Software notes

Ecography 40: 664–674, 2017
doi: 10.1111/ecog.02360

Subject Editor: Brody Sandel. Editor-in-Chief: Miguel Araújo. Accepted 7 August 2016

NicheMapR – an R package for biophysical modelling: the microclimate model

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Microclimatic variables are necessary for a wide range of pure and applied problems in environmental science. In ecology, microclimatic conditions are prerequisites for modelling the heat and water budgets of organisms, from which climatic constraints on behaviour, life histories, distribution and abundance can be inferred. Despite the critical importance of microclimates, there is no general-purpose, accessible microclimate model available for use in ecological studies.

Here we introduce and document the microclimate model of the biophysical modelling package NicheMapR, an R package that includes a suite of programs for mechanistic modelling of heat and mass exchange between organisms and their environments. The NicheMapR microclimate model is based on a Fortran program originally developed by Porter, Mitchell, Beckman and McCullough for predicting hourly above- and below-ground conditions from meteorological, terrain, vegetation and soil data. The model includes routines for computing solar radiation, including effects of shading, slope, aspect and horizon angles (hillshade), and can include variable substrate properties with depth.

Here we configure the program to be called from R as part of the NicheMapR package, and describe the model in detail including new functionality for modelling soil water balance and snow, optional input of hourly or daily weather input data, and an R implementation of the Global Aerosol Data Set for obtaining local estimates of aerosol profiles as input to the model. We include scripts for core operation of the model, for building a global, monthly long-term average dataset with all necessary environmental inputs, for computing physical properties of air, and for running the model with the global climate database. Example applications are provided in the paper and in the associated vignettes, including customisation the model to run with user-supplied weather inputs.

Microclimate models and their relevance

Climate and weather are of fundamental importance to the distribution, abundance and evolution of terrestrial organisms (Uvarov 1931, Andrewartha and Birch 1954). Ecologists now have access to a rich array of climate and weather data at different spatial and temporal scales across the planet, but for many applications this is not sufficient. Instead, microclimate conditions – the ‘climate near the ground’ or in the ‘boundary layer’ (Geiger 1950, Oke 1992) – are required. Microclimates are the physical conditions actually experienced by organisms, and which are relevant to the fundamental processes of heat and mass exchange. They include short- and long-wavelength radiation, air temperature, wind speed, humidity, substrate temperature and soil moisture. These conditions represent the interaction between weather/climatic conditions and habitat features such as shade, terrain (slope, aspect, hillshade) and vegetation. Weather station measurements are made approximately 1–2 m above the ground specifically to avoid these local influences, such that they provide a more regionally relevant measure, because local effects can be substantial. For example, Monteith (1960) observed that a weather station near London in July recorded 20°C at midday, but at about 10 cm above the ground in an alfalfa crop it was 5°C warmer. He remarked that one would have to travel as far as Florida on that particular day to find similarly warm conditions at the same height as the weather station. Whenever we want to make a direct connection between experimental measurements of organismal responses to temperature and moisture under field conditions, it is microclimate rather than weather or climate that is needed. This information must also be obtained at the appropriate spatial and temporal scale. The relevant scale will vary with organismal size and vagility but will often need to be in the order of cm–m and minutes–hours to capture relevant environmental variability and behavioural regulatory mechanisms (Helmuth 1998, 2002, Denny et al. 2006, Gilman et al. 2006, Pincebourde et al. 2007, Suggitt et al. 2011, Denny and Dowd 2012, Kearney et al. 2012).

While the measurement and modelling of microclimatic conditions has long been of interest to ecologists (Uvarov 1931, Jackson 1966, Willmer 1982), microclimates have become especially relevant in recent years for a number of technical and topical reasons (Potter et al. 2013, Bennie et al. 2014, Hannah et al. 2014). First, there has been an explosion of research on the climatic constraints of species distributions via the method of correlative species distribution models (SDMs) (Elith and Leathwick 2009). This research has been facilitated by the increasing availability of gridded environmental data, and has been motivated by the spectre of anthropogenic climate change impacts on biodiversity. In turn, this has led to an interest in the underlying bases for associations between climate and species occurrences, thereby reinvigorating ecophysiological studies of the thermal and hydric tolerances of species. The latter studies depend critically on accurate characterisation of microclimates. Second, the development of cheap environmental data loggers has facilitated the measurement of at least some critical microclimatic variables including air and soil temperature, and relative humidity (Suggitt et al. 2011, Ashcroft and Gollan 2012, Gillingham et al. 2012, Williams 2013). However, empirical measurements of microclimatic conditions will always be limited in space, time and in the range of microclimatic variables that can be measured (e.g. wind speed, solar radiation and soil moisture are rarely measured). Thus, there is great utility in being able to model microclimatic conditions from the increasingly detailed databases of climate, weather, terrain, soil and vegetation that are now available for different parts of the world.

A number of microclimate models have been developed for specific purposes or sites (Hungerford et al. 1989, Bennie et al. 2008, Maclean et al. 2016) but few have been made available for general use or provide all the required outputs for computing organismal heat budgets. One exception is SNTHERM (Jordan 1991), which has snow as its primary focus as well as a range of other useful microclimatic outputs. However, it does not have solar radiation routines and, as a stand-alone Fortran program, is relatively inaccessible.

The microclimate model we present here was originally developed by Porter and colleagues for modelling heat budgets of organisms in a desert environment, with Beckman et al. (1973) and Porter et al. (1973) providing overviews, McCullough and Porter (1971) describing the solar radiaton algorithms, and Porter et al. (1973) and James and Porter (1979) providing initial tests and applications. The model is designed to compute microclimatic conditions near the ground at a point, given the properties of the habitat and information on the weather conditions 1–2 m above the ground. It does not compute meso-scale phenomena that depend on surrounding conditions, like cold-air drainage, though such effects can be added directly via the driving weather input data. It also assumes habitat properties are uniform across an infinite plane and thus will not capture subtle spatial dynamics due to lateral heat or moisture flow. Various extensions have been made to the original model, including the capacity to simulate variable substrate properties with depth and time (Kearney et al. 2014b). Moreover, the model's ability to predict soil temperature has been tested extensively under a wide range of climates in Australia (Kearney et al. 2014b) and the USA (Kearney et al. 2014a), predictions of 3-h soil temperatures being within 10% of measured values when driven by gridded daily weather data.

This microclimate model has been applied in a wide range of ecological circumstances, including understanding the role of thermoregulation in buffering climate change (Kearney et al. 2009, Kearney 2013); the computation of nest temperatures for tuatara and sea-turtles and the implications for temperature dependent sex determination (Mitchell et al. 2008, Fuentes and Porter 2013); the generation of evaporation-driven resistance layers constraining the movement of toads (Bartelt et al. 2010); predicting translocation sites for endangered species (Mitchell et al. 2013); and predicting distribution constraints more generally for ectotherms (Kearney et al. 2008, Kearney 2012) and endotherms (Porter et al. 2002, 2006, Natori and Porter 2007, Kearney et al. 2010, Mathewson and Porter 2013, Briscoe et al. 2016). The model has also been used to produce a global dataset of microclimatic conditions (Kearney et al. 2014a). However, like SNTHERM, it was originally developed as a stand-alone Fortran program which limited its accessibility, and it has not, until now, been made publicly available.

The raw outputs of the microclimate model can be used directly or supplied as inputs for the ectotherm or endotherm models within the NicheMapR package. These latter models (to be described in subsequent software notes) use the microclimate model outputs for two shade extremes to compute heat, water and energy budgets given specified morphology, physiology and behavioural options, and include implementation of the dynamic energy budget model for the calculation of whole-life-cycle energetics (Kearney 2012, Kearney et al. 2013). In the remainder of this article we describe the Fortran program structure and underlying formulae of the NicheMapR microclimate model, as well as the R functions we have developed to interface with the model. We demonstrate its application with a global climate database developed by New et al. (New et al. 1999, 2002) and with hourly weather observations from the SCAN network.

The NicheMapR microclimate model structure

The NicheMapR microclimate model comprises a Fortran library – the core calculation engine – and a set of R functions that are used to set up the data input and to call the Fortran program (Fig. 1–2). The NicheMapR package also includes a number of documents relevant to the microclimate model (Table 1), some of which are included as appendices in the present paper.

Fortran routines

The Fortran library of the NicheMapR microclimate model comprises 20 subroutines and three functions (Fig. 1). The underlying theory and equations of these routines is documented in detail in Supplementary material Appendix 1 (Table 1). We here provide a brief overview of the function of each of the subroutines.

The subroutine MICROCLIMATE (Fig. 1a) acts as the I/O to R (via R function microrun, see next section and Fig. 2a) and controls each day's iteration. The MICROCLIMATE subroutine sets the initial substrate

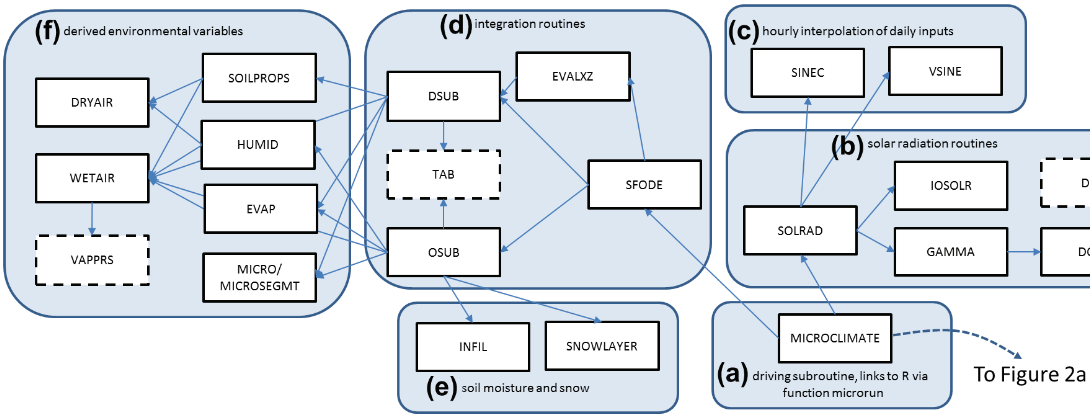

Figure 1. Structure of the Fortran library of the NicheMapR microclimate model. Solid boxes represent Fortran subroutines and dashed boxes represent Fortran functions.

temperature profile conditions and determines how many days are to be used to obtain a steady periodic solution for the substrate heat budget. The initial substrate temperature profile of the first run is set to the mean air temperature for the day and three iterations of the day are done before the outputs are saved. If the model is running for all days of a year, the initial conditions for all subsequent days are set as the last hour of the previous day's conditions and only one iteration is performed. If the model is running a subset of days of the year (e.g. weekly or monthly), all days are iterated three times starting with a uniform substrate profile of the mean daily air temperature. The MICROCLIMATE subroutine may also repeat the entire simulation for a second shade level, if requested by the user.

After setting the initial substrate temperatures MICROCLIMATE calls SOLRAD (Fig. 1b) which computes hourly solar conditions including zenith angles and direct and diffuse solar radiation via IOSOLR, GAMMA, DCHXY and DEXPI (Supplementary material Appendix 1, section 2). Having computed the time of sunrise, sunset and solar noon, SOLRAD also calls SINEC and VSINE (Fig. 1c) to convert daily minimum and maximum driving

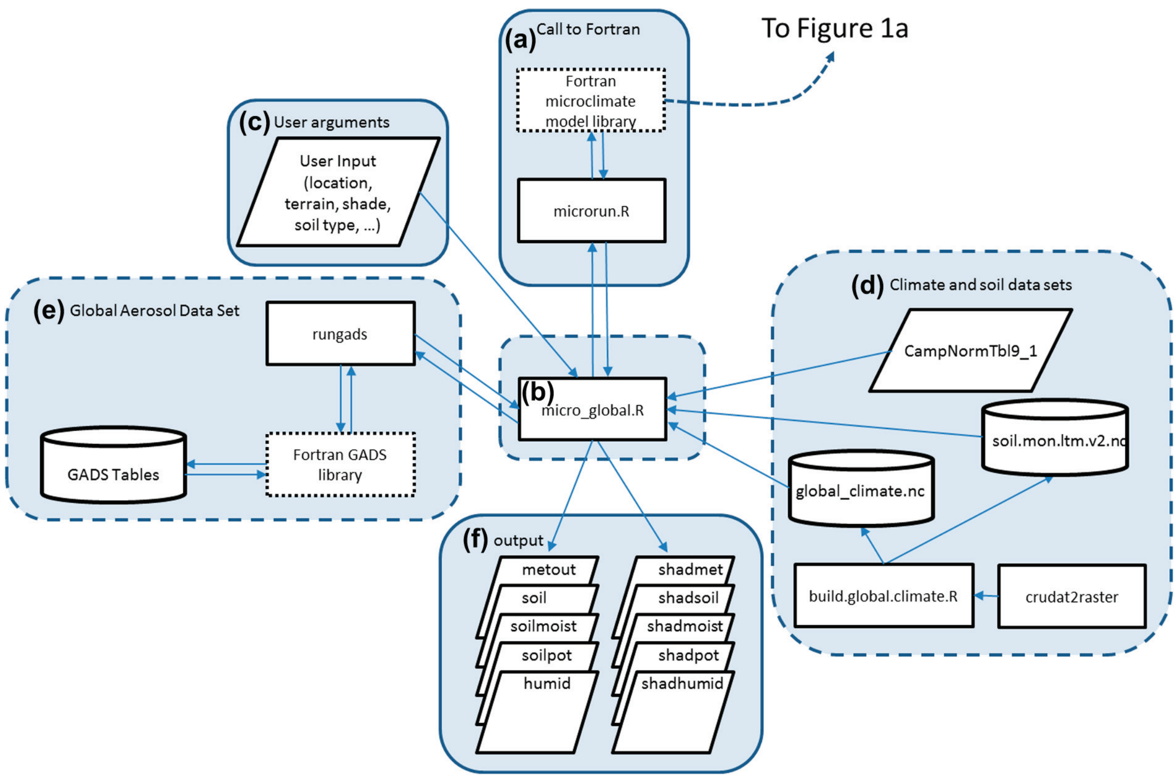

Figure 2. Structure of the R functions used to run the NicheMapR microclimate model with the global databases on climate, soil moisture and aerosols. User input data are represented by the trapezoid boxes and databases are indicated by cylinders. Fortran libraries are indicated by dashed boxes. Curved shaded boxes represent scripts specific to the application of the model with the global climate database and can be substituted with user-created R scripts for customisation to alternative environmental data sources.

Table 1. Documentation included in the NicheMapR package relating to the microclimate model.

Vignette	Description
Underlying theory and equations of the NicheMapR microclimate model	Supplementary material Appendix 1 of this paper, providing details of all calculations made by the Fortran microclimate model subroutine
Microclimate model input data	Supplementary material Appendix 2 of this paper, providing all direct inputs to the Fortran microclimate model
Microclimate monthly input example	Supplementary material Appendix 3 of this paper, providing an example mean monthly input and output setup script for the Fortran microclimate model subroutine – submits input to the Fortran program and retrieves the data
Microclimate hourly input example	Supplementary material Appendix 4 of this paper, providing an example hourly input setup script for the Fortran microclimate model subroutine – runs the model based on hourly weather data for a Soil and Climate Network (SCAN) site and compares the results to observed soil temperature and moisture.
Microclimate model tutorial	An overview of how to run the microclimate model using the micro_global function
Properties of air	A technical document summarising various physical properties of air developed by Tracy et al. (1980)

environmental inputs for air temperature, relative humidity, wind speed and cloud cover to hourly cycles given the user input of the timing of the maxima and minima (Supplementary material Appendix 1, section 4). This can be overridden if hourly weather input is available.

Once SOLRAD has executed for a given day, the subroutine SFODE is called to integrate substrate temperature profiles across the day (Fig. 1d). SFODE implements an Adams predictor-corrector method to solve the 9 simultaneous first order ordinary differential equations (ODEs) of the heat budget for each depth node (excluding the deepest node which acts as a boundary condition), using the Runge–Kutta method to obtain the initial conditions. The ODEs for the substrate heat budget are coded in subroutine DSUB (Supplementary material Appendix 1, section 7), with subroutine EVALXZ applying the Runge–Kutta algorithm. DSUB is also where longwave radiation calculations are performed (Supplementary material Appendix 1, section 3) and where the heat budget terms for the ODEs are finalised. The function TAB is used to obtain values of the time-dependent inputs derived from SOLRAD and SINEC and VSINE, using linear interpolations for obtaining sub-hourly values where required (Supplementary material Appendix 1, section 4). OSUB is called each hour to collate the results for output back to MICROCLIMATE, and soil moisture and snow calculations are also made via calls from OSUB to INFIL and SNOWLAYER, respectively (Supplementary material Appendix 1, sections 8 and 9) (Fig. 1e).

Above ground thermal conditions near the surface are simultaneously evolving through time as the program progresses. A set of subroutines are called by DSUB and OSUB to determine how air temperature, humidity and wind speed profiles change (Fig. 1f). These include MICRO and MICROSEGMT for obtaining wind speed profiles (Supplementary material Appendix 1, section 5), DRYAIR for obtaining thermal properties of air, WETAIR, HUMID and VAPPRS for determining water-vapour properties (Supplementary material Appendix 1, section 6), and SOILPROPS for determining soil thermal properties (Supplementary material Appendix 1, section 7).

Finally, output tables of hourly above and below ground conditions, under one or two shade levels (Fig. 2f and Table 3), are then reported back to R by MICROCLIMATE at the end of the simulation. All of the direct microclimate model inputs required by the Fortran program are documented in Supplementary material Appendix 2, and example setups with actual mean monthly input data for Madison Wisconsin, USA and hourly input data for Ford Dry Lake, California, USA are provided in Appendx 3 and 4, respectively (see also Table 1 and examples below). The outputs include hourly estimates of infrared thermal radiation (sky temperature), air temperature, and relative humidity conditions above ground as well as soil temperature and moisture states below ground, and are summarised in Table 2.

R functions

The NicheMapR package includes a set of R functions (Fig. 2) for inputting and retrieving data from the Fortran program, including its application with a 10′ (approx. 17 km) resolution global climate database derived from New et al. (New et al. 1999, 2002) and, optionally, 0.5° soil moisture data derived from the NOAA Climate Prediction Center (van den Dool et al. 2003, Fan and van den Dool 2004) and the 5° Global Aerosol Data Set from RASCIN (Koepke et al. 1997).

Function microrun acts as the core R wrapper for the Fortran library (Fig. 2a). It receives as input all the necessary input data and parameters required by the Fortran code and receives the computed microclimate outputs. In Fig. 2, the configuration to run the model with the global long-term average monthly climate dataset is illustrated. In this configuration, function micro_global (Fig. 2b) receives all user input (Fig. 2c), communicates with the global climate (Fig. 2d) and aerosol (Fig. 2e) databases, and ultimately returns the output data tables (Fig. 2g). Function micro_global includes error traps for the user inputs as well as code for splining the monthly long-term average climate data to more frequent time intervals (from monthly to daily), and for running the model over more than one year. It also makes use of the geocode function of the DISMO package to georeference place names via Google Maps. It configures the soil properties according to Table 9.1 from Campbell

Table 2. Microclimate model output tables.

a) Above ground conditions – output tables 'metout' (minimum shade) and 'shadmet' maximum shade.

Column	Variable	Description	Units
1	JULDAY	day of year	d
2	TIME	time of day	min
3	TALOC	air temperature at local[1] height	°C
4	TAREF	air temperature at reference[2] height	°C
5	RHLOC	relative humidity at local[1] height	%
6	RH	relative humidity at reference[2] height	%
7	VLOC	wind speed at local[1] height	m s^{-1}
8	VREF	wind speed at reference[2] height	m s^{-1}
9	SNOWMELT	snowmelt	mm
10	POOLDEP	water pooling on surface	mm
11	PCTWET	soil surface wetness	%
12	ZEN	zenith angle of sun (90 = below the horizon)	degrees
13	SOLR	solar radiation	W m^{-2}
14	TSKYC	sky radiant temperature	°C
15	DEW	dew presence	0 or 1
16	FROST	frost presence	0 or 1
17	SNOWFALL	snow predicted to have fallen	mm
18	SNOWDEP	predicted snow depth	cm

[1]specified by 'Usrhyt' variable, 1 cm by default.
[2]specified by 'Refhyt', 1.2 m default.

b) Soil temperature – output tables 'soil' (minimum shade) and 'shadsoil' maximum shade.

Column	Variable	Description	Units
1	JULDAY	day of year	d
2	TIME	time of day	min
3–12	D0cm ...	soil temperatures at each of the 10 specified depths	°C

c) Soil moisture – output tables 'soilmoist' (minimum shade) and 'shadmoist' maximum shade.

Column	Variable	Description	Units
1	JULDAY	day of year	d
2	TIME	time of day	min
3–12	WC0cm ...	soil moisture at each of the 10 specified depths	m^3 m^{-3}

d) Soil water potential – output tables 'soilpot' (minimum shade) and 'shadpot' maximum shade.

Column	Variable	Description	Units
1	JULDAY	day of year	d
2	TIME	time of day	min
3–12	PT0cm ...	soil water potential at each of the 10 specified depths	J kg^{-1} = kpa = bar/100

e) Soil relative humidity – output tables 'humid' (minimum shade) and 'shadhumid' maximum shade.

Column	Variable	Description	Units
1	JULDAY	day of year	d
2	TIME	time of day	min
3–12	RH0cm ...	soil relative humidity at each of the 10 specified depths	decimal %

and Norman (1998), which is included as a dataset in the package (Fig. 2d).

To set the microclimate model to run with custom inputs, the procedures in Fig. 2b, d and e, which act to draw together the necessary inputs for the function microrun.R (as summarised in Supplementary material Appendix 2), can be substituted with customised code and datasets as illustrated in Supplementary material Appendix 3 for long-term monthly minimum/maximum weather inputs and Supplementary material Appendix 4 for hourly weather inputs.

Also included in the package are R translations of the Fortran routines DRYAIR, WETAIR and VAPPRS, originally developed by Tracy et al. (1980) in their document 'Properties of air', now included in the NicheMapR package as a vignette (Table 1) (and also at <http://niche-mapper.com/apps/presto/index.html>). These functions can be used in preparing user-input data, e.g. for converting vapour pressure to relative humidity, given the air temperature.

Global aerosol data set

The rungads function is an R wrapper for the Fortran program gads22 <www.rascin.net/en/gads_des>, which extracts data from a global aerosol data set (Koepke et al. 1997). The output of gads22 includes optical depth of aerosols (among other variables) for 25 wavelengths between 250 and 4000 nm on a grid of 5 degrees resolution, for two seasons (winter and summer) and for 8 values of atmospheric relative humidity. Aerosol optical depth is used by the NicheMapR model as part of the computation of the attenuation of solar radiation as it travels through the atmosphere (Supplementary material Appendix 1, section 1). The gads Fortran library in NicheMapR is a modification of ver. 2.2b such that it provides attenuation for all wavelengths for a given location (rather than all locations for a given wavelength, as in the original program). This function is optionally called by micro_global to obtain aerosol profiles specific to the chosen location.

Global climate database

The NicheMapR microclimate model requires meteorological observations at a specified reference height for minimum and maximum daily air temperature, relative humidity and wind speed (reference height is usually 1.2 or 1.5 m for air temperature, but may be up to 2 m to account for snow in some areas, and 10 m for wind speed), as well as cloud cover and (for soil moisture and soil moisture calculations) precipitation and rainy days. Long-term (1960–1991) average monthly values of these variables are available at the global scale through the Climate Research Unit's CL ver. 1.0 and CL ver. 2.0 data sets (New et al. 1999, 2002). The latter is at 10′ (17 km) spatial resolution but does not include cloud cover, which is available in the former at 0.5° resolution.

The R function build.global.climate downloads the original CRU data and collates it into a single netCDF file 'global_climate.nc' at a user-specified folder. This involves downloading the CL ver. 2.0 data for precipitation, rainy days, mean daily air temperature, diurnal temperature range, mean daily relative humidity and wind speed, and converting them from tabular format to rasters. The associated digital elevation model (DEM) is also downloaded and rasterized. Daily minimum and maximum temperatures are derived by subtracting/adding half the diurnal temperature range, respectively, to the mean daily temperature. Relative humidity at the mean air temperature is adjusted to the minimum and maximum air temperatures (generating maximum and minimum relative humidity, respectively) using the WETAIR and VAPPRS R functions (see Properties of air manual, Table 1). The wind speed is corrected to 1.2 m (the height for air temperature and relative humidity) from 10m, and the minimum wind speed is (arbitrarily) assumed to be 1/10 of the reported value, the latter being taken as the maximum wind speed. Daily mean cloud cover from the 0.5° CL ver. 1.0 dataset is downloaded and converted to raster format from the raw ASCII (.dat) format using the function crudat2raster, and then interpolated to 10′ (17 km) spatial resolution. All grids are then converted from decimal to integer format (saving one decimal place), converted to a raster stack and then saved in netCDF format.

The build.global.climate routine also downloads the 0.5° resolution global soil moisture dataset from the NOAA Climate Prediction Center (van den Dool et al. 2003, Fan and van den Dool 2004), interpolates it to 10′ resolution and saves it as a netCDF file.

Example applications

To illustrate the basic use of the NicheMapR microclimate model, we first present calculations of microclimates under the default settings for Madison, Wisconsin USA using the global climate database (these settings can be found in Supplementary material Appendix 3, which shows the raw inputs to the model for this particular example). Additional examples using this same site and database, illustrating changes in slope and the soil moisture and snow model, are provided in the vignette 'Microclimate model tutorial' (Table 1) included in the package.

First, install the package. This can be done from source (for PC users, 'Rtools' must also be installed while, for OSX users, 'XCode' and the associated 'command line tools' and a compatible version of 'gfortran' must also be installed):

```
library(devtools)
install_github("mrke/NicheMapR")
```

Alternatively, the appropriate binary installation file can be downloaded from <https://github.com/mrke/NicheMapR/releases> (e.g. NicheMapR_x.x.x.tgz for OSX or NicheMapR_x.x.x.zip for Win32/64) and installed using R's install.packages function, e.g. for Windows

```
install.packages("path to file/NicheMapR_
1.1.2.zip", repos=NULL, type="win.
binary")
```

and for mac

```
install.packages("path to file/NicheMapR_
1.1.2.tgz", repos=NULL, type=.Plat
form$pkgType)
```

Second, download and unzip the global database (this can also be built from scratch using the function build.global.climate):

```
get.global.climate(folder="your
folder")
```

Next, run the model for Madison Wisconsin, using the global climate database and all the default settings. This will run the model to produce 12 d of output, one for each month of the year, without invoking the soil moisture or snow subroutines. In this mode of operation, the model does three iterations of each day, the first one starting with a uniform soil temperature profile and the first two acting as 'burn-in' runs prior to the third and final run which is provided as the final output.

```
micro <- micro_global(loc="Madison,
Wisconsin, USA")
```

The results are a list of tables in the object micro, as described in Table 2. The next lines extract the minimum shade (0% shade) results for above and below ground conditions in July and plot the air temperature at the reference height, air temperature at local height (by default, 1 cm) and soil temperature at 0 cm and 10 cm (Fig. 3a).

```
metout <- as.data.frame(micro$metout)
soil <- as.data.frame(micro$soil)
plot(TALOC ~ TIME, type='l',
ylim=c(10,60), data=subset(metout,
JULDAY==196))
points(TAREF ~ TIME, type='l', lty=2,
data=subset(metout, JULDAY==196))
points(D0cm ~ TIME, type='l',
col="grey", data=subset(soil,
JULDAY==196))
points(D10cm ~ TIME, type='l',
lty=2, col="grey", data=subset(soil,
JULDAY==196))
```

Figure 3b shows the identical plot but setting the substrate type to rock instead of the default of soil. Note how the more highly conductive rock substrate allows heat to penetrate more deeply into the substrate profile, resulting in less heat building up in the surface layers. It also has the effect that heat is released more slowly through the night such that the diurnal amplitude is reduced near the surface compared to the soil case, but increased deeper in the rock profile.

```
micro  <-  micro_global(loc="Madison,
Wisconsin, USA", soiltype=0)
```

As a second example at the other extreme of temporal input resolution, we have run the model using hourly weather input for Ford Dry Lake in California and compared the results against observed values of soil temperature and moisture for the site. The input data are provided as part of the package and comprise the tables SCAN_sites, which has summary information for all the SCAN sites, and SCAN_LakeFordDry_2015, which has hourly observations of weather and soil conditions for the year 2015. The detailed code and explanations to run this simulation is provided in Supplementary material Appendix 4 and we only provide a short overview here. The SCAN_LakeFordDry_2015 dataset includes hourly observations of air temperature, wind speed, relative humidity and

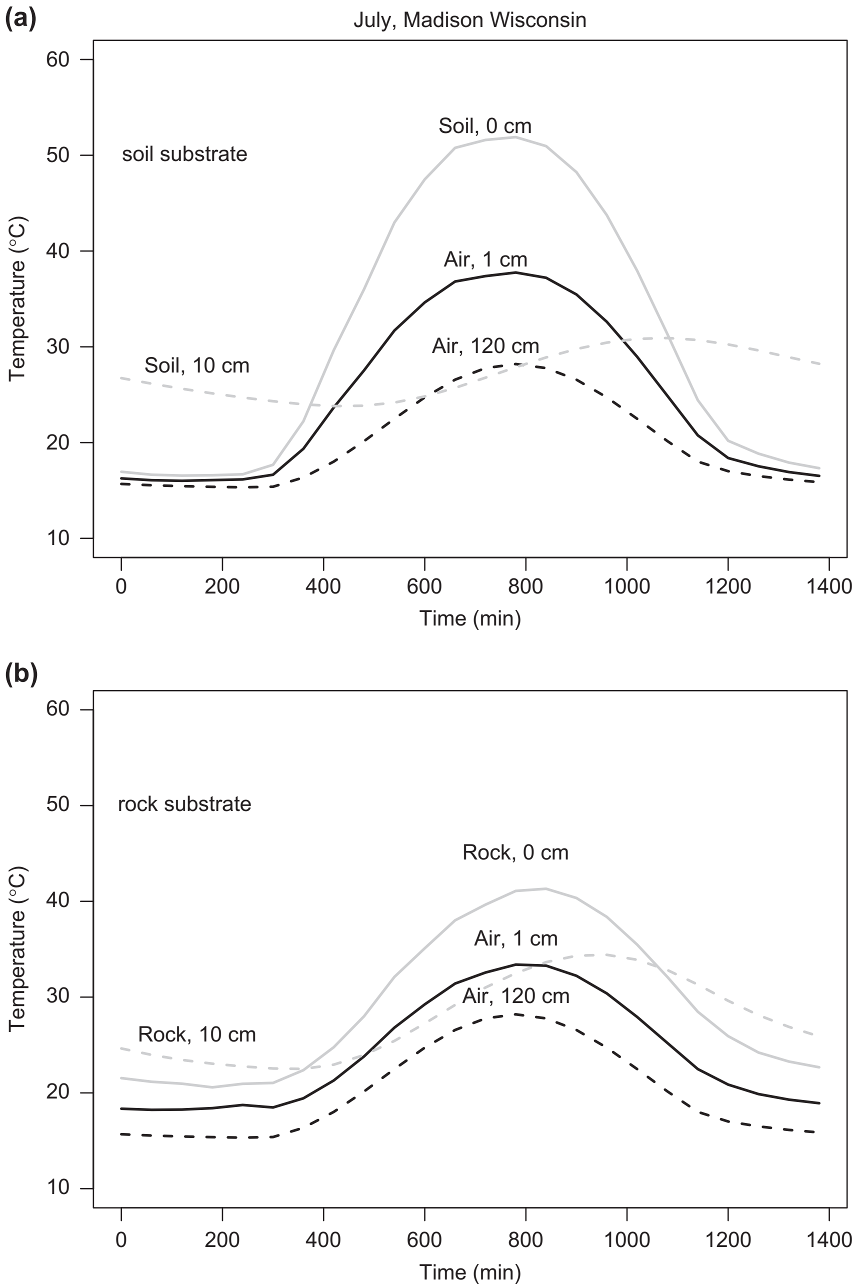

Figure 3. Example output from the microclimate model for Madison, Wisconsin in July, showing hourly air temperature at 1.2 m (black, dashed line) and 1 cm (black solid line) as well as soil temperature at the surface (grey solid line) and 10 cm deep (grey dashed line) for a) a soil substrate and b) a rock substrate. These simulations were driven from monthly long-term average weather data, using interpolation procedures to convert daily minimum/maximum values of weather observations to diurnal cycles.

solar radiation. Cloud cover is also required, from which estimates of downward long-wave radiation flux (output variable 'sky temperature') is computed. To approximate this, a preliminary microclimate model run is performed for the site using the 'micro_global' function with the 'clearsky' option turned on so that clear sky solar radiation is computed. The ratio of observed to clear sky solar radiation is then used as an estimate of the proportion of cloud cover. Once the data are collated, the model is run with uniform soil thermal properties, but with soil moisture properties for a sandy loam in the top 30 cm transitioning to a silt loam in the deeper layers. Figure 4 shows the match between the observed soil temperature and moisture and the model predictions from May to July.

Computational constraints

The input environmental vectors are unlimited in length so, for example, one could run the model with 100 years' worth of hourly input weather data. Computation time

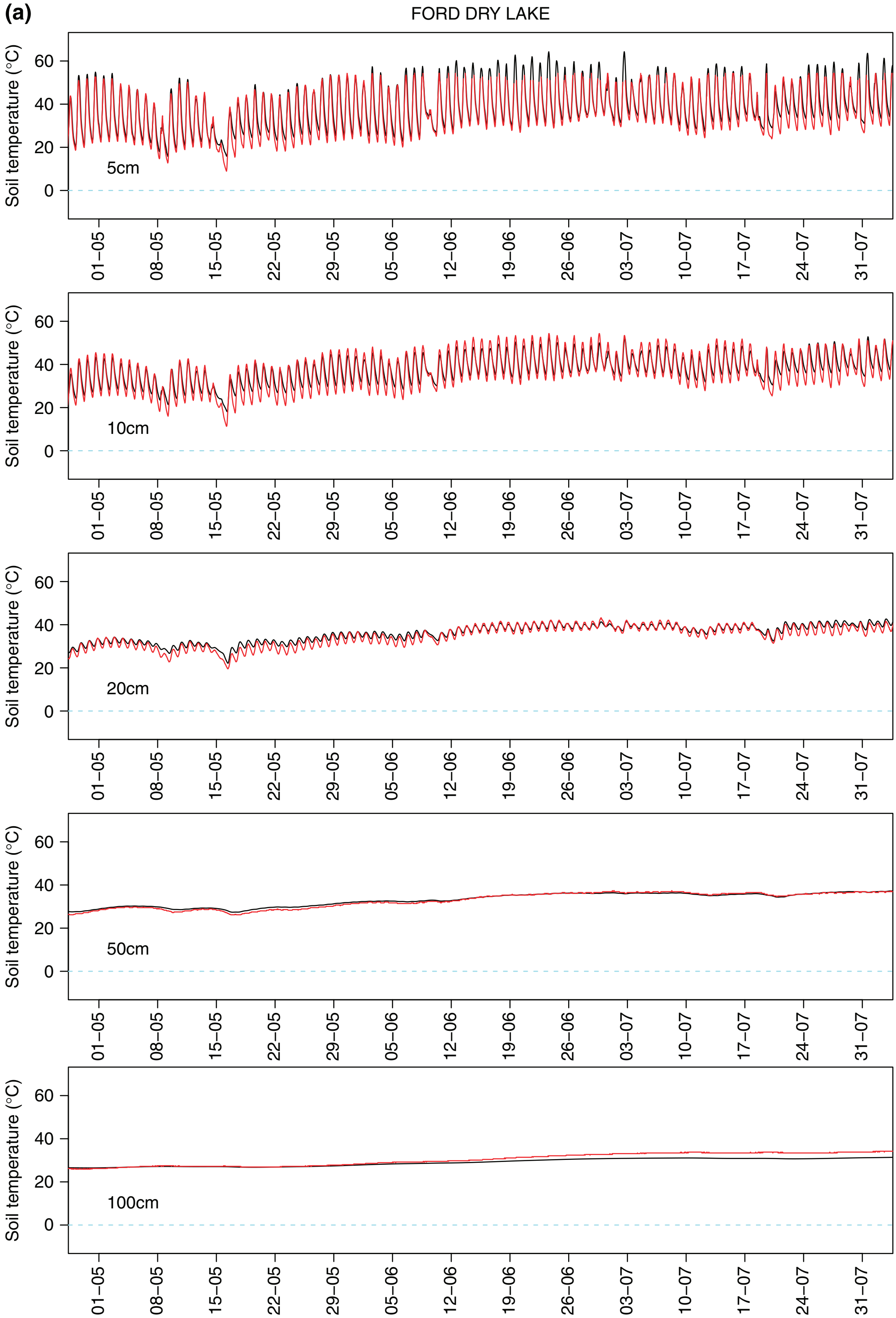

Figure 4. Example output from the microclimate model for May to July in Ford Dry Lake, California USA when driven by hourly input data from the Soil and Climate Network (SCAN) database. The figure shows observed (red) and predicted (black) soil temperature (a) and moisture (b) for 5, 10, 20, 50 and 100 cm below ground.

will vary depending on whether the soil moisture or snow options are invoked, with very moist soil conditions leading to longer calculations (see discussion in Campbell (1985), p. 87 on the use of matrix potential as a dependent variable, as implemented here, vs matrix flux potential). It may be necessary to adjust the integrator error parameter

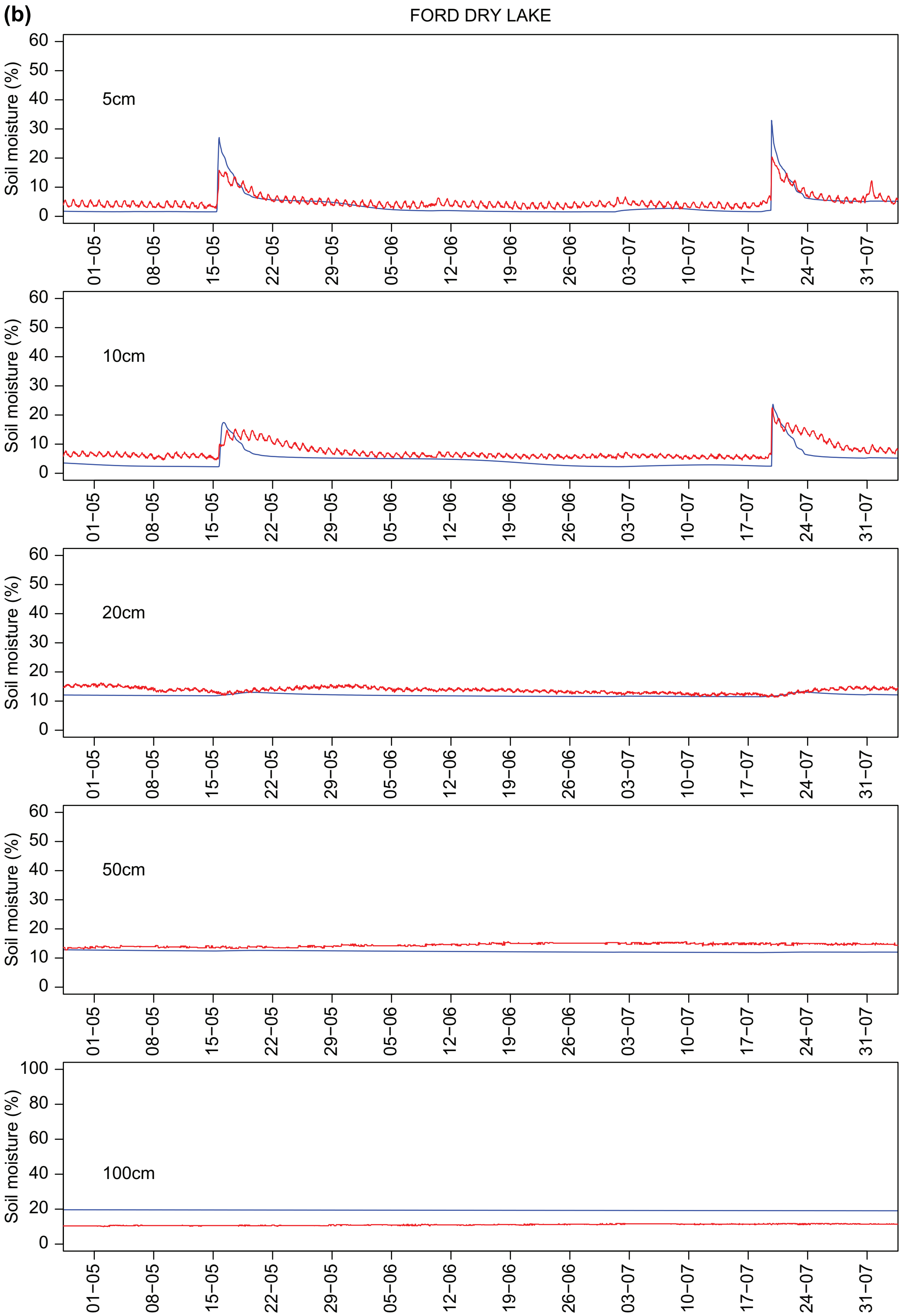

Figure 4. Continued.

'ERR' in some cases for successful solutions to be found. The Ford Dry Lake simulation of 365 d just illustrated took 8.7 s on a 2.8 GHz Intel® Core™ i7-4900Q CPU.

Online resources

The NicheMapR R package source is currently available at <https://github.com/mrke/NicheMapR>, with the current release at <https://github.com/mrke/NicheMapR/releases>.

To cite NicheMapR or acknowledge its use, cite this Software note as follows, substituting the version of the application that you used for 'version 0':

Kearney, M. R. and Porter, W. P. 2016. NicheMapR – an R package for biophysical modelling: the microclimate model. – Ecography 40: 664–674 (ver. 0).

Acknowledgements – This research was supported by an Australian Research Fellowship (MRK) from the Australian Research Council, DP110102813. Statement of authorship: MRK designed and wrote the R software, WPP and MRK designed and wrote the Fortran software, MRK and WPP wrote the ms.

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Supplementary material (Appendix ECOG-02360 at <www.ecography.org/appendix/ecog-02360>). Appendix 1–4.