Received: 14 May 2019 | Accepted: 16 October 2019

DOI: 10.1111/2041-210X.13330

APPLICATION

Methods in Ecology and Evolution | BRITISH ECOLOGICAL SOCIETY

A method for computing hourly, historical, terrain-corrected microclimate anywhere on earth

Michael R. Kearney[1] | **Phillipa K. Gillingham**[2] | **Isobel Bramer**[2] | **James P. Duffy**[3] | **Ilya M.D. Maclean**[3]

[1]School of BioSciences, The University of Melbourne, Parkville, Vic., Australia

[2]Faculty of Science and Technology, Bournemouth University, Poole, UK

[3]Environment and Sustainability Institute, University of Exeter Penryn Campus, Penryn, UK

Correspondence
Michael R. Kearney
Email: m.kearney@unimelb.edu.au

Ilya M. D. Maclean
Email: i.m.d.maclean@exeter.ac.uk

Funding information
Leverhulme Trust

Handling Editor: Sarah Goslee

Abstract

1. Microclimates are the thermal and hydric environments organisms actually experience, and estimates of them are increasingly needed in environmental research. The availability of global weather and terrain datasets, together with increasingly sophisticated microclimate modelling tools, makes the prospect of a global, web-based microclimate estimation procedure feasible.
2. We have developed such an approach for the R programming environment which integrates existing R packages for obtaining terrain and sub-daily atmospheric forcing data (ELEVATR and RNCEP), and two complementary microclimate modelling packages (NicheMapR and MICROCLIMA). The procedure can be used to generate NicheMapR's hourly time-series outputs of above- and below-ground conditions, including convective and radiative environments, soil temperature, soil moisture and snow cover, for a single point, using MICROCLIMA to account for local topographic and vegetation effects. Alternatively, it can use MICROCLIMA to produce high-resolution grids of near-surface temperatures, using NicheMapR to derive calibration coefficients normally obtained from experimental data.
3. We validate this integrated approach against a series of microclimate observations used previously in the tests of the respective models and show equivalent performance.
4. It is thus now feasible to produce realistic estimates of microclimate at fine (<30 m) spatial and temporal scales anywhere on earth, from 1957 to present.

KEYWORDS

biophysical ecology, GIS, microclimate, modelling, soil moisture, soil temperature, topograhy

1 | INTRODUCTION

The quantity and quality of gridded environmental datasets has been growing rapidly since the early 1980s (Hutchinson & Bischof, 1983), and they are now available across the globe for terrestrial (e.g. Fick & Hijmans, 2017) and marine (Assis et al., 2018) environments. However, the environments experienced by organisms, that is microclimates (Kearney, 2018a), are at a vastly smaller spatial and temporal scale than the environmental layers typically used in species distribution modelling (Potter, Woods, & Pincebourde, 2013). For many applications, it is preferable (Bennie, Wilson, Maclean, & Suggitt, 2014) or even necessary (Kearney & Porter, 2009) to model species' responses to microclimatic variation at hourly temporal scales and centimetre (e.g. soil depth) spatial scales. For these reasons, there has been a concerted effort to develop efficient and accurate approaches to measuring and modelling microclimates, especially in the fields of agriculture and ecology (Bramer et al., 2018).

One of the early microclimate models used in ecology (Porter, Mitchell, Beckman, & DeWitt, 1973) has now been generalized and incorporated into the R package NicheMapR for mechanistic niche modelling (Kearney & Porter, 2017). The NicheMapR system has been tested across a broad range of environments in the context of relatively simple terrain (Kearney, Isaac, & Porter, 2014; Kearney & Maino, 2018). However, it requires pre-adjustments of forcing data for important "mesoclimate" effects such as elevation-associated lapse rates, wind sheltering, coastal influences and cold air drainage. It also requires estimates of terrain variables such as slope, aspect and hill shade. Maclean, Suggitt, Wilson, Duffy, and Bennie (2017) developed a series of functions for such mesoclimate and terrain adjustments to extend the model of Bennie, Huntley, Wiltshire, Hill, and Baxter (2008), released as an R package microclima (Maclean, Mosedale, & Bennie, 2019), which includes additional functionality to account for canopy shading effects. The NicheMapR and microclima models are therefore complementary in their approaches.

In parallel to these developments, the required atmospheric forcing data and soil and terrain variables required to run the models have become readily available at a global scale. For example, the National Centers for Environmental Prediction (NCEP) reanalysis dataset of 6-hourly meteorological variables covers a period from 1957 to present on a ~2° grid, and an R package RNCEP has been developed to facilitate web-based queries of the data (Kemp, Emiel van Loon, Shamoun-Baranes, & Bouten, 2012). Crucially, digital terrain models are now available online at 30-m spatial resolution or finer for most of the planet and the R package elevatr (Hollister & Shah, 2018) provides a way to query them.

These developments set the stage for an integrated approach to microclimate modelling for the rapid generation of microclimate estimates at any time and place on earth in recent history. Here, we develop such an integration of these models and data and compare the results with those based on more location-specific datasets.

2 | INTEGRATION OF NicheMapR AND microclima

The microclima package includes functions for computing terrain-specific variables at meso- and micro-scales that drive microclimatic variation, as described in detail in Maclean et al. (2019). To convert these calculations into anomalies from reference temperature, however, the model must be calibrated with local observations of temperature at the height of interest. Moreover, the package does not directly incorporate the buffering influence of the underlying substrate due to the heat storage capacity of the soil, which is affected by soil thermal properties and moisture content.

In comparison, the NicheMapR microclimate model computes the full heat and water balance of the soil given depth-specific soil thermal and hydric properties (Kearney & Maino, 2018; Kearney & Porter, 2017). However, the treatment of direct and diffuse radiation, and of the effects of shade, is not as sophisticated as in microclima. We have therefore developed pipelines to allow these two models to provide each other with complementary information (Figure 1). Specifically, we have modified the microclima algorithms to provide time series of hourly forcing data that have been adjusted for the effects of terrain, vegetation and mesoclimatic influences. We have

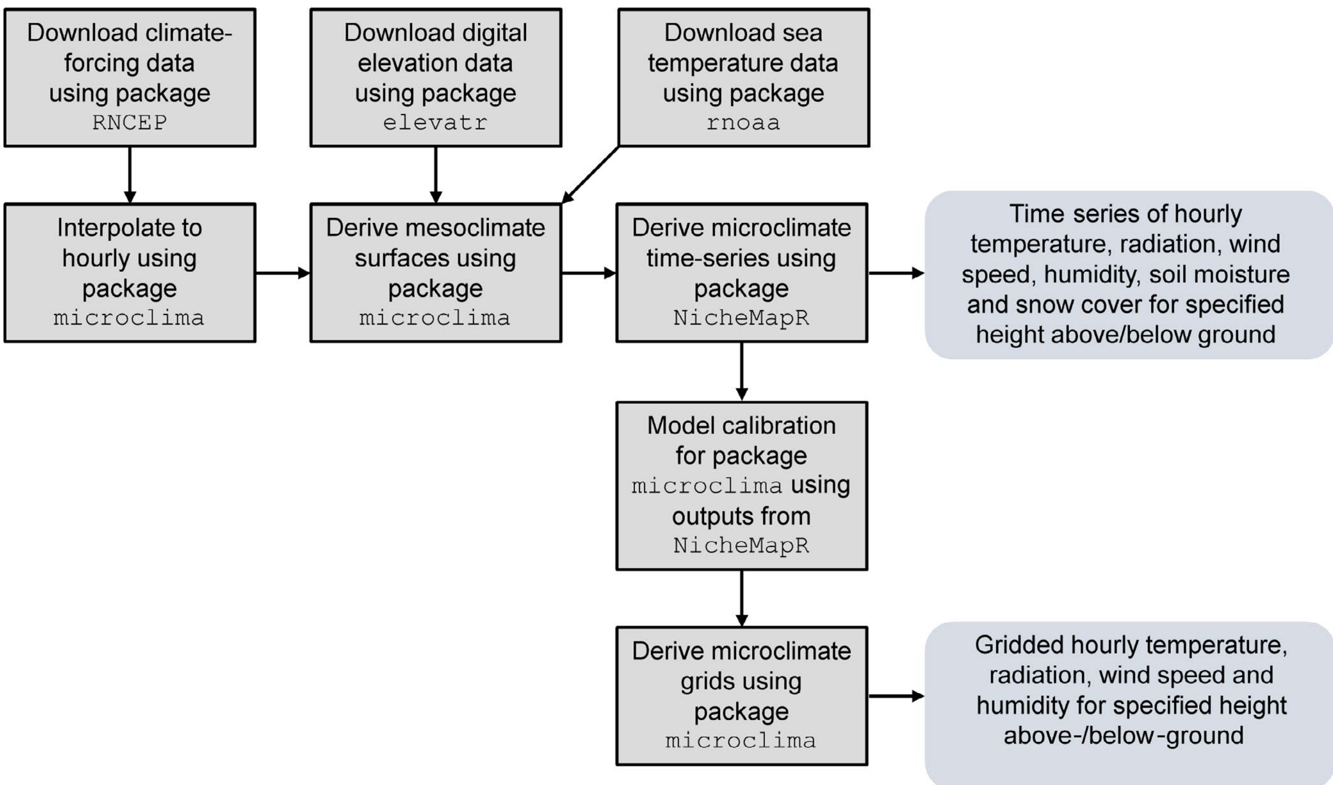


FIGURE 1 Conceptual flow diagram of methods used to generate time series and gridded datasets of microclimate anywhere on earth

additionally used NicheMapR to develop the microclima calibration functions normally obtained by empirical logger data.

3 | INTEGRATING NCEP DATA

Microclimate modelling requires data on longwave and shortwave radiation, air temperature, relative humidity, wind speed, air pressure and rainfall, all of which are available at six-hourly intervals from the NOAA-NCEP reanalyses program. We developed routines for interpolating these data to hourly, in the form of a new microclima function “hourlyNCEP” (see Appendix S1).

4 | TERRAIN, COASTAL AND SHADE ADJUSTMENTS

The NCEP data are on a ~2° grid (~200 km × 200 km) but we downscale these data by applying lapse corrections and cold air drainage effects with the use of digital elevation data. We therefore incorporated the elevatr package into our pipeline, which queries a global database of digital elevation data to obtain 30-m resolution at the coarsest scale, but down to 3 m in many areas. The wrapper function “get_dem” that incorporates this workstream is included in the microclima package.

Coastal effects can be optionally applied using routines within microclima, which model land-sea temperature differences within each hour as a function of sea exposure upwind and an aggregate measure of sea exposure in all directions. Sea surface temperature data are obtained using the package rnoaa (Chamberlain et al., 2019), and the workstream is embedded within function “coastalNCEP” associated with the microclima package.

Canopy shading is determined by leaf area and the distribution character of the canopy: at low solar angles, vertical orientations result in more shading. We allow for two approaches: (a) the user can specify leaf area and distribution angles as inputs into the model; (b) a habitat type can be specified and seasonally adjusted leaf areas and distribution angles are calculated automatically.

The terrain, coastal and shade adjustments are made using the microclima function “microclimaforNMR” which returns topographically adjusted air temperatures as well as daily precipitation. The list “microclima.out” is returned from the NicheMapR “micro_ncep” function and contains the interpolated NCEP data as well as the microclima outputs.

5 | CALIBRATING microclima USING NicheMapR

The microclima package uses a linear empirical model to compute the above-ground temperature anomaly from reference temperature as a function of net radiation and wind speed on the basis of locally measured calibration air temperatures (Maclean et al., 2019). Here, we instead replace the real temperature data with a time series of temperature estimates generated using NicheMapR for a point location at the centre of the grid for which microclimate data are required. This approach is limited because it does not incorporate the buffering influence of the underlying substrate. We therefore introduce a new parameterization for estimating sub-surface soil temperatures, whereby the temperature at a given time step is modelled as a function of temperature in the previous time step and heat exchanges with the soil surface and underlying soil layer (see Appendix S1).

6 | MODEL TESTS AND EXAMPLES

To assess the quality of the predictions of our modelling pipeline, we tested the NCEP hourly interpolation procedure against weather station data in the UK and the performance of the model in predicting soil temperature and moisture compared with previous tests in Australia using local gridded data. We also tested the performance of the NicheMapR-based calibration of microclima. Further details are provided in Appendices S1 and S2 including code to generate Figures 2 and 3b. Appendix S3 shows how to run the system to generate microclimate grids.

7 | RESULTS

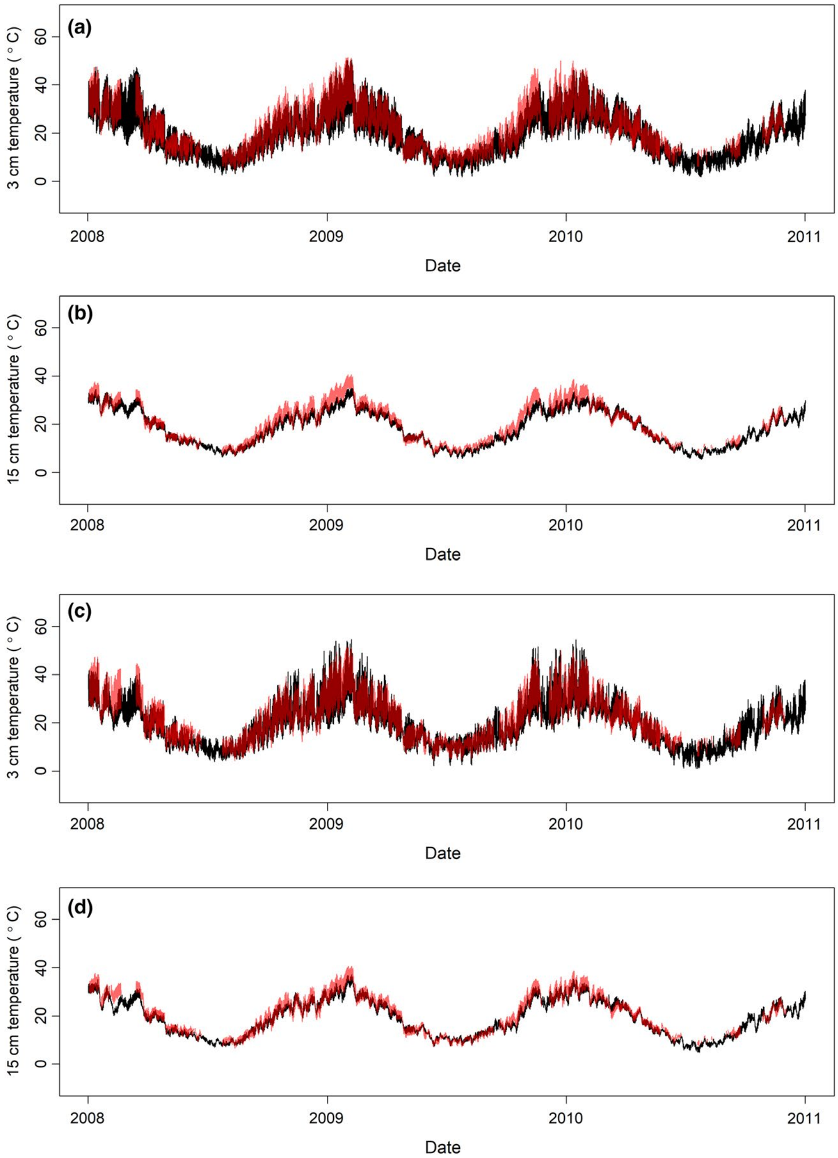
7.1 | Time series

NCEP-based NicheMapR predictions of soil temperature for the Australian OzNet soil moisture sites were as good, and sometimes superior, when compared to predictions driven by the Australia-specific weather grids (AWAP) (Table S1 in Appendix S1, Figure 2). The two approaches had similar correlation coefficients *r* overall, but with NCEP being significantly higher at 3–4 cm but slightly and significantly lower at 45 cm. The NCEP RMS error was slightly lower overall and statistically different at 3–4 cm (error was lower by 1.65°C at the latter depth and by 0.59°C overall).

7.2 | Microclimate grids

Spatial patterns in temperatures at 5 cm above the ground are well-reproduced by our automated procedure, in comparison with estimates generated using models calibrated with experimental data (Figure 3). However, temperatures were typically more variable than those derived from models calibrated using experimental data. Coefficient estimates, particularly for radiation, were higher when estimated using NicheMapR than when estimated using temperature logger data (Tables S4 in Appendix S1), though the radiation estimates themselves were less variable than when locally sourced data are used. Nonetheless, our fully automated method, in which canopy cover is estimated from specified habitat type, and ground and canopy albedo are fixed at 0.15 and 0.23, results in substantially improved estimates of temperatures derived from loggers in comparison with reference air temperature (model output: mean

FIGURE 2 Observed (red) and predicted (black) soil temperature for one of the Yanco OzNet sites (Y2) for the years 2008–2011 using (a) the Australian Water Availability Project (AWAP) daily weather grids or (b) downscaled and disaggregated National Centers for Environmental Prediction (NCEP) daily weather as forcing data



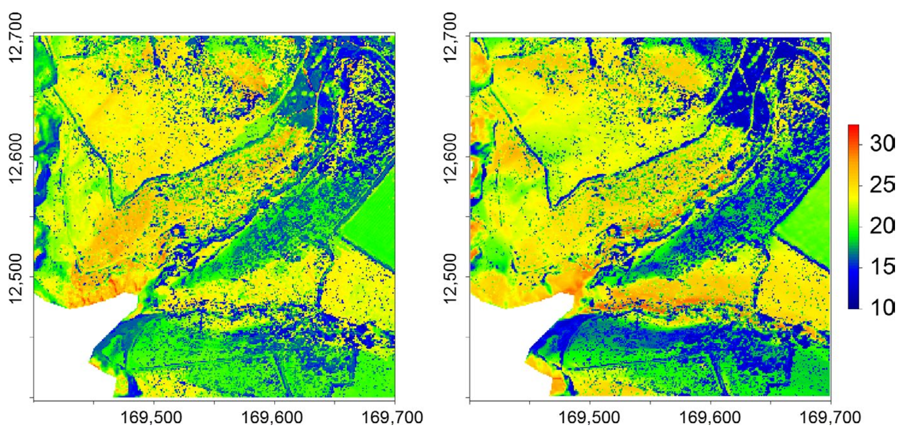


FIGURE 3 Side-by-side comparisons of a 1-m resolution dataset of temperatures at 5 cm height generated using methods described in Maclean et al. (2019) (a) compared to estimates at the same height using automated procedures for adjusting 250 km NCEP data (b) on 27 May 2010 13:00 hr at Caerthillian Valley on the Lizard Peninsula, UK. Here, canopy cover and ground and canopy albedo are specified by the user in the automated procedure and taken from Maclean et al. (2019) such that they are identical in both datasets

error = 0.616, RMS error = 0.802, r^2 = .891; reference temperature: mean error: 4.20; RMS error: 5.66, r^2 = .212; Figure S5 in Appendix S1).

Further test results, including of soil moisture, are provided in supporting information.

8 | DISCUSSION

The aim of this study was to develop a general procedure for deriving historical microclimate time series and grids for any location on earth. The opportunity to do this is presented by the NCEP gridded weather data, which we were able to successfully downscale from ~200 km 6-hourly data to hourly, terrain-adjusted (~30 m) forcing data for the NicheMapR microclimate model, using the rncep, elevatr and microclima packages (Figure S2 in Appendix S1). The NCEP data have been used previously to force biophysical models of intertidal organisms but without spatially explicit mesoclimatic downscaling (Mislan & Wethey, 2011).

Time series of soil temperature for our Australian test sites produced using our approach showed very similar, and sometimes slightly better, predictive accuracy in comparison with those generated using higher-resolution (~5 km) AWAP weather data (Figure 2, Table S1 in Appendix S1). Hourly historical soil temperatures could be predicted with an RMS error of ~3°C, depending on the depth, and correlation coefficients were generally well above 0.9. The performance of the NCEP-based predictions was considerably lower for soil moisture, however (Figure S3 in Appendix S1, Table S2 in Appendix S1), with a much lower correlation coefficient (NCEP 0.50, AWAP 0.65) but a similar overall RMS error (~7.5%). This is to be expected since we were not able to spatially correct the precipitation data from the original ~200 km resolution. Nonetheless, the NCEP-based soil moisture predictions captured the general seasonal patterns and overall variability of soil moisture well and should provide a good estimate of the expected seasonal dynamics of soil moisture for a given location (Figure S3 in Appendix S1).

The discrepancies between the microclimate model predictions and data obtained experimentally have several sources. Key among these is the error associated with the coarse-resolution climatic data used to drive the model. When tested against weather station data, estimates derived from NCEP do not always capture temperature extremes, particularly in highly coastal locations classed as “sea” as opposed to “land” as is the case for the Cornwall study site (Figure S1 in Appendix S1). In part, this can be attributed to localized mesoclimatic processes, but it is worth noting that the NCEP data are grid cell average estimates over a 6-hour period rather than point estimates at a location at the centre of each grid cell at a given point in time (Kalnay et al., 1996). In consequence, the effects of cloud cover on temperatures are integrated over several hours and across an entire region of ~200 × 200 km. The prevalence of the clear-sky conditions that lead to temperature extremes will thus be underestimated, and the performance of our model at this location can thus be viewed as a worst-case scenario.

Although our workstream currently enables air and soil temperature, and soil moisture metrics, to be estimated for point locations via the NicheMapR microclimate model's soil moisture and snow modules, we are yet to include the capacity to account for snow cover and soil moisture in our method for generating microclimate grids via microclima. Snow cover exerts a major influence on soil temperature, by reflecting solar radiation and thermally insulating the underlying soil layer, which in turn plays a key role in the function of polar ecosystems (Aalto, Scherrer, Lenoir, Guisan, & Luoto, 2018). Similarly, soil moisture is a direct determinant of ecosystem function, but also influences heat exchange between the soil and near-ground air layer. This is consistent with the tendency of microclima to not fully capture temperature extremes produced by NicheMapR during dry conditions.

The NCEP data are of course limited by the coarse spatial resolution, especially with respect to rainfall, but it can be supplemented by locally collected data. High-resolution terrain data beyond that provided by the elevatr can be provided to the pipeline for applications requiring very fine (e.g. cm) topographic effects. And, even if the system is not able to predict precise historical trajectories under some circumstances, for example because of inadequate rainfall data, it nonetheless provides realistic estimates of the nature of hourly extremes at different sites, with consequences that can be missed when, for example, using long-term average conditions (Kearney, Matzelle, & Helmuth, 2012).

The integration of the NCEP data into the microclimate modelling pipeline we have developed complements existing microclimate resources (Kearney, 2018b, 2019; Kearney et al., 2014; Levy, Buckley, Keitt, & Angilletta, 2016) by extending the spatial and/or temporal capacity to compute microclimates. The integration of the NicheMapR and microclima packages more generally provides enhanced capacity for incorporating processes at meso- and micro-scales than previously available with any one microclimate modelling system. This should improve our capacity to make accurate predictions of the environments experienced by terrestrial organisms across the globe.

ACKNOWLEDGEMENTS

This work was supported by a Leverhulme Trust grant to P.K.G., I.B., I.M.D.M. and M.R.K.. We thank Brian Helmuth and Jeffrey Hollister for constructive comments on the MS.

AUTHORS’ CONTRIBUTIONS

M.R.K. and I.M.D.M. conceived the project, developed the main functions, performed the analyses and wrote the manuscript. I.B. and P.K.G. facilitated the project and contributed to its conception. J.P.D. contributed to function development. I.B., P.K.G. and J.P.D. contributed to the writing of the MS.

ORCID

Michael R. Kearney https://orcid.org/0000-0002-3349-8744
Phillipa K. Gillingham https://orcid.org/0000-0002-9499-7627
Isobel Bramer https://orcid.org/0000-0002-7540-6190
James P. Duffy https://orcid.org/0000-0001-7971-3924

DATA AVAILABILITY STATEMENT

The NicheMapR release relevant to this paper (v2.0.0) is 10.5281/zenodo.3478635, and the microclima release (v2.0.0) is 10.5281/zenodo.3484589. The latter includes all data related to these findings with the exception of the Australian soil temperature and soil moisture observations which are freely accessible via the drop-down menus at http://www.oznet.org.au/mdbdata/mdbdata.html#M1. To access the data used in this manuscript, select "YANCO," "MURRUMBIDGIE," "ADELONG" or "KYEAMBA" from the sites list, then click on the "download" button for the relevant sites (i.e. y1 to y13 for Yanco, m1 to m7 for Murrumbidgee, a1 to a5 for Adelong and k1 to k14 for Kyeamba) and years (2008, 2009 or 2010). Alternatively, they can be download directly via (e.g. for Yanco site Y2, 2008) http://www.oznet.org.au/data/processed/webData/yanco/y2/y2_08_wi_sm.xls.

REFERENCES

Aalto, J., Scherrer, D., Lenoir, J., Guisan, A., & Luoto, M. (2018). Biogeophysical controls on soil-atmosphere thermal differences: Implications on warming Arctic ecosystems. *Environmental Research Letters*, *13*(7), 074003. https://doi.org/10.1088/1748-9326/aac83e

Assis, J., Tyberghein, L., Bosch, S., Verbruggen, H., Serrão, E. A., & Clerck, O. D. (2018). Bio-ORACLE v2. 0: Extending marine data layers for bioclimatic modelling. *Global Ecology and Biogeography*, *27*(3), 277–284. https://doi.org/10.1111/geb.12693

Bennie, J., Huntley, B., Wiltshire, A., Hill, M. O., & Baxter, R. (2008). Slope, aspect and climate: Spatially explicit and implicit models of topographic microclimate in chalk grassland. *Ecological Modelling*, *216*(1), 47–59. https://doi.org/10.1016/j.ecolmodel.2008.04.010

Bennie, J., Wilson, R. J., Maclean, I. M. D., & Suggitt, A. J. (2014). Seeing the woods for the trees – When is microclimate important in species distribution models? *Global Change Biology*, *20*(9), 2699–2700. https://doi.org/10.1111/gcb.12525

Bramer, I., Anderson, B. J., Bennie, J., Bladon, A. J., De Frenne, P., Hemming, D., … Gillingham, P. K. (2018). Advances in monitoring and modelling climate at ecologically relevant scales. *Advances in Ecological Research*, *58*, 101–161. https://doi.org/10.1016/bs.aecr.2017.12.005

Chamberlain, S., Anderson, B., Salmon, M., Erickson, A., Potter, N., Stachelek, J., Edmund, H. (2019).rnoaa: 'NOAA' weather data from R (Version 0.8.4). Retrieved from https://CRAN.R-project.org/package=rnoaa

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://doi.org/10.1002/joc.5086

Hollister, J., & Shah, T. (2018).elevatr: Access elevation data from various APIs (Version 0.2.0). Retrieved from https://CRAN.R-project.org/package=elevatr. https://doi.org/10.5281/zenodo.400259.

Hutchinson, M. F., & Bischof, R. J. (1983). A new method for estimating the spatial distribution of mean seasonal and annual rainfall applied to the Hunter Valley, New South Wales. *Australian Meteorological Magazine*, *Bremerhaven*, *PANGAEA*, *31*(3), 179–184. 10013/epic.37358.d001

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., … Joseph, D. (1996). The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society*, *77*(3), 437–472. https://doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2

Kearney, M. R. (2018a). Microclimate ecology. Oxford bibliographies. *Ecology*. https://doi.org/10.1093/obo/9780199830060-0194

Kearney, M. R. (2018b). MicroclimOz – A microclimate data set for Australia, with example applications. *Austral Ecology*, *44*(3), 534–544. https://doi.org/10.1111/aec.12689

Kearney, M. R. (2019). microclimUS: Hourly estimates of historical microclimates for the United States of America with example applications. *Ecology*, *100*(11), e02829. https://doi.org/10.1002/ecy.2829

Kearney, M. R., Isaac, A. P., & Porter, W. P. (2014). microclim: Global estimates of hourly microclimate based on long-term monthly climate averages. *Scientific Data*, *1*, 140006. https://doi.org/10.1038/sdata.2014.6

Kearney, M. R., & Maino, J. L. (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*, 662–673. https://doi.org/10.1016/j.jhydrol.2018.04.040

Kearney, M., Matzelle, A., & Helmuth, B. (2012). Biomechanics meets the ecological niche: The importance of temporal data resolution. *The Journal of Experimental Biology*, *215*(6), 922–933. https://doi.org/10.1242/jeb.059634

Kearney, M., & Porter, W. P. (2009). Mechanistic niche modelling: Combining physiological and spatial data to predict species' ranges. *Ecology Letters*, *12*, 334–350. https://doi.org/10.1111/j.1461-0248.2008.01277.x

Kearney, M. R., & Porter, W. P. (2017). NicheMapR – An R package for biophysical modelling: The microclimate model. *Ecography*, *40*(5), 664–674. https://doi.org/10.1111/ecog.02360

Kemp, M. U., Emiel van Loon, E., Shamoun-Baranes, J., & Bouten, W. (2012). RNCEP: Global weather and climate data at your fingertips: RNCEP. *Methods in Ecology and Evolution*, *3*(1), 65–70. https://doi.org/10.1111/j.2041-210X.2011.00138.x

Levy, O., Buckley, L. B., Keitt, T. H., & Angilletta, M. J. (2016). A dynamically downscaled projection of past and future microclimates. *Ecology*, *97*(7), 1888–1888. https://doi.org/10.1002/ecy.1444

Maclean, I. M. D., Mosedale, J. R., & Bennie, J. J. (2019). Microclima: An R package for modelling meso- and microclimate. *Methods in Ecology and Evolution*, *10*(2), 280–290. https://doi.org/10.1111/2041-210X.13093

Maclean, I. M. D., Suggitt, A. J., Wilson, R. J., Duffy, J. P., & Bennie, J. J. (2017). Fine-scale climate change: Modelling spatial variation in biologically meaningful rates of warming. *Global Change Biology*, *23*(1), 256–268. https://doi.org/10.1111/gcb.13343

Mislan, K. A. S., & Wethey, D. S. (2011). Gridded meteorological data as a resource for mechanistic macroecology in coastal environments. *Ecological Applications*, *21*(7), 2678–2690. https://doi.org/10.1890/10-2049.1

Porter, W. P., Mitchell, J. W., Beckman, W. A., & DeWitt, C. B. (1973). Behavioral implications of mechanistic ecology – Thermal and behavioral modeling of desert ectotherms and their microenvironment. *Oecologia*, *13*, 1–54. https://doi.org/10.1007/BF00379617

Potter, K. A., Woods, H. A., & Pincebourde, S. (2013). Microclimatic challenges in global change biology. *Global Change Biology*, *19*(10), 2932–2939. https://doi.org/10.1111/gcb.12257

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

How to cite this article: Kearney MR, Gillingham PK, Bramer I, Duffy JP, Maclean IMD. A method for computing hourly, historical, terrain-corrected microclimate anywhere on earth. *Methods Ecol Evol*. 2020;11:38–43. https://doi.org/10.1111/2041-210X.13330