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The easyclimate R package: Easy access to high-resolution daily climate data for Europe

Verónica Cruz-Alonso [a,b,*,1], Christoph Pucher [c,1], Sophia Ratcliffe [d], Paloma Ruiz-Benito [b,e], Julen Astigarraga [b], Mathias Neumann [c], Hubert Hasenauer [c], Francisco Rodríguez-Sánchez [f,g]

[a] Department of Landscape Architecture, Graduate School of Design, Harvard University, USA
[b] Universidad de Alcalá, Grupo de Ecología Forestal y Restauración (FORECO), Departamento de Ciencias de la Vida, Spain
[c] Institute of Silviculture, Department of Forest and Soil Sciences, University of Natural Resources and Life Sciences, Austria
[d] National Biodiversity Network Trust (NBN Trust), Nottingham, UK
[e] Universidad de Alcalá, Grupo de Investigación en Teledetección Ambiental (GITA), Spain
[f] Departamento de Biología Vegetal y Ecología, Universidad de Sevilla, Spain
[g] Estación Biológica de Doñana, Consejo Superior de Investigaciones Científicas, Spain

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ABSTRACT

In recent decades there has been an increasing demand in environmental sciences for harmonized climatic data at large spatial scales and long periods. Here we present *easyclimate*, a software package to obtain daily climatic data at high resolution (0.0083°, ~1 km) with R. The package facilitates the downloading and processing of precipitation, minimum and maximum temperatures for Europe from 1950 to 2020. Using *easyclimate* and given a set of coordinates (points or polygons) and dates (days or years), the user can download the climatic information as a tidy table or a raster object. In this package we implemented Cloud-Optimized GeoTIFFs which provide access to daily climate data for thousands of sites/days, without having to download huge rasters. Daily climate data are not available in many of the current climate databases and are essential for many research questions and applications in environmental modelling, forestry, and ecological and vegetation studies across Europe.

1. Introduction

In recent decades there has been an increasing demand for harmonized daily gridded climatic data at wide spatial scales and spanning long temporal periods. Such data is invaluable for vegetation, wildlife, climatic and hydrological studies and Earth system modelling (Hasenauer et al., 2003; Thornton et al., 2021). Examples are the assessment of climate effects and climate change impacts on European forests (Archambeau et al., 2020; George et al., 2021; Hlásny et al., 2017; Moreno et al., 2018; Neumann et al., 2017; Ruiz-Benito et al., 2020), the initialization of large-scale carbon cycle models (Pietsch and Hasenauer, 2006), the spatial-temporal variability of rainfall erosivity (Micić Ponjiger et al., 2021) or the creation of a European net primary production dataset (Neumann et al., 2016).

Plant distribution as well as plant growth, phenology, respiration and plant mortality are strongly driven by weather conditions (e.g. Kunstler et al., 2021). Any aggregation of climate data to average monthly or annual numbers may hide important climate effects on plants, specifically if we expect changing environmental conditions. In this sense, daily climate data are of interest for many ecological research questions and applications, including the study of the effects of late-spring frosts (Zohner et al., 2020), heat waves or dry periods on plant performance (Cruz-Alonso et al., 2020). However, accessing and processing such daily climate data is often cumbersome (Cáceres et al., 2018), even more if harmonized data are required at large spatial scales, and instead researchers use monthly or annually averaged climate data.

Here we present *easyclimate* (Cruz-Alonso et al., 2021), a software package (available from GitHub: https://github.com/VeruGHub/easyclimate) to download and process climate data with R (R Core Team, 2022). *Easyclimate* has been developed to facilitate the use of high-resolution (0.0083° × 0.0083°, ~1 km^2) daily climate data for Europe (24.5°W, 45.25°E, 25.25°N, 75.5°N; Fig. 1). Daily precipitation

* Corresponding author. Department of Landscape Architecture, Graduate School of Design, Harvard University, Cambridge, MA, USA.
E-mail address: veronica.cral@gmail.com (V. Cruz-Alonso).
[1] These authors share the first-author position.

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and minimum and maximum temperature data are currently available from 1950 to 2020 and hosted at University of Natural Resources and Life Sciences, Vienna, Austria.

The climatic dataset was originally produced by Moreno and Hasenauer (2016). For the production, the coarse daily E-Obs climate data (Cornes et al., 2018) was downscaled by using the finer-resolution WorldClim data (Fick and Hijmans, 2017). E-Obs provides gridded daily climate data for Europe at 0.25° resolution (approximately 30 km) by interpolating around 3700 weather stations for temperature and around 9000 stations for precipitation, and WorldClim provides global long-term monthly averages of several climatic variables at 0.0083° resolution (approximately 1 km).

Downscaling was performed by applying a spatial delta method with a monotone cubic interpolation of anomalies (Moreno and Hasenauer, 2016; Mosier et al., 2014). The delta method combines climate data sets with differing spatio-temporal resolutions to produce a new climate data set with a desired spatio-temporal resolution (Moreno and Hasenauer, 2016). The downscaling involves several steps (Fig. 2): (i) the WorldClim data is upscaled to the 0.25° E-OBS resolution, (ii) the difference between this upscaled WorldClim and the E-OBS cell is calculated, (iii) for each 0.0083° cell in the original WorldClim data its value is retrieved and the corresponding location is marked in the difference cell, (iv) the weighted difference between the selected 0.25° cell and its closest three adjacent cells is calculated, (v) the final downscaled value is calculated using the original WorldClim value retrieved earlier and the summed inverse distance-weighted difference value (Moreno and Hasenauer, 2016). The calculation of the downscaled value in the last step varies depending on whether temperature or precipitation are downscaled; see Moreno and Hasenauer (2016) for a more detailed description of the downscaling procedure.

Evaluation and validation of the downscaled climate data were performed by comparing weather station data used for the original E-OBS data, the E-OBS data, and the downscaled data. The comparison was performed by calculating the mean, minimum and maximum values for all three data sets and error metrics for the E-OBS and downscaled data (Moreno and Hasenauer, 2016). Additionally, validation of the E-OBS and downscaled data was performed using the same statistics but with independent data from 430 Austrian weather stations which were not used to create the original E-OBS data. The validation showed that for these points the downscaling improved the accuracy of the climatic variables compared to the original E-OBS data (Moreno and Hasenauer, 2016).

Since its original release, the downscaled climate data set has been further developed and updated, and two releases (v2 and v3) have been published (for a review of the main changes see Rammer et al. (2022) and Pucher and Neumann (2022)). The *easyclimate* R package enables easy and fast access to the latest version of the downscaled climate data (v3). We achieved this by exploiting GDAL (GDAL/OGR contributors, 2022) support for Cloud-Optimized GeoTIFFs (https://www.cogeo.org) which provide access to daily climate data for thousands of sites and days within minutes, without having to download huge rasters.

2. Functionality

The main function in *easyclimate* is *get_daily_climate*, which extracts daily climate data for a given set of coordinates (points or polygons) and a given period of days or years (see examples in *get_daily_climate* help page, and the vignettes Analysing the climate at spatial points for a given period and Analysing the climate of an area for a given period). The output can be either a data. frame or a (multilayer) SpatRaster object (Terra class; Hijmans, 2022) with daily climatic values for each point or polygon.

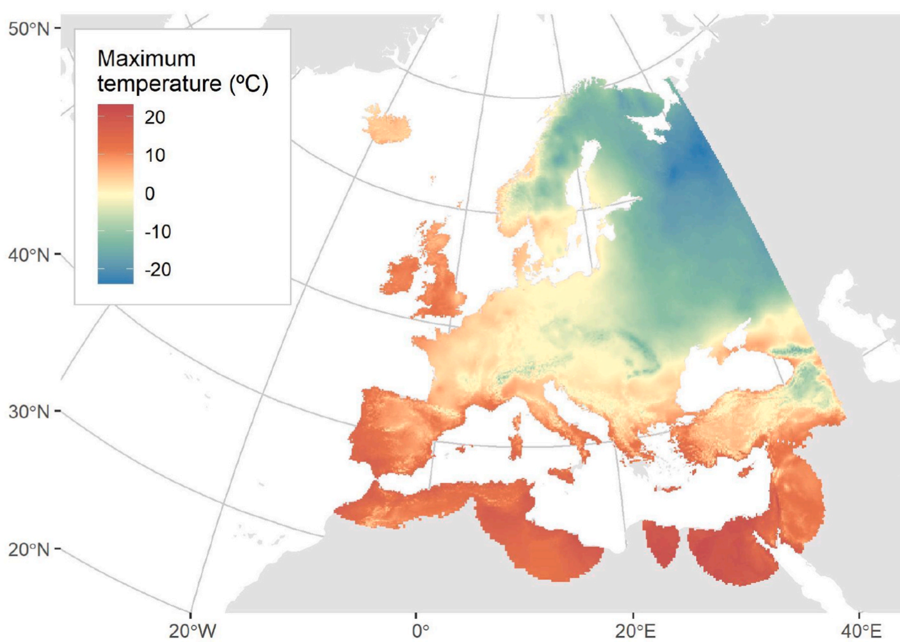

Fig. 1. Example raster of daily maximum temperature (°C) from January 1st 1950 to show the spatial coverage of the downscaled climate data.

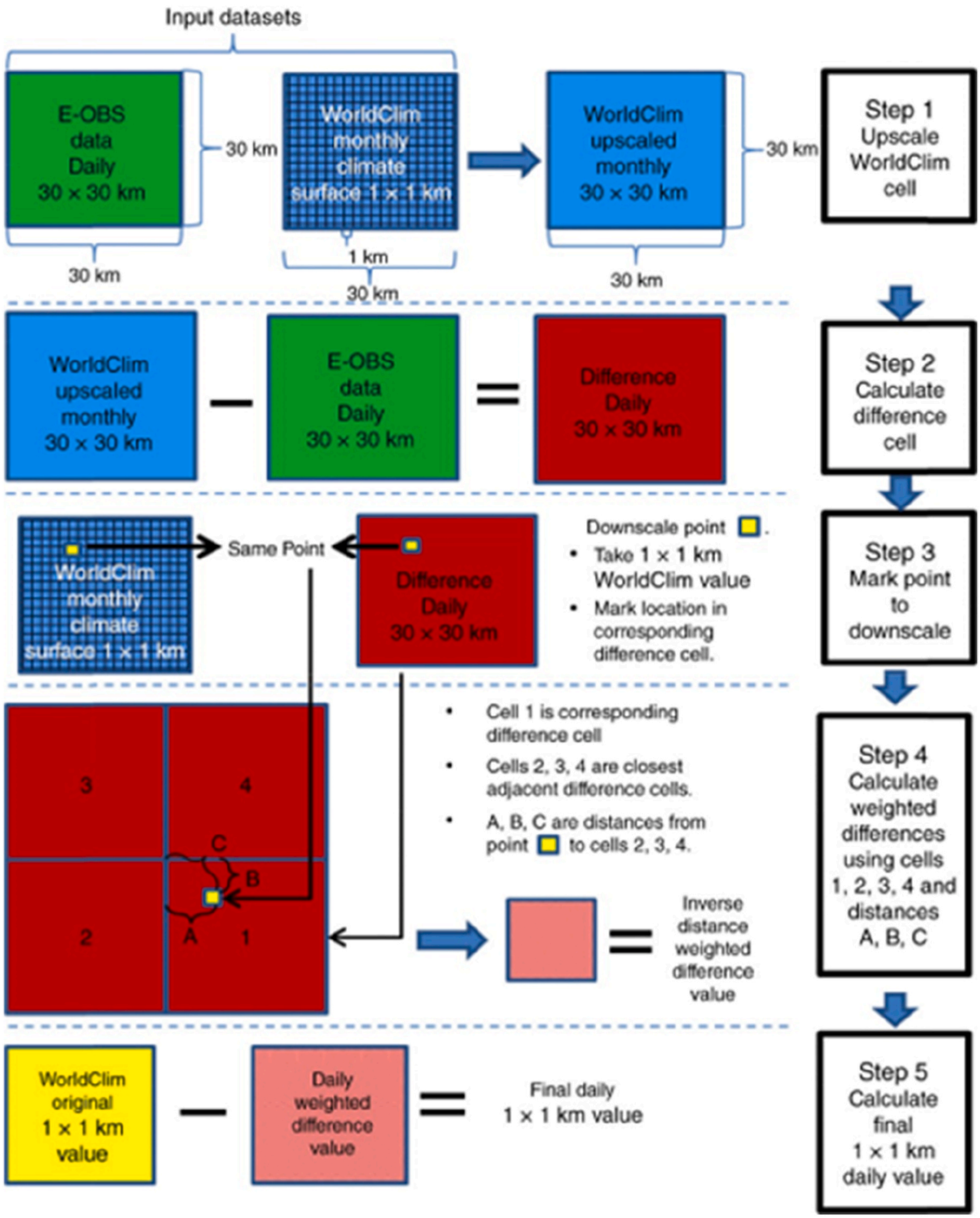

Fig. 2. Flow diagram explaining the delta downscaling algorithm. Reprinted from Moreno and Hasenauer (2016).

Table 1
Daily precipitation (Prcp; mm) for a given site obtained with easyclimate. Longitude (lon, x) and latitude (lat, y; WGS84) and date (YYYY-MM-DD) are shown.

lon	lat	date	Prcp
−5.36	37.4	2001-01-01	8.64
−5.36	37.4	2001-01-02	0.00
−5.36	37.4	2001-01-03	2.93

As an API (Application Programming Interface), by design, *easyclimate* yields tidy datasets (Wickham, 2014) that facilitate calculation of alternative climatic variables and indices following the tidyverse philosophy (Wickham et al., 2019). Also, the results of the package *easyclimate* can be used directly or serve as input to calculate climatic indices with other packages, such as ClimInd (Reig-Gracia et al., 2021) or SPEI (Beguería and Vicente-Serrano, 2017) (see some examples in the vignette Calculating basic climatic indices with data from easyclimate). Furthermore, *easyclimate* might be integrated in other software providing environmental variables (e.g. geodata; Hijmans et al., 2021).

3. Case studies

Two case studies have been selected to demonstrate the core utilities of *easyclimate* and visualize the two types of data outputs (i.e. data. frame and SpatRaster objects). In addition, we show a third case where climatic variables are easily calculated based on those outputs.

3.1. Getting tidy datasets of climatic values

Get_daily_climate is called to obtain precipitation data for a single site between 1st and 3rd of January 2001 (Table 1).

```
library(easyclimate)

coords <- data.frame(lon = -5.36, lat = 37.40)

precip <- get_daily_climate(coords,
                            period = "2001-01-01:2001-01-03",
                            climatic_var = "Prcp")
```

3.2. Getting rasters of climatic values

Get_daily_climate is called to obtain a multilayer raster with values of minimum temperature since May 1st 2020 to May 10th 2020 for a region (Tirol, Austria) delimited by a polygon (Fig. 3).

```
coords.poly <- terra::subset(geodata::gadm("Austria", level = 1, path =
tempdir()), NAME_1 == "Tirol", NSE = TRUE)

ras_tmax <- get_daily_climate(coords.poly, period = c("2020-05-01:2020-05-
10"), climatic_var = "Tmin", output = "raster")
```

3.3. Calculations based on easyclimate data

In the next example we download daily climatic data (precipitation, minimum and maximum temperature) for a five-year period for a specific location and we store the data in a data. frame. Then we calculate the mean temperature as the average between minimum and maximum temperature.

```
library(dplyr)

coords <- tibble(lon = -4.88, lat = 40.82)

daily_output <- get_daily_climate(coords, period = 2010:2015, climatic_var
= c("Prcp", "Tmin", "Tmax"))

daily <- daily_output |>
    mutate(Tmean = (Tmin + Tmax)/2)
```

To calculate average temperatures and aggregated precipitation by site or time period (Table 2), we can use group_by and summarise from dplyr, or by and aggregate from base R.

```
yearclimate <- daily |>
  mutate(year = lubridate::year(date)) |>
  group_by(year) |>
  summarise(Tmin.year = mean(Tmin),
            Tmean.year = mean(Tmean),
            Tmax.year = mean(Tmax),
            Prcp.year = sum(Prcp))
```

4. Discussion

Although the entire downscaled climatic data is available for downloading as GeoTIFF raster layers in a public FTP server (ftp://palantir.boku.ac.at/Public/ClimateData/), for small to moderately-sized areas (e.g. less than 10,000 sites or 10,000 km^2), the Cloud-Optimized GeoTIFF technology implemented in *easyclimate* allows to efficiently extract the data and saves significant time. Furthermore, with *easyclimate* we avoid downloading large rasters (several GB for each year) requiring storage space on local or remote servers, energy and resources (Hilty and Aebischer, 2015; Hischier et al., 2015). In this sense, *easyclimate* becomes even more efficient if we are interested in climate data for multiple years and a small number of sites. For querying climate data from large areas, it is recommended to download the raster layers and extract the data to local storage (e.g. using the extract function from terra R package; Hijmans, 2022), to avoid overloading the FTP server.

As a test comparing the two methodologies (i.e. using *easyclimate* vs. raster downloading and local extraction), we downloaded daily precipitation data for one year in an area of *ca.* 100 km^2. While the local download and extraction took 9–10 min in a laptop with good internet connection (>10 MB/s; Cooper, 2022) and stored ∼5960 Mb, *easyclimate* took ∼17 s to obtain the same data storing only the final dataset (2.3 Mb).

5. Summary and conclusions

This paper presents the R package *easyclimate* which facilitates access to high-resolution daily temperature and precipitation data for Europe for the period 1950 to 2020. The package enables downloading two types of data outputs (i.e. tidy tables and rasters). This climatic information is available by direct download from a FTP server, but the use of *easyclimate* can save time of downloading, processing and storage resources.

```r
library(terra)

# Method 1: Raster downloading and local data extraction

coords.poly <- terra::vect(sf::st_polygon(list(matrix(c(-5.039, 40.913, -
4.919, 40.913, -4.919, 40.825, -5.039, 40.825, -5.039, 40.913), ncol = 2,
byrow = TRUE))))

raster.url <-
"ftp://palantir.boku.ac.at/Public/ClimateData/v3/AllDataRasters/prec/Downs
caledPrcp2010.tif"

options(timeout = max(10000, getOption("timeout")))

system.time({
    download.file(raster.url, destfile = "prcp2010.tif", mode = "wb")
    prcp2010.ras <- terra::rast("prcp2010.tif")
    prcp2010.data <- terra::extract(prcp2010.ras, coords.poly, xy = TRUE)
})
```

```
   user  system elapsed
   3.86   16.38  541.56
```

```r
# Method 2: Obtain the same data using easyclimate

system.time(
   prcp2010.data_2 <- get_daily_climate(
     coords.poly,
     period = 2010,
     climatic_var = "Prcp"
   )
 )

   user  system elapsed
   2.14    2.76   17.21
```

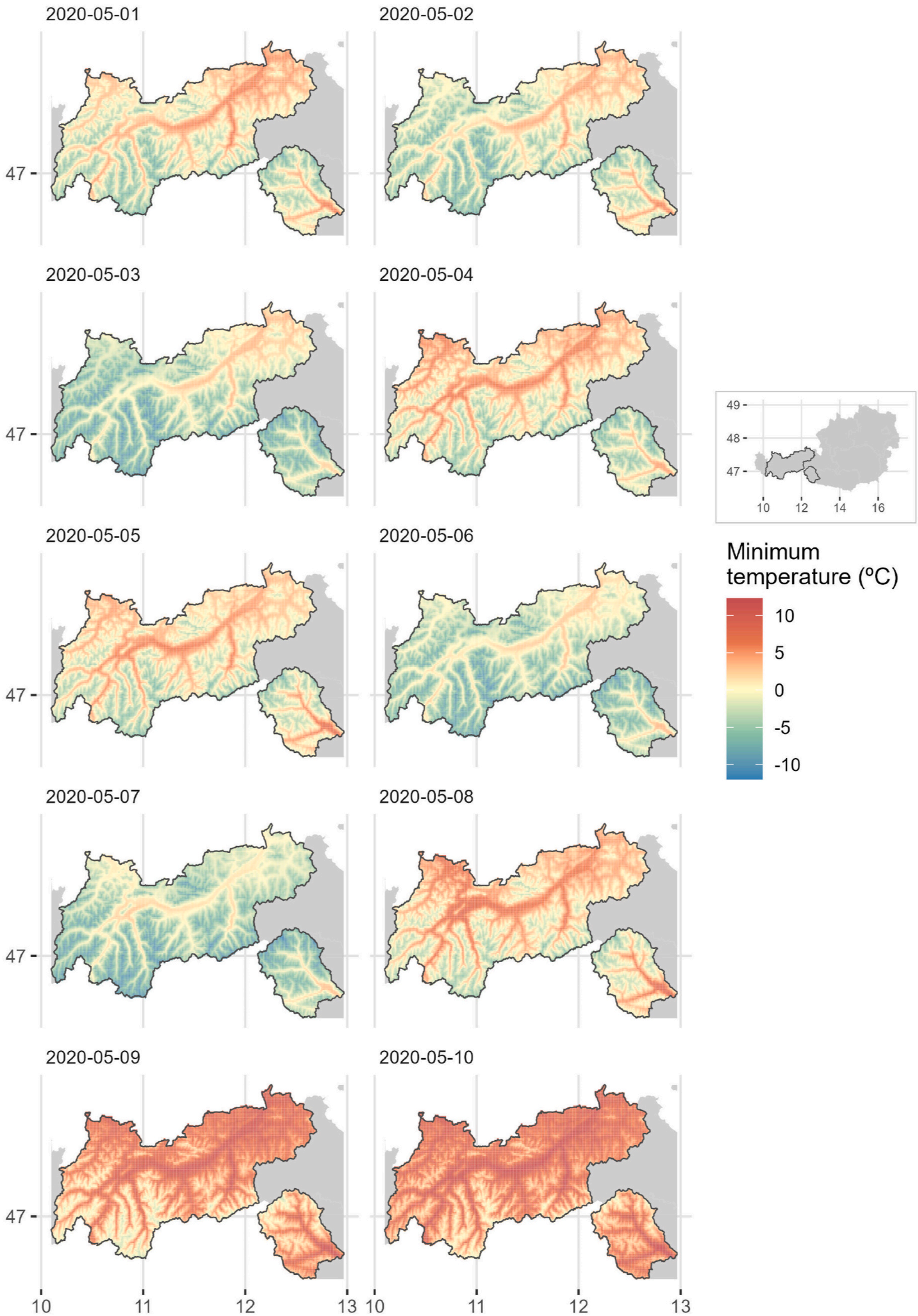

Fig. 3. A multilayer raster of minimum temperature values for a given polygon in ten different days of the year.

Table 2
Yearly climatic values for a given site extracted with easyclimate. Tmin.year = Minimum temperature (°C), Tmean.year = Mean temperature (°C), Tmax.year = Maximum temperature (°C), Prcp.year = Precipitation (mm).

year	Tmin.year	Tmean.year	Tmax.year	Prcp.year
2010	6.2	12.2	18.2	385.3
2011	6.9	13.3	19.7	281.9
2012	5.7	12.1	18.6	314.8
2013	5.7	11.8	18.0	354.9
2014	6.9	13.0	19.1	341.5
2015	6.7	13.3	19.8	221.3

Author contributions

Conceptualization: V.C.-A., P.R.-B., and F.R.-S. **Data curation:** C.P. and M.N. **Formal analysis:** V.C.-A. and F.R.-S. Funding **acquisition:** M. N. and H.H. **Investigation:** C.P. and M.N. **Methodology:** V.C.-A., S.R., P.R.-B., J.A., and F.R.-S. **Project administration:** V.C.-A. **Resources:** C. P., M.N., and H.H. **Software:** V.C.-A., S.R., and F.R.-S. **Supervision:** V. C.-A., P.R.-B., and F.R.-S. **Validation:** V.C.-A., P.R.-B., J.A., and F.R.-S. **Visualization:** V.C.-A., P.R.-B., and J.A. **Writing - original draft:** V. C.-A. and F.R.-S. **Writing - review & editing:** V.C.-A., C.P., S.R., P.R.-B., J.A., M.N., H.H., and F.R.-S.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and scripts are publicly available

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