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

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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 data sets, 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.

Introduction

The quantity and quality of gridded environmental data sets 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, i.e. microclimates (Kearney, 2018), 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 generalised 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 et al. (2017) developed a series of functions for such mesoclimate and terrain adjustments to extend the model of Bennie et al. (2008), released as an R package microclima (Maclean, Mosedale, & Bennie, 2018), 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 has 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 data sets.

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. (2018). 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 & Porter, 2017; Kearney & Maino, 2018). 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 (Fig. 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 additionally used NicheMapR to develop the microclima calibration functions normally obtained by empirical logger data.

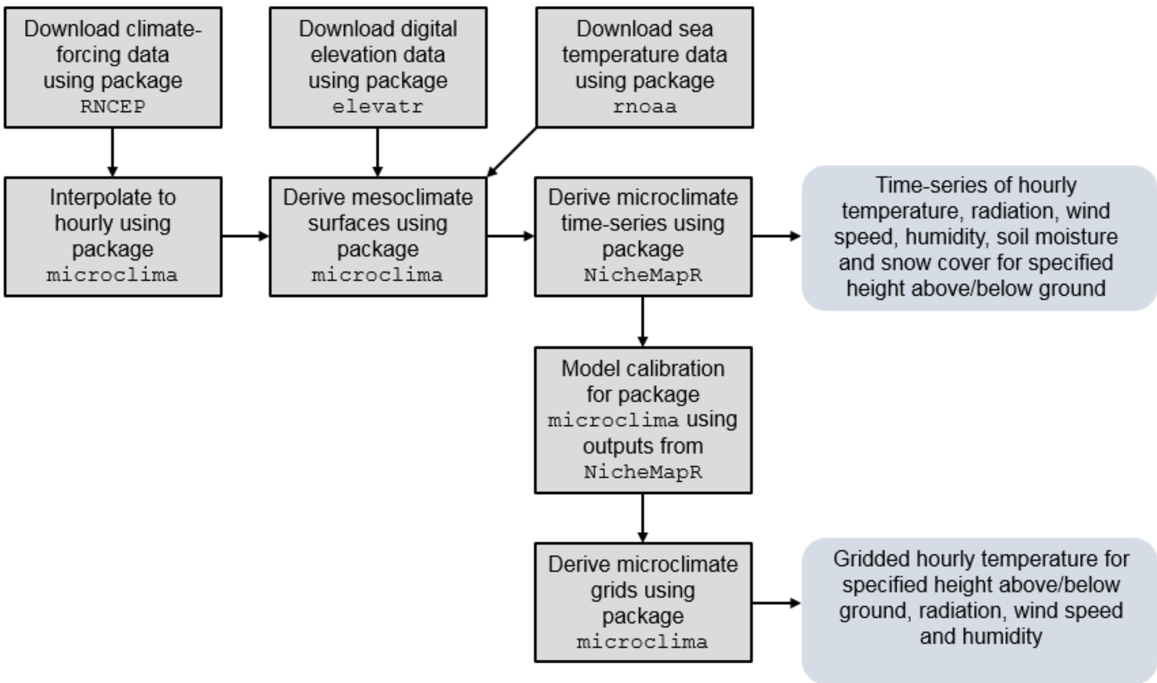


Figure 1. Conceptual flow diagram of methods used to generate time-series and gridded datasets of microclimate anywhere on earth.

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).

Terrain, coastal and shade adjustments

The NCEP data is on a ~2° grid (~200 km x 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 work-stream 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 work-stream 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: (1) the user can specify leaf area and distribution angles as inputs into the model; (2) 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.

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., 2018). 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 parameterisation 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).

Model tests and examples

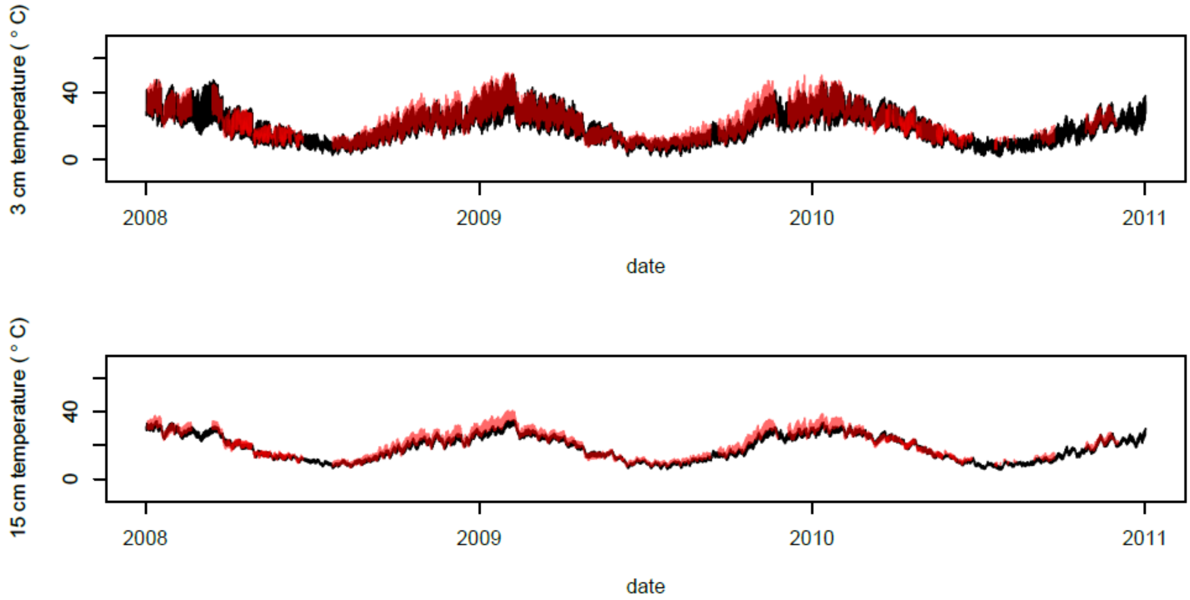
To assess the quality of the predictions of our modelling pipeline we tested the NCEP hourly interpolation procedure against weather station data in the UK and the performance of the model in predicting soil temperature and moisture compared with previous tests in Australia using local gridded data.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

Results

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, Fig. 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).

a) AWAP



b) NCEP

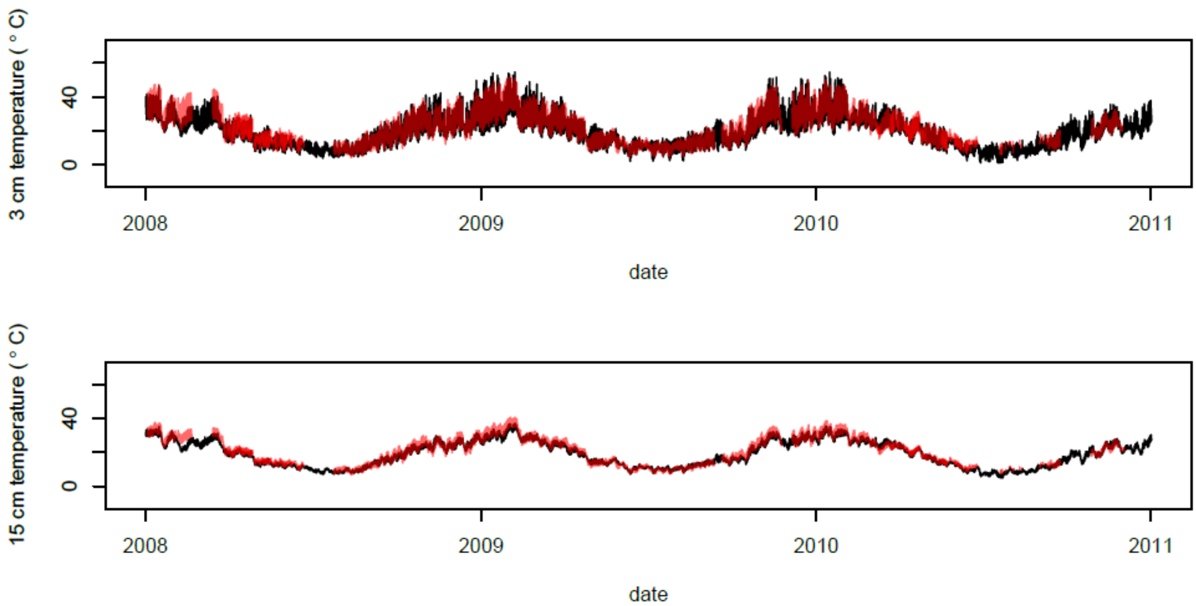


Figure 2. Observed (red) and predicted (black) soil temperature for one of the Yanco OzNet sites for the years 2008-10 using a) the Australian Water Availability Project (AWAP) daily weather grids or b) down-scaled and disaggregated National Centers for Environmental Prediction (NCEP) daily weather as forcing data.

Microclimate grids

Spatial patterns in temperatures at 5 cm above the ground are well-reproduced by our automated procedure, in comparison to estimates generated using models calibrated with experimental data (Fig. 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), 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 to reference air temperature (model output: mean error = 0.616, RMS error = 0.802, r^2 = 0.891; reference temperature: mean error: 4.20; RMS error: 5.66, r^2 = 0.212; Fig. S5).

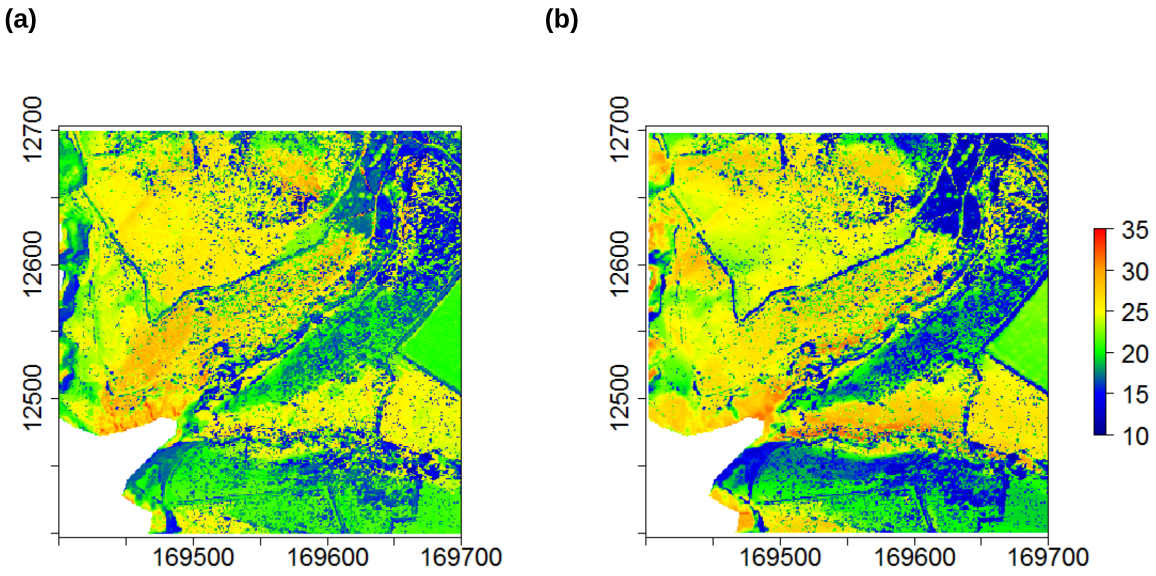


Fig. 3. Side by side comparisons of a one m resolution dataset of temperatures at 5 cm height generated using methods described in Maclean et al. (2018) (a) compared to estimates at the same height using automated procedures for adjusting 250 km NCEP data (b) on 27th May 2010 13:00 at Caerthillian Valley 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. (2018) such that they are identical in both datasets.

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

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 (Fig. S2). 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 to those generated using higher-resolution (~ 5 km) AWAP weather data (Fig. 2, Table 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 (Fig. S3, Table S2), 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 (Fig. S3).

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 (Fig. S1). In part this can be attributed to localised meso-climatic processes, but it is worth noting that the NCEP data are grid cell average estimates over a six-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 x 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 is of course limited by the coarse spatial resolution, especially in 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, e.g. 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 e.g. 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 et al., 2014; Levy, Buckley, Keitt, & Angilletta, 2016; Kearney, 2018b, 2019) 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 PKG, IB, IMDM and MRK. We thank Brian Helmuth and Jeffrey Hollister for constructive comments on the MS.

Author Contributions

MRK and IMDM conceived the project, developed the main functions, performed the analyses and wrote the manuscript. IB and PKG facilitated the project and contributed to its conception. JPD contributed to function development. IB, PKG and JPD contributed to the writing of the MS.

Data accessibility

The data used in this study are either included in the R packages or from online data sets as referred to in this MS or in cited articles. 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.

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