaled to organismal height (1 cm, dashed lines; right). Output can be compared to US Climate Reference Network (USCRN) weather station observations at reference (solid) or organismal (dashed) height. The depicted body temperature range for activity (green) and upper critical thermal limit (dashed red line) indicate that lizards will frequently overheat in summer if they are exposed to full sun. GLDAS, Global Land Data Assimilation System; NCEP, National Centers for Environmental Prediction.

column). Operative temperature estimates associated with ERA-5 and GLDAS scaled to 1 cm closely followed estimates based on weather temperature data during the summer. The microclimUS data product predicted the highest summer operative temperatures in Colorado. Overall, the alignment of operative temperature estimates between those parameterized with USCRN observations and those parameterized with environmental data products

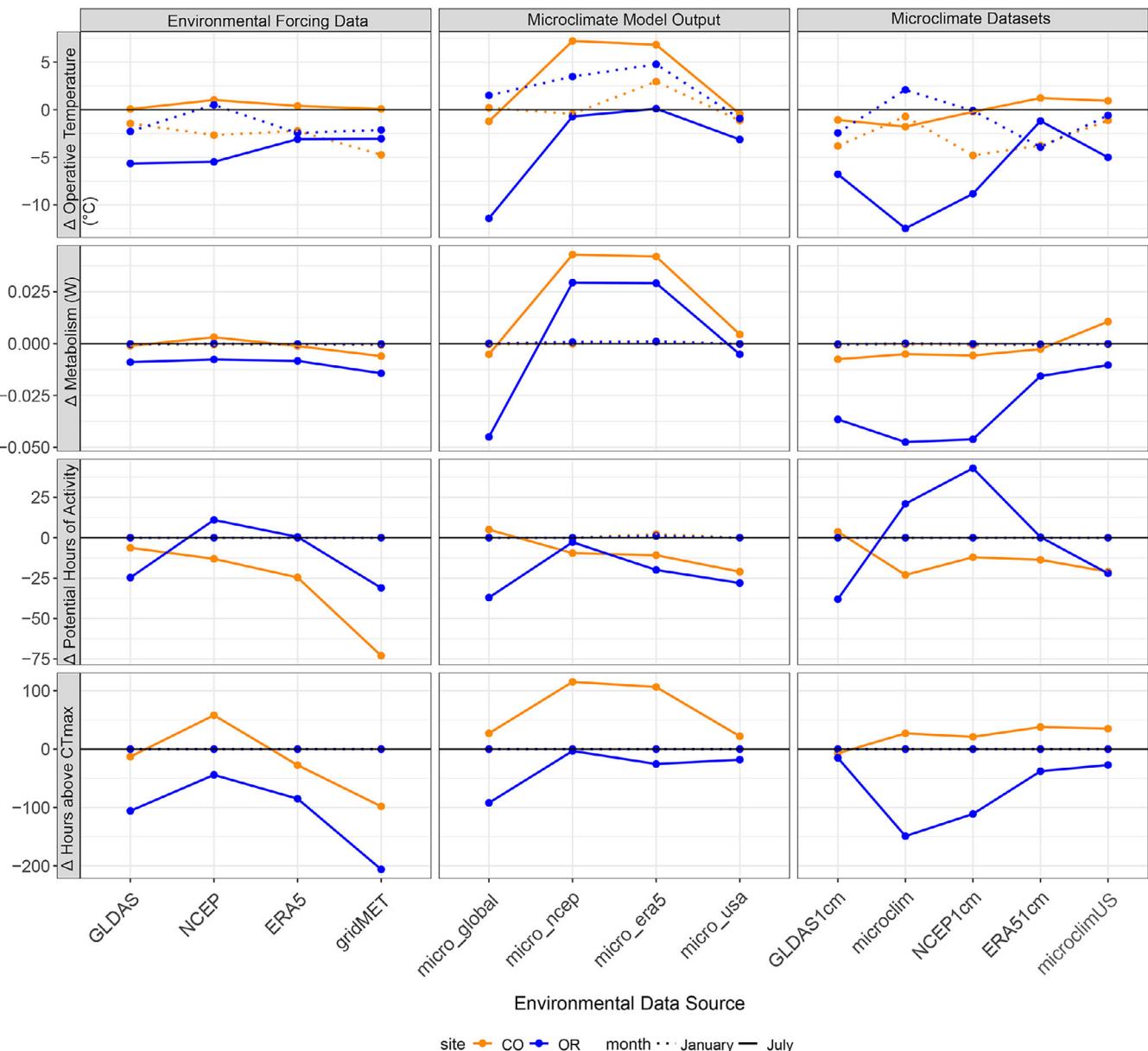
was often better than the alignment of input environmental variables (Figures 1 vs. 4). However, operative temperatures based on observations did often exceed those based on environmental data products, particularly in winter and at reference height.

Divergent time series for predicted body temperatures (operative temperatures) have consequences for biological estimates, which differ substantially between

locations and seasons (Figure 5). Differences in biological metrics from observations were often more similar for operative temperatures estimated using environmental forcing data at reference height than for microclimate output (Figure 5, left column vs. right columns). However, by omitting diurnal temperature variation, gridMET underpredicted hours of activity and warm temperatures exceeding thermal limits. ERA-5 scaled to

animal height performed consistently in terms of biological metrics. GLDAS performed somewhat less consistently, with a tendency to predict cold. The microclimUS dataset also performed consistently well.

Our analysis highlights the importance of scaling environmental data to reference height and considering operative rather than air temperatures in biological applications. We illustrate the differences using USCRN weather station



**FIGURE 5** Aggregating the operative temperature estimates depicted in Figure 4 into ecological metrics reveals the consequences of environmental dataset selection. All metrics are differences (deltas) from values for the US Climate Reference Network (USCRN) weather stations (at reference height in the first column, and subsequently scaled to 1 cm). From top to bottom, we depict average operative temperatures (in degrees Celsius), average basal metabolism (in watts), hours of potential activity (operative temperatures between 32 and 37°C, green band in Figure 4), and hours exceeding upper thermal tolerance (43°C). Lines are depicted connecting datasets to aid comparisons. The nearer to the x-axis, the closer the data are to the USCRN data. CTmax, critical thermal maximum; GLDAS, Global Land Data Assimilation System; NCEP, National Centers for Environmental Prediction.

observations (Appendix S1: Figure S5). Air and operative temperatures were generally considerably warmer at low, organismal heights than at reference heights. Air temperature at reference height varied from an average of 4.3°C colder in Oregon in July to 2.5°C warmer in Oregon in January compared to air temperature at animal height. Air temperature at reference height varied from an average of 0.5°C colder in Oregon in January to 8.4°C colder in Oregon in July compared to operative temperatures at reference height. Operative temperatures at reference height were on average 0.8°C warmer in Oregon in January and 3.4°C colder in Oregon in July compared to operative temperatures at animal height.

## DISCUSSION

The increasing availability of data sources for high temporal and spatial resolution environmental data enhances our capacity to predict biological responses at temporal and spatial scales relevant to organisms' interactions with their environments (Bramer et al., 2018; Lembrechts et al., 2019). We are optimistic that the increasing availability of environmental variables beyond air temperature, as well as tools for microclimate and biophysical modeling, will propel research to move beyond considering temporally averaged air temperatures far above the height of organisms (Briscoe et al., 2023). Compilations of environmental sensor data (Lembrechts et al., 2020) along with efforts to use the sensor data to estimate offsets between air temperature and soil (Lembrechts et al., 2022) or forest sub-canopy temperatures (Haesen et al., 2021) are also increasing capacity to account for the microclimates organisms experience.

Our analyses of operative temperature emphasize how body temperatures can differ substantially from air temperatures at reference height (Figure 4). Thus, accurately describing how organisms experience their environment and the implications for thermal or water stress, activity times, and energy budgets is crucial to projecting the biodiversity and ecosystem consequences of changes in climates and their variability (Briscoe et al., 2023). Many discussions of microclimate focus on spatial resolution, but studies such as ours are increasingly highlighting the importance of temporal microclimate variability (Kearney et al., 2012; Nadeau et al., 2017).

Selecting a microclimate dataset requires evaluating how organism-environment interactions influence performance and fitness outcomes (Dillon et al., 2016). For example, does the animal select habitats spatially or temporally in a manner that buffers them from exposure to thermal variability (Huey et al., 2012; Woods et al., 2015), lessening the importance of high-resolution data? There

is no one best dataset for all microclimate applications. A microclimate dataset must be chosen based on how particular applications prioritize factors such as temporal resolution, spatial resolution, and available variables while acknowledging the corresponding data tradeoffs (Bramer et al., 2018). Time periods and spatial requirements will further constrain data selection.

The correspondence of data products to weather station observations varies by season, variable, and location. However, ERA-5 is a top performer and a welcome addition to available microclimate datasets given its high spatial and temporal resolution for numerous environmental variables globally. GLDAS is another excellent global resource that provides earlier historical data as well as some additional variables. These datasets can be easily readied for use in biophysical models by using vertical temperature profiles to scale them to animal height.

Operative temperatures estimated using the output of microclimate models exhibited mixed performance when compared to USCRN observations. However, some discrepancies arise due to differences in how environmental variables are measured and modeled. USCRN surface temperatures are measured using an infrared thermometer pointed toward the surface. So, the USCRN observations can correspond to snow or vegetation temperatures, whereas the microclimate algorithms predict temperatures at the ground surface. Microclimate algorithms offer flexibility in terms of input environmental datasets and their output, including data at numerous heights and shade levels, which are designed for microclimate applications. However, they can be computationally intensive. Pre-computed microclimate datasets offer ease of use, but they entail tradeoffs such as lack of temporal resolution (*microclim*) or coarse spatial resolution (*microclimUS*). Pre-computed microclimate datasets also offer limited choices of substrate types, shade levels, and heights. Microclimate algorithms also have a greater capacity to account for slopes and other aspects of topography (Sears et al., 2019). We are optimistic that emerging data storage and access tools will make microclimate data more available and easier to use (see Appendix S4).

We hope our review, R Shiny application, and user guides prove useful for selecting environmental datasets. Accessing data for numerous environmental variables at high spatial and temporal resolution can be daunting, but our user guides should aid the process. Given that data selection can influence biological outcomes, repeating analyses with different data sources can ensure the robustness of analyses. Such repetition is common for future climate projections, but seldom implemented for past data. Applications of microclimate and biophysical models benefit from analyses of sensitivity to parameter values, particularly for uncertain biological parameters (Briscoe et al., 2019).

Our analysis builds on other demonstrations that the inclusion and choice of microclimate data can have dramatic implications for derived biological estimates (Bütkofer et al., 2020). Repetition of biological analysis with two data sources can yield differences of 10°C average operative temperature, 0.05 W average metabolic rate, 60 activity hours, and 150 hours above critical thermal maximum (Figure 5). Temporal variability can be at least as important as accounting for spatial variability (Denny, 2017; Kearney et al., 2012; Woods et al., 2015), as exemplified by gridMET with a daily resolution (Figure 5). These biological implications of microclimate data choice can propagate into dramatically different conclusions for performance, fitness, and persistence of populations and species (Briscoe et al., 2019).

Robust biological analyses require moving beyond temporally averaged air temperatures at reference height to consider how organisms experience climate variability and change (Dillon et al., 2016; Helmuth et al., 2010). Indeed, the heat budget of organisms is influenced by environmental conditions such as solar radiation, surface temperature, and vapor pressure deficit in addition to air temperature (Briscoe et al., 2023). Vertical profiles cause environmental conditions at organismal height to vary from conditions at reference height, and body temperatures can depart dramatically from air temperatures (Kearney et al., 2021). Choosing the most appropriate microclimate data sources and ensuring robustness through repeated analyses with different data sources will assist in understanding and anticipating organismal responses to climate variability and change.

## AUTHOR CONTRIBUTIONS

Abigail V. Meyer, Lauren B. Buckley, and Michael R. Kearney conceived and designed the research. Abigail V. Meyer and Yutaro Sakairi led the tool building and analyses. Abigail V. Meyer and Lauren B. Buckley led manuscript writing and figure creation. All authors contributed to refining the tools and analyses and editing the manuscript.

## ACKNOWLEDGMENTS

We thank R. Huey, C. Johnson, and J. Smith for their assistance and input. The research was supported by the National Science Foundation (DBI-1349865).

## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

All code for accessing and analyzing data (Sakairi et al., 2023) are available from Zenodo: <https://doi.org/10.5281/zenodo.7690026>. Environmental data sources (Table 1) are linked at [https://map.trenchproject.com/RShiny\\_Microclim/](https://map.trenchproject.com/RShiny_Microclim/).

Additional details for accessing environmental data are available in our users' guide: [https://bookdown.org/huckley/microclimate\\_users\\_guide/](https://bookdown.org/huckley/microclimate_users_guide/).

## ORCID

Michael R. Kearney  <https://orcid.org/0000-0002-3349-8744>

Lauren B. Buckley  <https://orcid.org/0000-0003-1315-3818>

## REFERENCES

- Abatzoglou, J. T. 2013. "Development of Gridded Surface Meteorological Data for Ecological Applications and Modelling." *International Journal of Climatology* 33: 121–31.
- Adolph, S. C., and W. P. Porter. 1993. "Temperature, Activity, and Lizard Life-Histories." *American Naturalist* 142: 273–95.
- Araújo, M. B., R. P. Anderson, A. M. Barbosa, C. M. Beale, C. F. Dormann, R. Early, R. A. Garcia, et al. 2019. "Standards for Distribution Models in Biodiversity Assessments." *Science Advances* 5: eaat4858. <https://doi.org/10.1126/sciadv.aat4858>.
- Bakken, G. S. 1992. "Measurement and Application of Operative and Standard Operative Temperatures in Ecology." *Integrative and Comparative Biology* 32: 194–216.
- Bramer, I., B. J. Anderson, J. Bennie, A. J. Bladon, P. De Frenne, D. Hemming, R. A. Hill, M. R. Kearney, C. Körner, and A. H. Korstjens. 2018. "Advances in Monitoring and Modelling Climate at Ecologically Relevant Scales." *Advances in Ecological Research* 58: 101–61.
- Briscoe, N. J., J. Elith, R. Salguero-Gómez, J. J. Lahoz-Monfort, J. S. Camac, K. M. Giljohann, M. H. Holden, B. A. Hradsky, M. R. Kearney, and S. M. McMahon. 2019. "Forecasting Species Range Dynamics with Process-Explicit Models: Matching Methods to Applications." *Ecology Letters* 22: 1940–56.
- Briscoe, N. J., H. McGregor, D. Roshier, A. Carter, B. A. Wintle, and M. R. Kearney. 2022. "Too Hot to Hunt: Mechanistic Predictions of Thermal Refuge from Cat Predation Risk." *Conservation Letters* 15: e12906.
- Briscoe, N. J., S. D. Morris, P. D. Mathewson, L. B. Buckley, M. Jusup, O. Levy, I. M. D. Maclean, et al. 2023. "Mechanistic Forecasts of Species Responses to Climate Change: The Promise of Biophysical Ecology." *Global Change Biology* 29: 1451–70.
- Buckley, L. B. 2008. "Linking Traits to Energetics and Population Dynamics to Predict Lizard Ranges in Changing Environments." *American Naturalist* 171: E1–E19.
- Buckley, L. B., A. F. Cannistra, and A. John. 2018. "Leveraging Organismal Biology to Forecast the Effects of Climate Change." *Integrative and Comparative Biology* 58: 38–51.
- Buckley, L. B., and R. B. Huey. 2016. "Temperature Extremes: Geographic Patterns, Recent Changes, and Implications for Organismal Vulnerabilities." *Global Change Biology* 22: 3829–42.
- Buckley, L. B., and J. G. Kingsolver. 2019. "Environmental Variability Shapes Evolution, Plasticity and Biogeographic Responses to Climate Change." *Global Ecology and Biogeography* 28: 1456–68.
- Bütkofer, L., K. Anderson, D. P. Bebb, J. J. Bennie, R. I. Early, and I. M. Maclean. 2020. "The Problem of Scale in Predicting Biological Responses to Climate." *Global Change Biology* 26: 6657–66.
- Campbell, G., and J. Norman. 2000. *An Introduction to Environmental Biophysics*. New York: Springer.

- Cobos, M. E., A. T. Peterson, L. Osorio-Olvera, and D. Jiménez-García. 2019. "An Exhaustive Analysis of Heuristic Methods for Variable Selection in Ecological Niche Modeling and Species Distribution Modeling." *Ecological Informatics* 53: 100983.
- Daly, C. 2006. "Guidelines for Assessing the Suitability of Spatial Climate Data Sets." *International Journal of Climatology: A Journal of the Royal Meteorological Society* 26: 707–21.
- De Frenne, P., F. Rodríguez-Sánchez, D. A. Coomes, L. Baeten, G. Verstraeten, M. Vellend, M. Bernhardt-Römermann, C. D. Brown, J. Brunet, and J. Cornelis. 2013. "Microclimate Moderates Plant Responses to Macroclimate Warming." *Proceedings of the National Academy of Sciences of the United States of America* 110: 18561–5.
- Denny, M. 2017. "The Fallacy of the Average: On the Ubiquity, Utility and Continuing Novelty of Jensen's Inequality." *Journal of Experimental Biology* 220: 139–46.
- Dillon, M. E., H. A. Woods, G. Wang, S. B. Fey, D. A. Vasseur, R. S. Telemeco, K. Marshall, and S. Pincebourde. 2016. "Life in the Frequency Domain: The Biological Impacts of Changes in Climate Variability at Multiple Time Scales." *Integrative and Comparative Biology* 56: 14–30.
- Duursma, R. A. 2015. "Plantecophys—An R Package for Analysing and Modelling Leaf Gas Exchange Data." *PLoS One* 10: e0143346.
- Elith, J., M. Kearney, and S. Phillips. 2010. "The Art of Modelling Range Shifting Species." *Methods in Ecology and Evolution* 1: 330–42.
- Fick, S. E., and R. J. Hijmans. 2017. "WorldClim 2: New 1-km Spatial Resolution Climate Surfaces for Global Land Areas." *International Journal of Climatology* 37: 4302–15.
- Gates, D. M. 1980. *Biophysical Ecology*. New York: Springer-Verlag.
- Gleixner, S., T. Demissie, and G. T. Diro. 2020. "Did ERA5 Improve Temperature and Precipitation Reanalysis over East Africa?" *Atmosphere* 11: 996.
- Haesen, S., J. J. Lembrechts, P. De Frenne, J. Lenoir, J. Aalto, M. B. Ashcroft, M. Kopecký, et al. 2021. "ForestTemp—Sub-Canopy Microclimate Temperatures of European Forests." *Global Change Biology* 27: 6307–19.
- Helmhuth, B., B. R. Broitman, L. Yamane, S. E. Gilman, K. Mach, K. A. S. Mislan, and M. W. Denny. 2010. "Organismal Climatology: Analyzing Environmental Variability at Scales Relevant to Physiological Stress." *Journal of Experimental Biology* 213: 995–1003.
- Huey, R. B., M. R. Kearney, A. Krockenberger, J. A. M. Holtum, M. Jess, S. E. Williams, R. B. Huey, M. R. Kearney, A. Krockenberger, and J. A. M. Holtum. 2012. "Predicting Organismal Vulnerability to Climate Warming: Roles of Behaviour, Physiology and Adaptation." *Philosophical Transactions of the Royal Society B: Biological Sciences* 367: 1665–79.
- Kearney, M. R. 2019a. "Microclim US: Hourly Estimates of Historical Microclimates for The United States of America with Example Applications." *Ecology* 100: e02829.
- Kearney, M. R. 2019b. "MicroclimOz—A Microclimate Data Set for Australia, with Example Applications." *Austral Ecology* 44: 534–44.
- Kearney, M. R., A. P. Isaac, and W. P. Porter. 2014. "Microclim: Global Estimates of Hourly Microclimate Based on Long-Term Monthly Climate Averages." *Scientific Data* 1: 140006.
- Kearney, M. R., and J. L. Maino. 2018. "Can Next-Generation Soil Data Products Improve Soil Moisture Modelling at the Continental Scale? An Assessment Using a New Microclimate Package for the R Programming Environment." *Journal of Hydrology* 561: 662–73.
- Kearney, M. R., A. Matzelle, and B. Helmuth. 2012. "Biomechanics Meets the Ecological Niche: The Importance of Temporal Data Resolution." *The Journal of Experimental Biology* 215: 922–33.
- Kearney, M., and W. Porter. 2009. "Mechanistic Niche Modelling: Combining Physiological and Spatial Data to Predict species' Ranges." *Ecology Letters* 12: 334–50.
- Kearney, M. R., and W. P. Porter. 2017. "NicheMapR—An R Package for Biophysical Modelling: The Microclimate Model." *Ecography* 40: 664–74.
- Kearney, M. R., and W. P. Porter. 2020. "NicheMapR—An R Package for Biophysical Modelling: The Ectotherm and Dynamic Energy Budget Models." *Ecography* 43: 85–96.
- Kearney, M. R., W. P. Porter, and R. B. Huey. 2021. "Modelling the Joint Effects of Body Size and Microclimate on Heat Budgets and Foraging Opportunities of Ectotherms." *Methods in Ecology and Evolution* 12: 458–67.
- Kearney, M., S. J. Simpson, D. Raubenheimer, and B. Helmuth. 2010. "Modelling the Ecological Niche from Functional Traits." *Philosophical Transactions of the Royal Society B: Biological Sciences* 365: 3469–83.
- Klinges, D. H., J. P. Duffy, M. R. Kearney, and I. M. D. Maclean. 2022. "mcera5: Driving Microclimate Models with ERA5 Global Gridded Climate Data." *Methods in Ecology and Evolution* 13: 1402–11.
- Lembrechts, J. J., J. Aalto, M. B. Ashcroft, P. De Frenne, M. Kopecký, J. Lenoir, M. Luoto, I. M. Maclean, O. Roupsard, and E. Fuentes-Lillo. 2020. "SoilTemp: A Global Database of Near-Surface Temperature." *Global Change Biology* 26: 6616–29.
- Lembrechts, J. J., I. Nijs, and J. Lenoir. 2019. "Incorporating Microclimate into Species Distribution Models." *Ecography* 42: 1267–79.
- Lembrechts, J. J., J. van den Hoogen, J. Aalto, M. B. Ashcroft, P. De Frenne, J. Kemppinen, M. Kopecký, et al. 2022. "Global Maps of Soil Temperature." *Global Change Biology* 28: 3110–44.
- Levy, O., J. D. Borchert, T. W. Rusch, L. B. Buckley, and M. J. Angilletta. 2017. "Diminishing Returns Limit Energetic Costs of Climate Change." *Ecology* 98: 1217–28.
- Levy, O., L. B. Buckley, T. H. Keitt, and M. J. Angilletta. 2016. "A Dynamically Downscaled Projection of Past and Future Microclimates." *Ecology* 97: 1888–8.
- Maclean, I. M., and D. H. Klinges. 2021. "Microclim: A Mechanistic Model of Above, Below and Within-Canopy Microclimate." *Ecological Modelling* 451: 109567.
- Maclean, I. M. D., J. R. Mosedale, and J. J. Bennie. 2019. "Microclima: An r Package for Modelling Meso- and Microclimate." *Methods in Ecology and Evolution* 10: 280–90.
- Malishev, M., C. M. Bull, and M. R. Kearney. 2018. "An Individual-Based Model of Ectotherm Movement Integrating Metabolic and Microclimatic Constraints." *Methods in Ecology and Evolution* 9: 472–89.
- Muir, C. D. 2019. "tealeaves: An R Package for Modelling Leaf Temperature Using Energy Budgets." *AoB Plants* 11: plz054.
- Nadeau, C. P., M. C. Urban, and J. R. Bridle. 2017. "Coarse Climate Change Projections for Species Living in a Fine-Scaled World." *Global Change Biology* 23: 12–24.

- New, M., D. Lister, M. Hulme, and I. Makin. 2002. "A High-Resolution Data Set of Surface Climate over Global Land Areas." *Climate Research* 21: 1–25.
- Potter, K. A., H. A. Woods, and S. Pincebourde. 2013. "Microclimatic Challenges in Global Change Biology." *Global Change Biology* 19: 2932–9.
- Sakairi, Y., A. Meyer, and L. Buckley. 2023. "trenchproject/RShiny\_Microclim: Ecosphere Manuscript Version (v1.0.0)." Zenodo. <https://doi.org/10.5281/zenodo.7690026>.
- Scherrer, D., and C. Koerner. 2010. "Infra-Red Thermometry of Alpine Landscapes Challenges Climatic Warming Projections." *Global Change Biology* 16: 2602–13.
- Sears, M. W., M. J. Angilletta, M. S. Schuler, J. Borchert, K. F. Dilliplane, M. Stegman, T. W. Rusch, and W. A. Mitchell. 2016. "Configuration of the Thermal Landscape Determines Thermoregulatory Performance of Ectotherms." *Proceedings of the National Academy of Sciences of the United States of America* 113: 10595–600.
- Sears, M. W., E. Raskin, and M. A. Angilletta. 2011. "The World Is Not Flat: Defining Relevant Thermal Landscapes in the Context of Climate Change." *Integrative and Comparative Biology* 51: 666–75.
- Sears, M. W., E. A. Riddell, T. W. Rusch, and M. J. Angilletta, Jr. 2019. "The World Still Is Not Flat: Lessons Learned from Organismal Interactions with Environmental Heterogeneity in Terrestrial Environments." *Integrative and Comparative Biology* 59: 1049–58.
- Suggitt, A. J., R. J. Wilson, N. J. B. Isaac, C. M. Beale, A. G. Auffret, T. August, J. J. Bennie, et al. 2018. "Extinction Risk from Climate Change Is Reduced by Microclimatic Buffering." *Nature Climate Change* 8: 713–7.
- Sunday, J. M., A. E. Bates, M. R. Kearney, R. K. Colwell, N. K. Dulvy, J. T. Longino, and R. B. Huey. 2014. "Thermal-Safety Margins and the Necessity of Thermoregulatory Behavior across Latitude and Elevation." *Proceedings of the National Academy of Sciences of the United States of America* 111: 5610–5.
- Tattersall, G. J. 2017. "Thermimage: Thermal Image Analysis." <https://CRAN.R-project.org/package=Thermimage>.
- Wang, G., and M. E. Dillon. 2014. "Recent Geographic Convergence in Diurnal and Annual Temperature Cycling Flattens Global Thermal Profiles." *Nature Climate Change* 4: 988–92.
- Warren, D. L., and S. N. Seifert. 2011. "Ecological Niche Modeling in Maxent: The Importance of Model Complexity and the Performance of Model Selection Criteria." *Ecological Applications* 21: 335–42.
- Woods, H. A., M. E. Dillon, and S. Pincebourde. 2015. "The Roles of Microclimatic Diversity and of Behavior in Mediating the Responses of Ectotherms to Climate Change." *Journal of Thermal Biology* 54: 86–97.

## SUPPORTING INFORMATION

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

**How to cite this article:** Meyer, Abigail V., Yutaro Sakairi, Michael R. Kearney, and Lauren B. Buckley. 2023. "A Guide and Tools for Selecting and Accessing Microclimate Data for Mechanistic Niche Modeling." *Ecosphere* 14(4): e4506. <https://doi.org/10.1002/ecs2.4506>