climenv: download, extract and visualise climatic and elevation data

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Abstract

Understanding the relationship between climate and vegetation requires climate data to be linked with ecological data, including habitat types and vegetation mapping. Our new R package `climenv` allows researchers to efficiently acquire, extract, and visualise datasets that are commonly used by researchers to quantify the climatic envelope of vegetation. `climenv` offers integrated downloading and processing capabilities for three globally recognised data sets, including WorldClim 2, CHELSA, and NASA's SRTM elevation data. The package allows users to easily download and extract these data sets for single and multi-geospatial polygon and point datasets, facilitating studies that explore the relationship between vegetation and climate. Furthermore, `climenv` allows users to plot traditional Holdridge Life Zone classification, Walter-Lieth climate diagrams, and new customised plots, which combines aspects of both these systems with other biologically relevant climate variables. By enhancing the usability and flexibility of these datasets, `climenv` helps to explore the intricacies of the relationships between climate and vegetation. Our package is accessible from CRAN (https://CRAN.R-project.org/package=climenv) or GitHub (https://github.com/jamestsakalos/climenv).

Keywords

CHELSA; Climate data; Climate diagram; Holdridge Life Zones; R package; WorldClim

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Introduction

Understanding the intricate relationship between climate and vegetation is crucial for predicting the impact of future climate patterns, safeguarding biodiversity, and informing policy and decision-making for our planet's future (Cavender-Bares, Gamon, & Townsend 2020). Building upon centuries of research that initially linked specific vegetation types with climatic zones, altitude, and latitude, modern studies heavily rely on historical data analysis to explore this crucial relationship. However, the diverse nature of climate data, with variations in sources, formats, and resolutions, poses significant challenges for selecting, integrating, and quantifying the climate-vegetation relationship (e.g., Nash et al., 2021; Reig-Gracia et al., 2021).

To the challenges of working with climate data, researchers face a series of decisions, encompassing the selection of data sources, software for downloading, extracting, analysing, and graphically illustrating the trends. Even in a simplified case where there are only two choices for each step of selecting, downloading, and extracting, eight potential pathways emerge (i.e., 2 × 2 × 2). The landscape of climatic data sources is extensive, including options like WorldClim (Fick & Hijmans, 2017) and climatologies at high resolution for the earth's land surface areas (i.e., CHELSA, Karger et al. 2017). Researchers have many software options to choose from for downloading data, such as Google Earth Engine, web browsers and Python scripts. Extraction of climate data for a specific coordinate or over the extent of an area can be accomplished using tools like ESRI's ArcMap, Quantum Geographic Information System or the R environment for statistical computing and graphics (R Core Team, 2023). The combination of these options results in 18 (i.e., 2 × 3 × 3) pathways. This underscores the urgent need to enhance open science through the development of a simple and clear workflow that unifies these processes, producing more precise and reliable analyses with meaningful ecological interpretations.

The current landscape of R packages on the CRAN repository includes approximately 19,000 packages, of which 126 are related to climate data. However, there is a pressing need for a comprehensive and user-friendly package that seamlessly manages the selection, download, extraction, and preparation of climate data for diverse terrestrial areas or specific sampling points. While existing packages are used by scientists in various research fields such as agriculture (Brown, de Sousa & van Etten, 2023) and forestry (Reyer et al., 2020), they often provide specialised solutions focused on specific regions or limited spatial resolutions, lacking a unified and user-friendly workflow. This gap in the current landscape of R packages has motivated the development of our `climenv` R package, short for 'climatic envelope.'

Our new `climenv` R package, hosted by the CRAN and GitHub repositories, serves as a unified solution, providing tools and illustrative examples to streamline the download, extraction, processing, and preparation of climatic variables. What sets `climenv` apart is its enhanced adaptability and versatility through geospatial data extraction capabilities. Preliminary versions of the package have played a pivotal role in identifying biomes across Europe (Mucina, Divíšek & Tsakalos, 2023), Southern Africa (Mucina et al., 2022), South America (Luebert 2021) and the Southern Hemisphere (Mucina, 2023). By providing user-friendly vignettes and powerful functionalities, our package aims to empower ecologists engaged in descriptive vegetation science (e.g., Preislerová et al., 2022; Wiser et al., 2022), equipping researchers with the necessary tools to overcome the challenges of working with climate data and fostering accurate analysis and meaningful ecological interpretations.

Software description

`climenv` provides functions to download (`ce_download`), extract (`ce_extract`), and plot (`plot_h, plot_wl and plot_ce`) climatic envelopes in areas defined by geospatial multi-point or multi-polygon data sets. `ce_download` sources WorldClim 2 (Fick & Hijmans, 2017) or CHELSA (Karger et al., 2017, 2021) climatic data. Because of the close relationship between temperature and altitude (i.e., 0.6–1 °C per 100 m), our package also includes access to digital elevation data NASA Earth Explorer's SRTM (Farr et al., 2007) or Mapzen terrain tiles (Hollister & Shah, 2018). `ce_extract` extracts point intersects or average surface values (i.e., polygons) of the downloaded data (i.e., monthly-minimum, -maximum and -average temperature and -average precipitation, and elevation). `plot_h`, `plot_wl`, and `plot_c` presents this data in Holdridge, Walter-Lieth, and custom plotting formats.

The main functions provided by the package are as follows:

1. `ce_download(output_dir, location, c_source, e_source)` downloads climatic and elevation data into the output directory (`output_dir`). The user must supply a geospatial point or polygon `location` file to define the download extent. Users can control the climatic source (`c_source`) by supplying `"WorldClim"` or `"CHELSA"` and can control the elevation source (`e_source`) using `"SRTM"` or `"Mapzen"`.
2. `ce_extract(output_dir, location, location_g)` extracts the climate and elevation data stored in the output directory for the supplied `location`. The data can be extracted for every object in the location file, or the data can be grouped (`location_g`) by shared attributes.
3. `plot_c(data, geo_id, …)` is a function that produces our new custom climatic envelopes. The extracted data can be plotted for different geographic features (`geo_id`) contained in the data. Plotting functions `plot_h`, `plot_wl`, for Holdridge and Walter-Lieth diagrams, follow the same syntax.

`climenv` presents three additional functions, including `chelsa()`, `worldclim()` and `elev()`. These functions allow climate and elevation data to be downloaded separately. For example, a user who requires only elevation data, may use `elev()`. The package manual, which is available upon sourcing our package from CRAN or GitHub provides details on the usage of all the functions within the package. Furthermore, we have developed an online resource that provides a package description, installation instructions, references to all functions, and an article explaining how to use the package, all accessible through a standard web browser.

Illustrative examples

The subsequent section illustrates the main functions of `climenv`, demonstrating the download, extraction and visualisation of climate and elevation data from the Italian Biome polygon data set (“`it_py`”) included with the package. This geospatial data set, capturing the Mediterranean and Nemoral Biomes of Italy (Mucina, Divíšek & Tsakalos, 2023), demonstrates the package's functionality to extract biologically meaningful information across extensive mapped regions. The package is also effective when working at finer scales or with geospatial point data.

Step 1. Downloading climate and elevation data

`ce_download` downloads both climate and elevation data. A user may select climate data from either WorldClim 2 (Fick & Hijmans, 2017) or CHELSA (Karger et al., 2017, 2021). For elevation, a user can select either the NASA Earth Explorer's SRTM (Farr et al., 2007) or Mapzen terrain tiles (Hollister & Shah, 2018).

CHELSA and WorldClim are available at a spatial resolution of 30 arc-seconds (~1 km^2). The data are provided freely as a series of raster tiles (one for each month), with their spatial extent spanning the globe. Specifically, the function downloads the mean, minimum, and maximum temperature and mean precipitation using the climatic predictions for 1979–2013 (CHELSA) and 1970–2000 (WorldClim 2). The approximate download size of CHELSA is ~ 6.5 GB. As for the WorldClim data, if you wish to download it for the entire globe, it will be ~ 13.5 GB. However, in the case of this specific dataset, we offer the option to download smaller, tiled sections to save space and time. It is important to note that due to the substantial file sizes involved, the execution of the function may require a significant amount of time, especially if you have limited internet connectivity.

The `ce_download` function conveniently integrates the `elevation_3s` function from the `geodata` R package (Hijmans et al., 2023), allowing easy access to NASA's SRTM data. Our function streamlines the process by automatically downloading and merging high-resolution (~90 m) tiles across latitudes from -60° to 60° into a single raster scene. Furthermore, `ce_download` also incorporates the `get_elev_raster` function from the `elevatr` R package (Hollister & Shah, 2018) to access the Mapzen terrain tiles. In this case, our function enables the download of a single tile at a resolution of ~611.5 m at 60° latitude, ~864.8 m at 45° latitude, and 1223 m at 0° latitude. It is important to note that Mapzen tiles, a synthesis product, encompass NASA's SRTM, ArcticDEM and EUDEM (a digital elevation model covering Europe; Mouratidis & Ampatzidis, 2019). This expanded coverage allows the Mapzen tiles to span larger global areas, including regions north of 60° latitude.

```
library(climenv)
data(“it_py”)
ce_download(output_dir=“../training”, location=it_py)
```

Step 2. Extracting the zonal statistics for each climatic variable

After downloading climate and elevation data, the next step is to use `ce_extract` to extract the climatic data using the `italy_py` geospatial data set. This function reads the downloaded data as raster stacks and then crops and masks the data according to features from the geospatial data set. For example, the code below extracts data for all features in the “`location_g`” argument.

```
data <- ce_extract(
     path = "../training",
     location = it_py,
     location_g = "GB"
)
```

The `ce_extract` function returns an object of class list with a length of 12. Out of these, 11 objects are data frames, while the last object is a compilation note. Among the data frames, eight contain climate data, providing information on the mean and standard deviation of variables such as tmax, tmean, tmin, and prec. Each column within these data frames represents a month (Jan-Dec), while each row represents a geospatial polygon feature (i.e., Mediterranean or Nemoral Biome). The returned values are either degrees Celsius for (tmax, tmean, tmin) or mm (prec). The remaining three data frames show the elevation (mean and standard deviation), latitude and absolute minimum temperature for each month. Critically, these data sets are amenable to further use by the user, such as covariates in any number of exercises such as ordinations which reveal the potential drivers of the present-day distribution of plant communities (Tsakalos et al., 2018; Bonari et al., 2021), and variables for species distribution modelling (Mateo et al., 2019).

Step 3. Visualising the climatic and elevation data

One of our graphical outputs is the Holdridge (1967) life zone classification plot. Holdridge's life zone classification plot, also known as the Holdridge Life Zone System or Holdridge Bioclimatic Classification System, is based on three main factors that influence the distribution of vegetation globally. By combining temperature, precipitation, and potential evapotranspiration Holdridge's classification plot divides the Earth's surface into distinct life zones or biomes (*sensu* Holdridge). It allows for the identification and characterisation of different biomes, such as tropical rainforests, deserts, grasslands, and tundra, based on their distinct climatic conditions and provides a unified framework for studying vegetation patterns, ecological dynamics, and potential shifts in response to climate change. For example, the Mediterranean Biome across Italy features potential evapotranspiration ratios between 1–2 and mean annual precipitation between 500–1000 mm rendering it within Holdridge's (1967) “Very Dry Forest” life zone (Figure 1). To simplify the visualisation of life zone data, we have implemented the automatic creation of Holdridge plots by the addition of the `plot_h` function which provides a convenient wrapper from within `climenv` for the function `PlotHoldridge` within the `Ternary` R package (Smith 2017), which has been developed to complement `climenv`.

```
plot_h(data, geo_id = "MED")
```

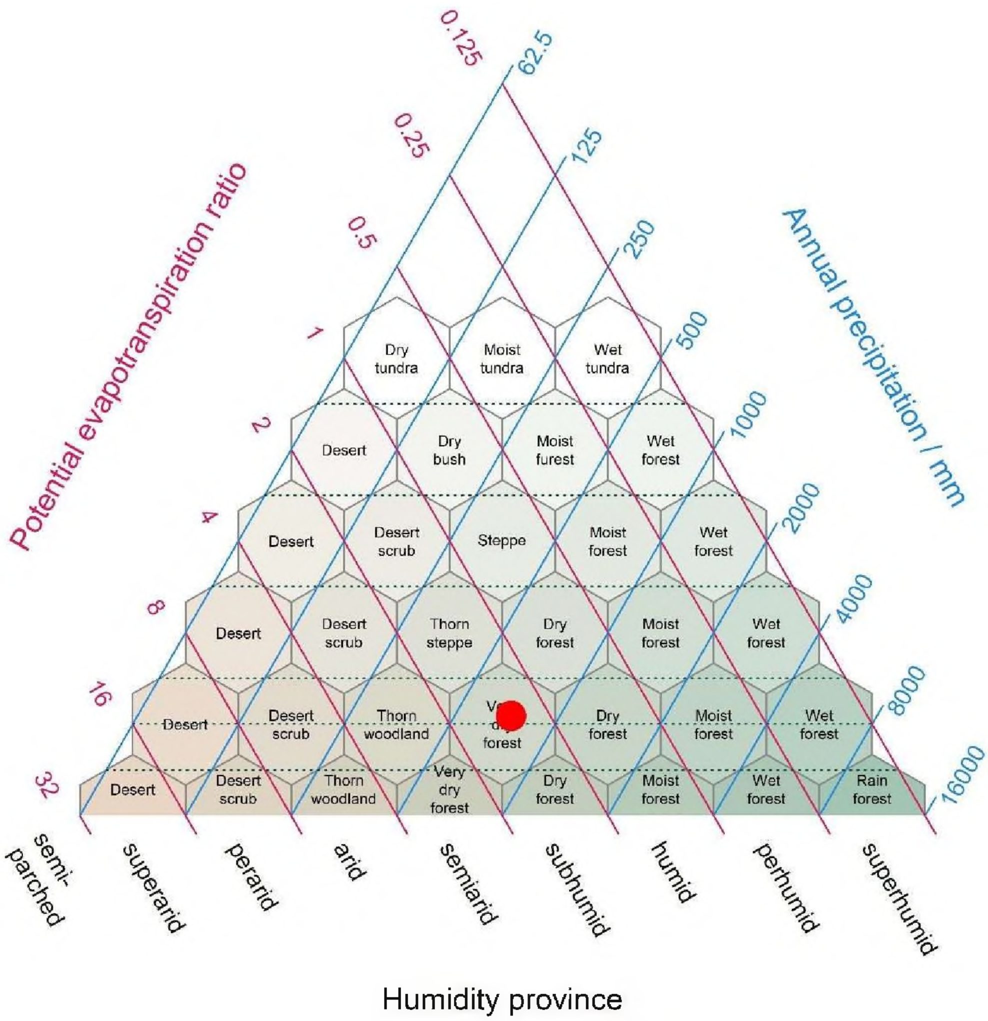

Figure 1 Position of the Mediterranean Biome within the territory of Italy derived using WorldClim climate within Holdridge's (1967) life zone classification. The surface shading in the background is a new addition to the original life zone classification. It helps interpretation by converting a point in evapotranspiration-precipitation space to an appropriate cross-blended hypsometric colour – in this intuitive instance colours tending towards the red spectrum feature higher temperatures blended with lower precipitation while colours leaning towards the blue colour spectrum have lower temperatures and higher precipitation.

Another common graphical output is the Walter-Lieth (1960) climatic diagram. Here our package is a wrapper for the existing `diagwl` function of the `climatol` R package (Guijarro, 2019). This diagram consists of two primary components: temperature and precipitation, which, when combined in a single diagram, is supposed to allow for a comprehensive visualisation of climate patterns. Specifically, it provides insights into seasonal variations, the duration and intensity of wet and dry periods, and the overall climate regime of a particular location (or the average for an area encompassed by a spatial polygon) throughout the year. By analysing the position and shape of the climatic zones represented in the graph, one can identify different climate types, such as mediterranean-type, tropical, temperate, or arid regions. The red-shaded region in Figure 2 clearly depicts the dry summer period, a predominant feature in mediterranean-type climates such as those exhibited by the Mediterranean Biome of Italy (Mucina, Divíšek & Tsakalos, 2023).

```
plot_wl(data, location_g = "MED")
```

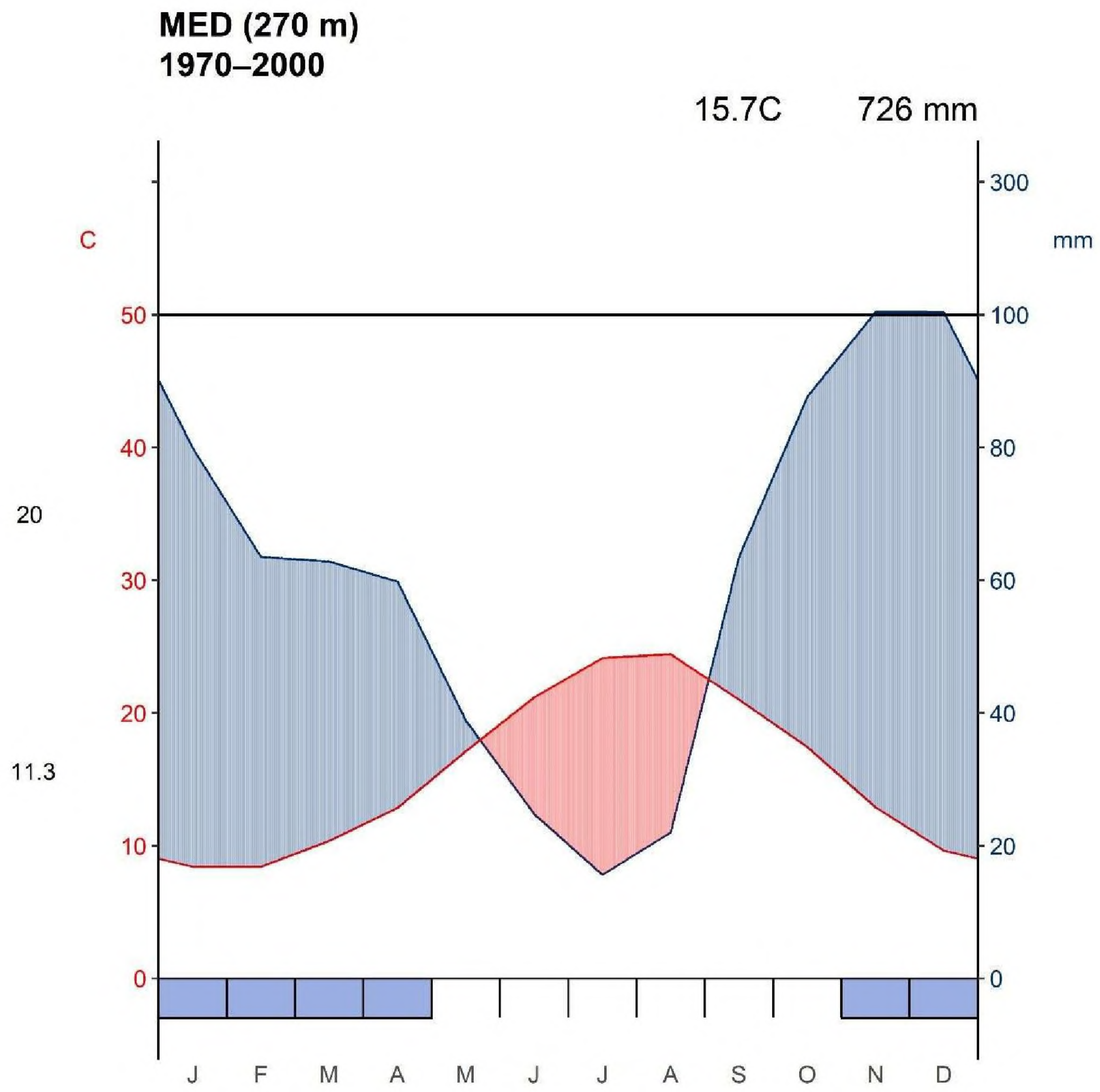

Figure 2 Walter-Lieth climatic diagram (1960) of the Mediterranean Biome within Italy derived using WorldClim. When precipitation is > 100 mm, the scale increases from 2 mm C^{-1} to 20 mm C^{-1} (as indicated by the black horizontal line) to avoid too-high diagrams in very wet locations. A black horizontal line indicates this change, and the graph over is filled in solid blue. When the precipitation graph lies under the temperature graph (P < 2T) we have a dry period (filled in dotted red vertical lines). Otherwise, the period is considered humid (filled in light blue). The daily maximum average temperature of the hottest month and daily minimum average temperature of the coldest month are labelled in black on the left margin of the diagram.

Lastly, we present our custom diagrams which incorporate elements from Holdridge's (1967) life zone classification, Walter-Lieth climatic diagram (1960), and the widely utilised bioclimatic variables (Hijmans et al., 2005) commonly employed in ecological and environmental research. These variables are crucial in describing environmental factors that shape the distribution and behaviour of organisms, including plants, as evidenced by the high citation count of works by Holdridge, Walter-Lieth, and Hijmans. Our diagram offers a unique approach by incorporating these sources and presenting the variables in a tabulated format alongside the classic temperature/precipitation plot. This combination allows for a comprehensive and insightful representation of climatic conditions, distinguishing it from other packages like `climatol` (Guijarro, 2019).

```
plot_c(data, location_g = "MED")
```

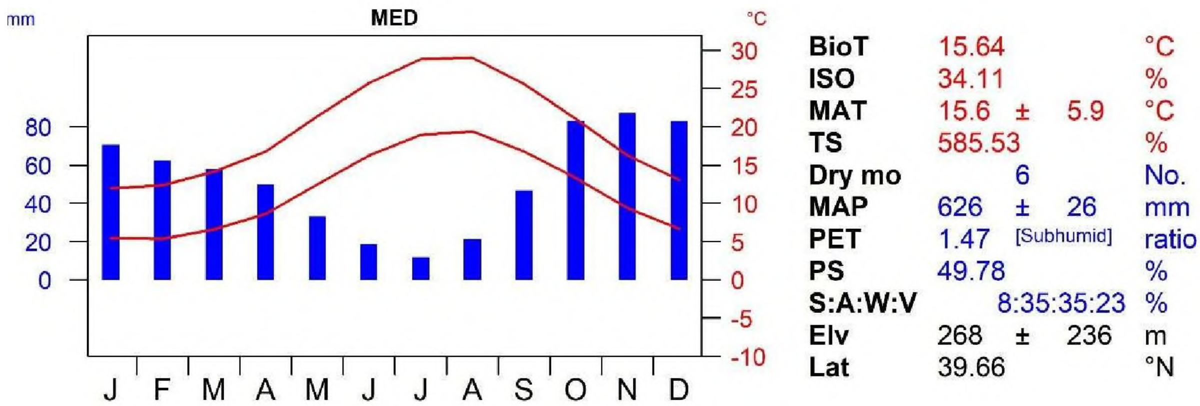

Figure 3 Custom diagram showing the climatic envelope of the Italian Mediterranean Biome. The abbreviations used are as follows: biotemperture (BioT), isothermality (ISO), mean annual temperature (MAT), temperature seasonality (TS), number of dry months with < 50 mm rainfall during the month (Dry mo), mean annual precipitation (MAP), potential evapotranspiration (PET), precipitation seasonality (PS), seasonal rainfall percentage in Summer (S), Autumn (A), Winter (W), Vernal (V), elevation (Elv) and latitude (Lat).

The package includes a vignette that offers an additional two demonstrations. Firstly, it showcases the complete set of functions using fully simulated climate, elevation, and spatial location data sets. This can be helpful for users who are unsure about the specific structure of the required data. Secondly, it explores the properties of the Italian Biome data sets, using the full suite of functions. Furthermore, within this section, a data-driven approach is described. This approach employs the Random Forests machine learning algorithm (Breiman, 2001) to quantify the climatic envelope of the

Biomes of Italy using climatic variables (including Bioclim and Holdridge’s) and elevation variables. Users can also estimate variable importance from the model output of the Random Forest algorithm. This vignette demonstrates how to quantify the 'climatic envelope' empirically and assists users in selecting climatic variables that are closely related to their study sites. Users can access the vignette through the package or can interact with it online (https://jamestsakalos.github.io/climenv/).

Discussion

In this manuscript, we present the new R package `climenv`. We made this package to facilitate easy downloading, extraction, and visualisation of three of the most globally recognised modeled data sets, including: WorldClim 2 (Fick & Hijmans, 2017), CHELSA (Karger et al., 2017, 2021) and NASA's SRTM elevation data (Farr et al., 2007). It allows a user to download and visualise data corresponding to a specific region or points of interest. `climenv` works with multi or single geospatial polygon and point data, and the extracted data outputs can be used, for example, as covariates, for any number of ecological studies. Easy access and extraction of globally recognisable data sets extend this package's usability and flexibility for various applications.

Further considerations should be taken regarding the choice of modeled climatology data (e.g., Maria & Udo, 2017; Morales-Barbero & Vega-Álvarez, 2019). We propose two specific considerations in this regard.

Firstly, it is highly recommended that users conduct their review and inspection of the extracted data, comparing it against local literature sources and climate stations. This ensures the utilisation of the most appropriate modelled climatology for the study regions. Emerging local climatic variables, as observed in Sardinia (Canu et al., 2015), Brazil (Ramoni-Perazzi et al., 2022), and Chile (Pliscoff et al., 2014), often provide improved accuracy due to their comprehensive collection of local weather patterns. Future versions of this package could incorporate access to these higher-quality climate data sources, offering users greater flexibility in data selection.

Secondly, carefully selecting climate and derived variables is crucial for effectively quantifying specific regions or points of interest. To determine suitable climatic variables, various data-driven approaches can be employed. For instance, researchers can use machine learning algorithms such as CART, random forests, boosted regression trees, and others to identify the most appropriate variables that empirically define 'climatic envelopes' robustly and ecologically meaningfully. These methods also offer ways to sift through the numerous potential climatic and derived variables to select the most important ones. In our vignette, we used the Random Forests algorithm on the Italian Biome dataset and a complete set of climatic variables. Through this analysis, we identified the mean temperature of the coldest quarter, minimum temperature of the coldest month, mean annual biotemperature, and precipitation seasonality as essential factors for delineating between the Mediterranean and Nemoral Biomes. By employing these methods, one can make more informed decisions about the choice of climatic variables that play a key role in characterising and distinguishing the climatic envelopes of the various biomes in their study areas.

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In conclusion, the `climenv` R package is a valuable tool for researchers studying climate-vegetation relationships. By providing seamless access, extraction, and visualisation capabilities for globally recognised climate datasets such as WorldClim 2, CHELSA, and NASA's SRTM elevation data, `climenv` enables users to explore the intricate relationship between climate and vegetation efficiently. With specialised plotting functions for generating traditional Holdridge life zone classifications, Walter-Lieth climate diagrams, and custom plots, `climenv` enhances the usability and flexibility of analysing climate data. Overall, `climenv` empowers researchers to gain insights into the complex dynamics between climate and vegetation, contributing to a better understanding of our changing environment.

Author's contribution

LM & JLT conceptualised the package. JLT wrote the manuscript and R package. FL contributed to earlier versions of the R code. MRS produced the Holdridge plotting functions and reviewed the R package. All authors reviewed and approved the definitive version of the manuscript.

Conflicts of interest

None to declare.

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Data availability statement

The data from the illustrative examples is openly available in the R package.

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