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Scientific Data

https://doi.org/10.1038/s41597-026-06834-y

Article in Press

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Received: 24 November 2025

Accepted: 6 February 2026

Cite this article as: Lehner, S., Schlögl, M. Climate indicators for Austria since 1961 at 1 km resolution. *Sci Data* (2026). https://doi.org/10.1038/s41597-026-06834-y

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Climate indicators for Austria since 1961 at 1 km resolution

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Abstract

Climate indicators are essential for monitoring ongoing climate change, supporting climate impact research, conducting spatial hot spot analyses and assessing attribution questions. These efforts rely on high-quality, reliable datasets that adhere to FAIR data principles. We present a curated dataset of 117 climate indicators for Austria, covering the period from 1961 onward at a 1-km spatial resolution. The dataset includes climate indicators related to temperature, precipitation, radiation, snow, runoff and humidity, with spatial (area means) and temporal (climatological reference period means) aggregations to enable rapid climate impact analysis. The workflow used to compute these indices is supported by a careful technical validation procedure and is designed to ingest diverse climate datasets, enabling the creation of climate indices beyond the scope presented here. Both the dataset and the workflow thus offer a robust, flexible and user-friendly resource for advancing climate research and supporting informed decision-making.

Keywords: climate change, climate indicators, climate impact, climate monitoring, regional climate, climate trends

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Background & Summary

Climate change is one of the most pressing issues that affect humanity in the 21st century [1]. Addressing this global issue requires access to high-quality, reliable data to facilitate robust analyses of the climate system, assess emerging impacts, and inform evidence-based decision making [2]. Climate indicators, which distill raw meteorological data into useful impact-oriented metrics, are an important concept to isolate robust and significant signals from the noise of daily and internal climate variability [3]. However, a notable gap persists in the availability of accessible, user-friendly, high-resolution and well-curated climate indicator datasets. To bridge this gap, we introduce a comprehensive and quality-controlled dataset encompassing 117 climate indicators, covering common meteorological variables (temperature, precipitation, radiation, snow, runoff and humidity).

This dataset is intended to serve as a comprehensive catalog of climate indicators across various temporal scales and meteorological parameters, designed to accelerate climate (impact) analyses. Climate indicators are provided for seasonal and annual aggregation periods, as well as temporal averages across two adjacent climatological standard normals covering periods of 30 years each. Following the World Meteorological Organization (WMO) recommendation [4], the reference period 1961–1990 is included in order to provide consistent comparisons with historical analyses, alongside the most recent reference period, 1991–2020, as adopted by the Copernicus Climate Change Service (C3S) [5].

To facilitate rapid assessments across time, we provide spatial averages of all climate indicators, thereby simplifying the analysis of time series trends, shifts in governing patterns and extreme events. The dataset is built upon quality-controlled input data, and all climate indicators undergo thorough technical validation to ensure reliable outputs.

An earlier version of this dataset has already been used in [6] to investigate physioclimatic regions of Austria. In that study, the climate indicators served as a basis for dimensionality reduction and high-dimensional clustering to delineate spatial clusters representing regional physioclimatic characteristics. Future research plans include a spatial hot spot analysis of climate change patterns and a comprehensive correlation analysis of climate indicator signals to identify the most representative indicators to transport information on relevant patterns. These efforts aim to (1) address challenges posed by multicollinearity, particularly in data-driven climate impact research applications that involve statistical and machine learning models, as well as (2) enhance climate science communication.

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Existing climate indicator datasets often have limitations, such as a restricted number of indicators [7, 8], data limited to averages across climatological periods [10], availability only at coarse spatial resolutions [11, 12], or a narrow focus [9]. This dataset seeks to overcome these gaps by providing high-resolution climate indicators that encompass many meteorological variables, multiple temporal aggregation windows, and climatological averages.

We aim to update the data repository annually once all source data are available, ensuring timely integration of the previous year to maintain the practical relevance of this dataset. We further intend to extend the workflow to future datasets, including the next generation of Austrian climate scenarios.

Methods

Input data

All climate indicators are derived from a range of existing datasets that provide comprehensive meteorological and hydrological variables. These datasets include daily records of minimum, average and maximum temperature [13], precipitation totals [14], sunshine duration [15], snow-related variables (snow depth, snowmelt, total snow water equivalent and surface runoff) [16] and drought-related variables (reference evapotranspiration and the derived Standardized Precipitation Evapotranspiration Index, SPEI) [17].

All input data are available at a daily resolution, spanning the time period from 1961–2025. The dataset covers Austria and its surrounding catchments, extending beyond national borders, and is provided in the *ETRS89 / Austria Lambert* projected coordinate system (`EPSG:3416`). These datasets are openly available from the GeoSphere Austria Data Hub [18, 19, 20]. They are derived from quality-controlled input data, primarily observations from automatic weather stations, ensuring their reliability and consistency. For details on the quality of the underlying data, please refer to the original publications and their evaluation sections [13, 14, 15, 16, 17].

The data were primarily used in their original form without additional preprocessing. This streamlined approach ensures compatibility and consistency across all input data sources.

Calculation of climate indicators

The climate indicators are derived following established definitions and guidelines [21, 22, 23, 24] in order to cover a wide range of use cases. Detailed definitions

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for all climate indicators are provided in Appendix A. To ensure transparency and reproducibility, all routines required to replicate the calculation of climate indicators are open source (see the Code Availability section). The Python-based implementation includes boilerplate code for handling data input/output, managing metadata, and performing indicator calculations. These calculations are executed either by wrapping the `xclim` library [24] or through custom-built routines. In some cases, pull requests have been contributed upstream to the main `xclim` repository. The code also supports data aggregation across different dimensions, and all steps in the computation processes are logged for traceability.

The calculation workflow is controlled via a configuration file, which specifies the technical metadata, such as input data paths. A pseudocode representation of the workflow is provided in Algorithm Algorithm 1.

Algorithm 1 Pseudocode for the calculation of a climate indicator

```
Read config
for year ∈ [START_YEAR, END_YEAR] do                ▷ inclusive
    Load data for year
    if threshold required then
        if precomputed threshold exists then
            Load threshold
        else
            Compute threshold
        end if
    end if
    Compute climate indicator
    Set attributes
    Write output files
end for
Run aggregation and evaluation routines
```

The main workflow for calculating climate indicators consists of the following steps:

1. **Load input data:** The appropriate input dataset is loaded based on the specific climate indicator being calculated. For precipitation data, metadata is corrected to accurately represent precipitation as a flux quantity ($\mathrm{kg\,m^{-2}\,day^{-1}}$), addressing inconsistencies in the original input data.
2. **Calculate thresholds (if required):** Some indicators rely on thresholds, which may be constant values or percentiles derived for a specific time period.

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Constant thresholds require no additional computation, while percentile-based thresholds are calculated once and stored separately to optimize computational efficiency. Detailed definitions of all climate indicators are provided in Appendix A.

3. **Calculate climate indicator:** Climate indicators are computed by either wrapping the `xclim` library [24], if the required indicator is implemented, or custom-built routines for indicators not covered by `xclim`.

4. **Set attributes:** Output NetCDF data is stored with metadata attributes to ensure that the results are well-documented and self-descriptive. Metadata is structured in accordance with the CF Metadata Conventions, specifically adhering to CF-1.7 standards.

5. **Write output files:** The calculated climate indicators are saved as NetCDF files, organized by year. Each output file includes comprehensive metadata to facilitate data handling, interpretation and reuse.

6. **Aggregation and evaluation:** The computed climate indicators are aggregated and evaluated. Climatological reference periods are calculated by temporally averaging over 1961–1990 and 1991–2020, respectively, yielding maps of climatological averages. Additionally, a two-tailed Mann-Whitney U test is performed for all climate indicators to assess differences between the two climatological periods at a 95% confidence level, with the resulting p-values stored for further analysis. Furthermore, spatial averages are derived by computing the arithmetic mean across all grid cells, yielding time series for all climate indicators.

This workflow is repeated for all 117 climate indicators.

To ensure reproducibility and efficient workflow management, we leverage `pytask` as a workflow management system [25]. `pytask` creates a directed acyclic graph (DAG) to resolve task dependencies, automates the execution of the processing steps outlined above, and ensures that all calculations are reproducible and consistent. This approach minimizes manual intervention, streamlines the processing of large datasets, and enhances the overall transparency of the data analysis pipeline.

Data Records

The dataset is publicly available via Zenodo [26]. It is organized into six zipped folders, containing the climate indicators along with various aggregations and deriva-

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tions. Additionally, an image file (`snow_yea_warming_stripes.png`) is included as an example visualization, showcasing a small subset of the data in an aggregated form. The folders are structured hierarchically, with all six representing the top level of the directory tree.

```
> austrian_climate_indicators[1]
 └── group[2]
     └── climate_indicator[3]
         └── aggregation_period[4]
             └── netcdf_files.nc[5]
```

The hierarchical structure of the dataset comprises the following levels and corresponding folders:

- [1]**Root directory**: The top-level directory of the zipped folders (detailed further in the subsequent sections) includes the following folders:
  - `austrian_climate_indicators`
  - `austrian_climate_indicators_areamean`
  - `austrian_climate_indicators_clim_1961_1990`
  - `austrian_climate_indicators_clim_1991_2020`
  - `austrian_climate_indicators_significance`
  - `austrian_climate_indicators_plots`
- [2]**group**: This level organizes the different input parameters for the climate indicators into groups. The subfolders influde: `humidity`, `precipitation`, `precipitation_temperature`, `radiation`, `runoff`, `snow`, `temperature`, and `thresholds`. The `thresholds` subfolder contains pre-calculated thresholds required for specific climate indicators.
- [3]**climate_indicator**: This hierarchical level is named according to the abbreviation of the respective climate indicator. A complete list of climate indicators and their abbreviations can be found in Appendix A.
- [4]**aggregation_period**: This level specifies the temporal aggregation periods, which vary depending on the climate indicator. Most indicators are available with both annual (`yea`) and seasonal (`sea`) aggregations, but some are defined for hydrological periods (`hydrological_year`), or half-year periods (`summer_halfyear`, `winter_halfyear`).

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- [5]**netcdf_files**: This final level contains the data as NetCDF (`.nc`) files. Each file contains self-describing metadata.

This hierarchical structure was chosen to organize the dataset systematically and allow for straightforward navigation and access to the data. The contents and descriptions of the compressed folders are outlined in the following subsections.

The `austrian_climate_indicators.zip` file

This zipped folder contains the complete set of annual and seasonal climate indicators for the full spatial grid. It represents the main dataset for climate impact analyses and provides data at full spatiotemporal resolution, enabling detailed investigations of climate patterns and trends. Figure 1 illustrates an example of a climate indicator (mean annual daily average temperature, `TGmean`), showcasing the full spatiotemporal dimensionality of the data. Additionally, Figure 2 presents an exemplary metadata structure for a `TGmean` output file for the year 1961.

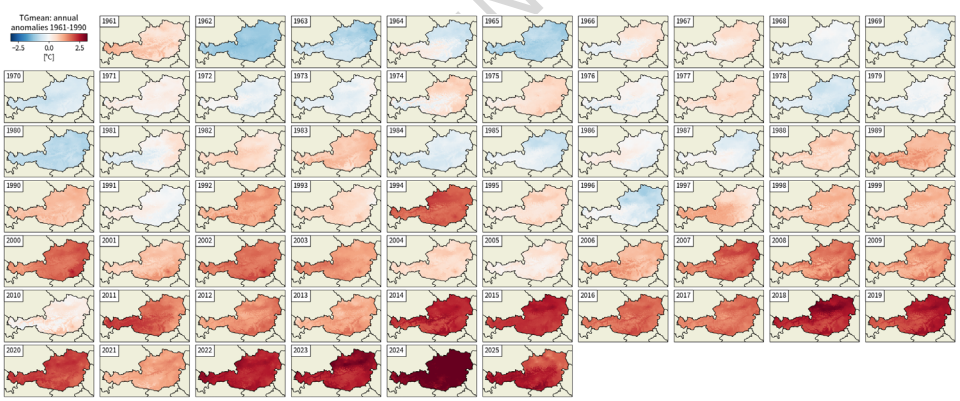


Figure 1: Stampplot of a climate indicator (`TGmean`) as anomaly relative to the reference period 1961–1990, demonstrating the full spatiotemporal dimensionality of the dataset.

The `austrian_climate_indicators_areamean.zip` file

This folder contains spatially averaged time series for all climate indicators, providing an aggregated view of the data for national-scale analyses in time. Figure 3 shows an example of anomaly time series derived from the spatially averaged data, highlighting deviations from the 1961–1990 climatological average while providing a comparison with the most recent climatological standard normal 1991–2020.

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```
netcdf TGmean_1961 {
dimensions:
    x = 584 ;
    y = 329 ;
    time = 1 ;
variables:
    double x(x) ;
        x:_FillValue = NaN ;
        x:units = "m" ;
        x:long_name = "x coordinate of projection" ;
        x:standard_name = "projection_x_coordinate" ;
        x:axis = "X" ;
    double y(y) ;
        y:_FillValue = NaN ;
        y:units = "m" ;
        y:long_name = "y coordinate of projection" ;
        y:standard_name = "projection_y_coordinate" ;
        y:axis = "Y" ;
    int64 time(time) ;
        time:long_name = "time" ;
        time:axis = "T" ;
        time:units = "days since 1961-01-01 00:00:00" ;
        time:calendar = "proleptic_gregorian" ;
    double TGmean(time, y, x) ;
        TGmean:_FillValue = NaN ;
        string TGmean:units = "°C" ;
        TGmean:long_name = "daily mean of air temperature" ;
        TGmean:standard_name = "surface_temperature" ;
        TGmean:description = "Average mean temperature" ;
        TGmean:grid_mapping = "spatial_ref" ;
    int64 spatial_ref ;
        spatial_ref:crs_wkt = "PROJCS[\"ETRS89 / Austria Lambert\",GEOGCS[\"ETRS89\",DATUM[\"European_Terrestrial_Reference_System_1989\",SPHEROID[\"GRS 1980\",6378137,298.257222101,AUTHORITY[\"EPSG\",\"7019\"]],
AUTHORITY[\"EPSG\",\"6258\"]],PRIMEM[\"Greenwich\",0,AUTHORITY[\"EPSG\",\"8901\"]],UNIT[\"degree\",0.0174532925199433,AUTHORITY[\"EPSG\",\"9122\"]],AUTHORITY[\"EPSG\",\"4258\"]],PROJECTION
[\"Lambert_Conformal_Conic_2SP\"],PARAMETER[\"latitude_of_origin\",47.5],PARAMETER[\"central_meridian\",13.3333333333333],PARAMETER[\"standard_parallel_1\",49],PARAMETER[\"standard_parallel_2\",46],PARAMETER
[\"false_easting\",400000],PARAMETER[\"false_northing\",400000],UNIT[\"metre\",1,AUTHORITY[\"EPSG\",\"9001\"]],AXIS[\"Northing\",NORTH],AXIS[\"Easting\",EAST],AUTHORITY[\"EPSG\",\"3416\"]]" ;
        spatial_ref:semi_major_axis = 6378137. ;
        spatial_ref:semi_minor_axis = 6356752.31414036 ;
        spatial_ref:inverse_flattening = 298.257222101 ;
        spatial_ref:reference_ellipsoid_name = "GRS 1980" ;
        spatial_ref:longitude_of_prime_meridian = 0. ;
        spatial_ref:prime_meridian_name = "Greenwich" ;
        spatial_ref:geographic_crs_name = "ETRS89" ;
        spatial_ref:horizontal_datum_name = "European Terrestrial Reference System 1989" ;
        spatial_ref:projected_crs_name = "ETRS89 / Austria Lambert" ;
        spatial_ref:grid_mapping_name = "lambert_conformal_conic" ;
        spatial_ref:standard_parallel = 49., 46. ;
        spatial_ref:latitude_of_projection_origin = 47.5 ;
        spatial_ref:longitude_of_central_meridian = 13.3333333333333 ;
        spatial_ref:false_easting = 400000. ;
        spatial_ref:false_northing = 400000. ;
        spatial_ref:spatial_ref = "PROJCS[\"ETRS89 / Austria Lambert\",GEOGCS[\"ETRS89\",DATUM[\"European_Terrestrial_Reference_System_1989\",SPHEROID[\"GRS 1980\",6378137,298.257222101,AUTHORITY[\"EPSG\",
\"7019\"]],AUTHORITY[\"EPSG\",\"6258\"]],PRIMEM[\"Greenwich\",0,AUTHORITY[\"EPSG\",\"8901\"]],UNIT[\"degree\",0.0174532925199433,AUTHORITY[\"EPSG\",\"9122\"]],AUTHORITY[\"EPSG\",\"4258\"]],PROJECTION
[\"Lambert_Conformal_Conic_2SP\"],PARAMETER[\"latitude_of_origin\",47.5],PARAMETER[\"central_meridian\",13.3333333333333],PARAMETER[\"standard_parallel_1\",49],PARAMETER[\"standard_parallel_2\",46],PARAMETER
[\"false_easting\",400000],PARAMETER[\"false_northing\",400000],UNIT[\"metre\",1,AUTHORITY[\"EPSG\",\"9001\"]],AXIS[\"Northing\",NORTH],AXIS[\"Easting\",EAST],AUTHORITY[\"EPSG\",\"3416\"]]" ;

// global attributes:
        :title = "Climate Indicators for Austria" ;
        :institution = "GeoSphere Austria, Vienna, Austria" ;
        :contact = "GeoSphere Austria (sebastian.lehner@geosphere.at)" ;
        :Conventions = "CF-1.7" ;
        :creation_date = "2025-07-30 11:49:44" ;
}
```

Figure 2: Example metadata for a climate indicator (`TGmean`) generated via `ncdump -h`.

The `austrian_climate_indicators_clim_1961_1990.zip` file

This folder contains temporally averaged climate indicators for the 1961–1990 climatological standard normal. These aggregated data are provided for convenience, as this reference period is widely used in climate research. Figure 4 illustrates an example, comparing spatial averages for two climatological periods.

The `austrian_climate_indicators_clim_1991_2020.zip` file

This folder contains temporally averaged climate indicators for the 1991–2020 climatological standard normal, similar to the previous section, but for the more recent period.

The `austrian_climate_indicators_significance.zip` file

This folder contains results from significance tests between the two climatological periods (1961–1990 and 1991–2020). These data are provided to support analysis of statistically significant changes in climate indicators over time, which is a common

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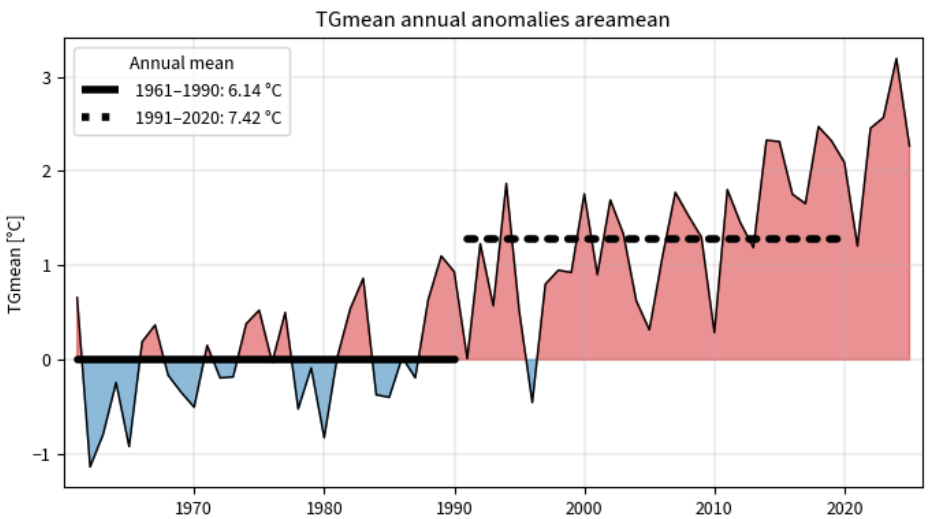


Figure 3: Spatially averaged anomalies of an annual climate indicator (`TGmean`). Anomalies are computed with respect to the 1961–1990 climatological average (solid line; by definition at 0, but included to visually emphasize the temporal reference period) and compared to the 1991–2020 climatological average (dashed line).

use case in climate impact analyses.

The `austrian_climate_indicators_plots.zip` file

This folder contains visualizations of the climate indicators, offering a convenient way to explore the data. The following types of plots are included:

- **Time series**: Spatially averaged anomalies relative to the 1961–1990 climatological reference period, with comparisons to the recent 1991–2020 average (Figure 3).
- **Spatial plots**: Single fields for climatologies and composite plots showing both climatologies and their differences (Figure 4).
- **Stampplots**: Visualizations of the full spatiotemporal dimensionality of the data (Figure 1).
- **Grouped significance plots**: Portions of significant changes within a parameter group (e.g., temperature, precipitation) across periods (not shown).

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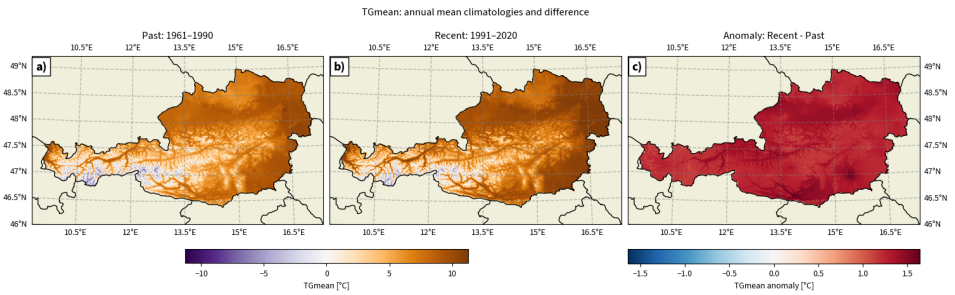


Figure 4: Aggregated fields for one climate indicator (`TGmean`) over two climatological reference periods: a) spatial average for 1961–1990 (past), b) spatial average for 1991–2020 (recent), and c) their difference (recent minus past).

- **Composite warming stripes**: Standardized anomalies for all climate indicators grouped by parameter category (not shown).

Technical Validation

The technical validation of the generated dataset was conducted through a series of checks to ensure data integrity, consistency, and plausibility. Specifically, the following steps were performed:

- **File size check**: All generated files were verified to exceed a predefined size threshold to capture erroneously produced files.
- **File count validation**: The number of output files per climate indicator was checked against the expected count, which is determined by the configured stard and end year (as each year is saved in a separate file).
- **Value verification**: Files were checked to ensure that they contain valid values and are not populated solely with missing values (NaNs).

The results of these technical validation checks are logged to a file to provide a detailed record for identifying and addressing any errors.

In addition, all generated figures were manually reviewed to confirm the plausibility and quality of the curated data. This step ensures that the visual representations align with expected climate patterns and trends from a climatological perspective.

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The source data itself adheres to internal quality standards established by the Austrian national service for geology, geophysics, climatology, and meteorology (GeoSphere Austria), ensuring validity and reliability of the input data.

Concerning software, the Python libraries used in the workflow incorporate robust quality control mechanisms, including testing, thorough code review and internal metadata checks. These checks enforce conventions, proper units and other relevant standards (see [24] for details). Together, these measures provide a high level of quality assurance for both the dataset and the underlying computational processes, thereby upholding stringent standards and conventions that are essential to foster trust in reliable climate research.

Usage Notes

The climate indicators provided in this dataset are well-suited for studies investigating changes, trends, or dependencies in related climate impact phenomena. These encompass a wide range of areas, including natural hazards [27], forestry [28], public health [29], socio-ecologic systems, and economic impacts such as crop yields [30, 31]. For comprehensive impact analyses, it is essential to incorporate additional risk drivers beyond climate variables to ensure a holistic characterization of impacts and associated risks [32, 27]. Furthermore, the choice of reference periods for all applications should be carefully considered and thoroughly documented. Comparing indicators based on different reference periods can cause unexpected and diverging results, in particular for percentile-based extreme indices [33]. Therefore, indicators that rely on a reference period for threshold calculation should, whenever possible, be compared based on the same reference period. Note that no homogenization procedure is applied within the presented workflow. However, the input data are derived from a consistent set of quality-controlled station data. Nevertheless, trend analyses should account for possible discrepancies compared to fully homogenized time series.

The dataset can also be used to train climate impact models, offering a robust foundation for exploring the relationships between climate indicators and various impact metrics.

Users of this dataset should be mindful of multicollinearity, which is a common characteristic of meteorological variables and, by extension, climate indicators derived from the same input data. When working with multiple climate indicators, it is essential to carefully assess correlations between them and employ appropriate feature selection techniques. These techniques should be guided by the underlying

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research question, with careful consideration of the balance between predictive accuracy and explanatory aims [34]. Neglecting to address this issue can lead to issues such as reduced model performance and biased inference (e.g. in feature importance assessments) within statistical learning models [35, 36]. Spatial multicollinearities among the climate indicators in this dataset have been analyzed and discussed in [6], providing additional insights for users seeking to incorporate these data in their analyses.

Data Availability

All calculated climate indicators, spatiotemporal aggregations, and generated figures are publicly available via Zenodo at https://doi.org/10.5281/zenodo.16928609.

The source data used to calculate all climate indicators can be accessed through the GeoSphere Austria DataHub, specifically the gridded datasets (a) SPARTACUS (https://doi.org/10.60669/m6w8-s545), (b) WINFORE (https://doi.org/10.60669/f6ed-2p24), and (c) SNOWGRID (https://doi.org/10.60669/fsxx-6977).

Code Availability

All code for calculating climate indicators, performing aggregations and significance tests, as well as generating visualizations, is open source and available on GitHub at https://github.com/seblehner/austrian-climate-indicators.

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Funding

This research was supported through the Austrian Climate Research Program of the Federal Ministry for Agriculture and Forestry, Climate and Environmental Protection, Regions and Water Management under grant agreement FO999901443.

Author contributions

SL contributed to project conceptualization, data acquisition and processing, validation, code development and manuscript writing. MS contributed to project conceptualization, data acquisition, validation, code review, manuscript writing and supervision.

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Competing Interests

The authors declare no competing interests.

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Appendix A Definitions of climate indicators

This section provides definitions for all climate indicators. Here, x represents the data points (parameter), t corresponds to a daily timesteps for all days within the respective time period (annual or seasonal, etc.), and n denotes the number of days within the same time period. To simplify the presentation, all climate indicators are calculated on a per-gridcell basis, hence the spatial dimension is excluded in the definitions.

Temperature-based climate indicators

The input variables used are `TX` for daily maximum temperature, `TN` for daily minimum temperature and `TG` for daily average temperature, all in degrees Celsius.

`TGmean`: The average daily mean temperature, calculated as:

$$f(\mathrm{TG}) = \frac{1}{n}\sum_{t=1}^{n} \mathrm{TG}_t \tag{1}$$

`TNmean`: The average daily minimum temperature, calculated as:

$$f(\mathrm{TN}) = \frac{1}{n}\sum_{t=1}^{n} \mathrm{TN}_t \tag{2}$$

`TXmean`: The average daily maximum temperature, calculated as:

$$f(\mathrm{TX}) = \frac{1}{n}\sum_{t=1}^{n} \mathrm{TX}_t \tag{3}$$

`FD`: The number of frost days, calculated as:

$$f(\mathrm{TN}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TN}_t < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

`SU`: The number of summer days, calculated as:

$$f(\mathrm{TX}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TX}_t > 25 \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

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HD: The number of hot days, calculated as:

$$f(\mathrm{TX}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TX}_t > 30 \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

ID: The number of icing days, calculated as:

$$f(\mathrm{TX}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TX}_t < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

TR: The number of tropical nights, calculated as:

$$f(\mathrm{TN}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TN}_t > 20 \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

KYS: Kysely days are defined as the count of days in periods of at least 3 consecutive days where (1) TX $\geq$ 30 °C on the first day, (2) TX $\geq$ 25 °C on all subsequent days, and (3) and the average maximum temperature across all days in the period fulfills TX $\geq$ 30 °C.

GSS: The day of the year corresponding to the first day of a four-day period during which TG $>$ 5 °C on all days in the window.

GSL: The number of days between the start and end of the growing season. The growing season begins with a 6-day period where TG $>$ 5 °C on all days in the window and ends with a 6-day period where TG $<$ 5 °C on all days.

spring_backlash: The number of events counted as days where $\mathrm{TN}_t < -2$ °C for all days t after GSS and up to day 180 of the year. This is associated with spring frost.

SBI: The spring backlash index represents the growing degree days above 5 °C (see GDD5) for all days t occurring after GSS and up to the last spring backlash event.

TXx: The maximum daily maximum temperature, calculated as:

$$f(\mathrm{TX}) = \max(\mathrm{TX}) \tag{9}$$

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`TNx`: The maximum daily minimum temperature, calculated as:

$$f(\mathrm{TN}) = \max(\mathrm{TN}) \tag{10}$$

`TXn`: The minimum daily maximum temperature, calculated as:

$$f(\mathrm{TX}) = \min(\mathrm{TX}) \tag{11}$$

`TNn`: The minimum daily minimum temperature, calculated as:

$$f(\mathrm{TN}) = \min(\mathrm{TN}) \tag{12}$$

`TN10p`: This indicator represents the percentage of days where the daily minimum temperature (TN_t) is below the 10th percentile (TN_{10p}) of the reference period (1991–2020). It is calculated as:

$$f(\mathrm{TN}) = \frac{100[\%]}{n_d} \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TN}_t < \mathrm{TN}_{10p} \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

where n_d is the number of days in the period under consideration (e.g. annual or seasonal). For the annual aggregation, TN_{10p} is derived from all data in the reference period. For seasonal aggregation, TN_{10p} is calculated using data specific to each season within the reference period.

`TX10p`: Defined similarly to Equation 13, but with TX instead of TN:

$$f(\mathrm{TX}) = \frac{100[\%]}{n_d} \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TX}_t < \mathrm{TX}_{10p} \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

`TN90p`: Defined similarly to Equation 13, but with $\mathrm{TN}_t > \mathrm{TN}_{90p}$:

$$f(\mathrm{TN}) = \frac{100[\%]}{n_d} \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TN}_t > \mathrm{TN}_{90p} \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

`TX90p`: Defined similarly to Equation 13, but for TX instead of of TN and $\mathrm{TX}_t > \mathrm{TX}_{90p}$:

$$f(\mathrm{TX}) = \frac{100[\%]}{n_d} \sum_{t=1}^{n} \begin{cases} 1, & \text{if } \mathrm{TX}_t > \mathrm{TX}_{90p} \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

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`CFD`: Consecutive frost days, defined as the maximum length of consecutive periods where TN < 0 °C.

`CSU`: Consecutive summer days, defined as the maximum length of consecutive periods where TX > 25 °C.

`WSDI`: The warm spell duration index reflects the number of days within warm spells. Warm spells are defined as consecutive periods of at least 6 days where TX $>$ TX$_{90p}$. Here, TX$_{90p}$ is the 90th percentile of TX based on the reference period 1991–2020.

`CSDI`: The cold spell duration index reflects the number of days within cold spells. Cold spells are defined as consecutive periods of at least 6 days where TN $<$ TN$_{10p}$. Here, TN$_{10p}$ is the 10th percentile of TN based on the reference period 1991–2020.

`HSF`: The hot spell frequency denotes the number of hot spells as defined in the `WSDI` indicator.

`CSF`: The cold spell frequency denotes the number of cold spells as defined as in the `CSDI` indicator.

`CE`: Cold episodes reflect the number of cold spells, defined as continuous periods of at least 5 days where TX < 0 °C.

`EID`: The number of days where TN < -7 °C and TX < 0 °C.

`TPD`: The number of days where TG > 1.5 °C.

`FTD`: The number of days where TN < 0 °C and TX > 0 °C.

`FTD2`: The number of days where TN < -2 °C and TX > 2 °C.

`continentality`: The difference between the maximum and minimum average monthly temperature:

$$f(\mathrm{TG}) = \max(\mathrm{TG}_{mon}) - \min(\mathrm{TG}_{mon}) \tag{17}$$

where TG$_{mon}$ represents the average monthly TG.

`GDD0`: The growing degree days, defined as the sum of daily temperature differences above a threshold of 0 °C:

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$$f(\mathrm{TG}) = \sum_{t=1}^{n} \begin{cases} \mathrm{TG}_t - c, & \text{if } \mathrm{TG}_t > c \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

where c is a constant with value 0 °C.

GDD5: Similar to Equation 18 but with a threshold of $c = 5$ °C.

GDD10: Similar to Equation 18 but with a threshold of $c = 10$ °C.

DTR: The average daily temperature range, calculated as:

$$f(\mathrm{TX}, \mathrm{TN}) = \frac{1}{n_d} \sum_{t=1}^{n} \mathrm{TX}_t - \mathrm{TN}_t \tag{19}$$

where n_d is the number of days in the period under consideration (e.g. annual or seasonal).

ETR: The extreme temperature range is defined as the difference between the maximum daily maximum temperature (TXx) and the minimum daily minimum temperature (TNn):

$$f(\mathrm{TX}, \mathrm{TN}) = \mathrm{TX}x - \mathrm{TN}n \tag{20}$$

BIO01: First bioclimatic indicator, representing the mean temperature calculated specifically for an annual aggregation period. It is equivalent to the general mean temperature as defined in Equation 1.

BIO02: The mean diurnal temperature range is calculated as the average difference between daily maximum temperature (TX_t) and daily minimum temperature (TN_t):

$$f(\mathrm{TX}, \mathrm{TN}) = \frac{1}{n} \sum_{t=1}^{n} (\mathrm{TX}_t - \mathrm{TN}_t) \tag{21}$$

BIO03: The ratio of the mean diurnal temperature range (BIO02) and the annual temperature range (BIO07):

$$f(\mathrm{TX}, \mathrm{TN}) = \frac{\mathrm{BIO02}}{\mathrm{BIO07}} \tag{22}$$

BIO04: Temperature seasonality is defined as the annual coefficient of variation in

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temperature, expressed as percentage:

$$f(\mathrm{TG}) = 100[\%] \cdot \frac{\sigma_{\mathrm{TG}}}{\mu_{\mathrm{TG}}} \tag{23}$$

where σ_{TG} is the standard deviation daily mean temperature (TG) per year, and μ_{TG} the mean of TG for the same year.

`BIO05`: The maximum daily maximum temperature (see Equation 9) for an annual aggregation period. Note that this definition aligns with the ANUCLIM definitions [37] as implemented in `xclim` but differs from the Bioclim definition, which refers to the maximum temperature *of the warmest month*.

`BIO06`: The maximum daily maximum temperature (see Equation 12) for an annual aggregation period. Note that this definition aligns with the ANUCLIM definitions [37] as implemented in `xclim` but differs from the Bioclim definition, which refers to the minimum temperature *of the coldest month*.

`BIO07`: The difference between the maximum daily maximum temperature (TXx) and the minimum daily minimum temperature (TNn). This is equivalent to Equation 20 for an annual aggregation period.

`BIO10`: The mean temperature for the warmest quarter, calculated as:

$$f(\mathrm{TG}) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{TG}_j \tag{24}$$

where j is limited to the days within the season where

$$\text{season} = \arg\max(\mathrm{TG}_{sea}) \tag{25}$$

with TG_{sea} denoting the seasonal average temperature.

`BIO11`: The mean temperature for the coldest quarter, calculated as:

$$f(\mathrm{TG}) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{TG}_j \tag{26}$$

where j is limited to the days within the season where

$$\text{season} = \arg\min(\mathrm{TG}_{sea}) \tag{27}$$

with TG_{sea} denoting the seasonal average temperature.

`CDDcold18.3`: The sum of daily temperature differences above a threshold of 18.3

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°C, calculated as:

$$f(\mathrm{TG}) = \sum_{t=1}^{n} \begin{cases} \mathrm{TG}_t - c, & \text{if } \mathrm{TG}_t > c \\ 0, & \text{otherwise.} \end{cases} \tag{28}$$

where c is a constant with value 18.3 °C.

`HDDheat20`: The sum of daily temperature differences below a threshold of 20 °C, calculated as:

$$f(\mathrm{TG}) = \sum_{t=1}^{n} \begin{cases} c - \mathrm{TG}_t, & \text{if } \mathrm{TG}_t < c \\ 0, & \text{otherwise.} \end{cases} \tag{29}$$

where c is a constant with value 20 °C.

Precipitation-based climate indicators

The input variable used is `RR` for daily precipitation totals in mm (corresponding to $\mathrm{kg\,m^{-2}\,day^{-1}}$). Wet days are defined as days where RR > 1 mm.

`PRCPTOT`: The total precipitation accumulated over a specified period, calculated as:

$$f(\mathrm{RR}) = \sum_{t=1}^{n} \mathrm{RR}_t \tag{30}$$

`Rx1day`: The maximum daily precipitation within a specified period, calculated as:

$$f(\mathrm{RR}) = \max(\mathrm{RR}_t) \tag{31}$$

`Rx5day`: The maximum 5-day precipitation within a specified period, calculated as:

$$f(\mathrm{RR}) = \max(\mathrm{RR}_{5t}) \tag{32}$$

where RR_{5t} represents the total precipitation accumulated within a 5-day rolling window.

`RR90pct`: The 90th percentile of daily precipitation totals for wet days ($\mathrm{RR}_{wet,90p}$) within a specified period:

$$f(\mathrm{RR}) = \mathrm{RR}_{wet,90p}) \tag{33}$$

`RR95pct`: Similar to Equation 33 but for the 95th percentile.

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`RRmean`: The average daily precipitation within a specified period, calculated as:

$$f(\mathrm{RR}) = \frac{1}{n}\sum_{t=1}^{n}\mathrm{RR}_t \tag{34}$$

`SDII`: The simple daily precipitation intensity index is defined as the average precipitation intensity on wet days, calculated as:

$$f(\mathrm{RR}) = \frac{1}{n_{wet}}\sum_{t=1}^{n_{\mathrm{wet}}}\mathrm{RR}_{t,wet} \tag{35}$$

where n_{wet} is the number of wet days in the period under consideration, and $\mathrm{RR}_{t,wet}$ represents the precipitation totals on wet days.

`R10mm`: The count of moderate wet days, calculated as:

$$f(\mathrm{RR}) = \sum_{t=1}^{n}\begin{cases}1, & \text{if } \mathrm{RR}_t > c\\ 0, & \text{otherwise.}\end{cases} \tag{36}$$

where $c = 10$ mm.

`R20mm`: Similar to Equation 36 but with $c = 20$ mm.

`R30mm`: Similar to Equation 36 but with $c = 30$ mm.

`R40mm`: Similar to Equation 36 but with $c = 40$ mm.

`R50mm`: Similar to Equation 36 but with $c = 50$ mm.

`CDD`: Consecutive dry days, defined as the number of days in the longest consecutive period where daily precipitation is less than 1 mm.

`CWD`: Consecutive wet days, defined as the number of days in the longest consecutive period where daily precipitation exceeds 1 mm.

`Rsum30min`: The minimum accumulated precipitation within any 30-day rolling window over a specified period, calculated as:

$$f(\mathrm{RR}) = \min(\sum_{t}^{n}\mathrm{RR}_{30t}) \tag{37}$$

where RR_{30t} denotes the precipitation totals accumulated within a rolling 30-day

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window.

Rsum30max: The maximum accumulated precipitation over any rolling 30-day window, calculated as:

$$f(\mathrm{RR}) = \max(\sum_{t}^{n} \mathrm{RR}_{30t}) \tag{38}$$

where RR_{30t} represents the total precipitation accumulated within a 30-day rolling window.

R75p: The total precipitation accumulated on moderately wet days within a specified period, which are defined as days with daily precipitation exceeding the 75th percentile of wet day precipitation during the reference period (1991–2020). The indicator is calculated as:

$$f(\mathrm{RR}) = \sum_{t=1}^{n} \begin{cases} \mathrm{RR}_t, & \text{if } \mathrm{RR}_t > \mathrm{RR}_{wet,75p} \\ 0, & \text{otherwise.} \end{cases} \tag{39}$$

where $\mathrm{RR}_{wet,75p}$ is the 75th percentile of RR_{wet} for all wet days during the reference period 1991–2020.

R90p: Similar to Equation 39, but for the 90th percentile.

R95p: Similar to Equation 39, but for the 95th percentile.

R99p: Similar to Equation 39, but for the 99th percentile.

R90pTOT: The percentage contribution of precipitation totals from $\mathrm{RR} > \mathrm{RR}_{wet,90p}$ within a specified period, calculated as:

$$f(\mathrm{RR}) = \frac{100[\%]}{\sum_{t=1}^{n} \mathrm{RR}_t} \sum_{t=1}^{n} \begin{cases} \mathrm{RR}_t, & \text{if } \mathrm{RR}_t > \mathrm{RR}_{wet,90p} \\ 0, & \text{otherwise.} \end{cases} \tag{40}$$

where $\mathrm{RR}_{wet,90p}$ is the 90th percentile of RR_{wet} for all wet days during the reference period 1991–2020.

R95pTOT: Similar to Equation 40, but for the 95th percentile.

R99pTOT: Similar to Equation 40, but for the 99th percentile.

API07_Q95: This temporally aggregated version of the antecedent precipitation index (API) represents the 95th percentile of a weighted sum of daily precipitation totals over a specified time window with a length of k days and a weighting exponent

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p. The basic API is calculated as:

$$f(\mathrm{RR}_t) = \sum_{i=t}^{t-k} \mathrm{RR}_i \cdot p^i \tag{41}$$

where $k = 7$ and $p = 0.935$. This indicator is the 95th percentile of that.

`API14_Q95`: Similar to Equation 41, but with $k = 14$.

`API28_Q95`: Similar to Equation 41, but with $k = 28$.

`PCI_Q95`: This temporally aggregated version of the precipitation concentration index (PCI) represents the 95th percentile of the PCI, which quantifies the concentration of monthly precipitation totals within a given period. The PCI is defined as follows:

$$f(\mathrm{RR}) = \frac{\sum_j \left(\mathrm{RR}_{mon}^2\right)}{\left(\sum_{i=1}^{n} \mathrm{RR}_t\right)^2} \tag{42}$$

where RR_{mon} denotes the monthly accumulated precipitation totals, and j represents all months in the specified period (e.g. months within a season or year).

`BIO12`: This indicator represents the total annual precipitation, calculated as the sum of daily precipitation totals over an entire year. It is equivalent to Equation 30, with the aggregation specifically applied to an annual time scale.

`BIO13`: The maximum daily precipitation within a year:

$$f(\mathrm{RR}) = \max \mathrm{RR}_t \tag{43}$$

`BIO14`: The minimum daily precipitation within a year:

$$f(\mathrm{RR}) = \min \mathrm{RR}_t \tag{44}$$

`BIO15`: The annual coefficient of variation of precipitation, expressed as a percentage:

$$f(\mathrm{RR}) = 100[\%] \cdot \frac{\sigma_{\mathrm{RR}}}{\mu_{\mathrm{RR}}} \tag{45}$$

where σ_{RR} is the standard deviation of RR per year, and μ_{RR} the mean of RR for the same year.

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BIO16: The total precipitation during the wettest season of the year, calculated as:

$$f(\mathrm{RR}) = \sum_{j=1}^{n} \mathrm{RR}_j \tag{46}$$

where j is limited to the days within the season where

$$\text{season} = \arg\max(\mathrm{RR}_{sea}) \tag{47}$$

with RR_{sea} denoting the total accumulated precipitation for each season.

BIO17:

$$f(\mathrm{RR}) = \sum_{j=1}^{n} \mathrm{RR}_j \tag{48}$$

where j is limited to the days inside the season where

$$\text{season} = \arg\min(\mathrm{RR}_{sea}) \tag{49}$$

where RR_{sea} is the seasonal total accumulated precipitation.

RR_summerhalf:

$$f(\mathrm{RR}) = \sum_{j=1}^{n} \mathrm{RR}_j \tag{50}$$

where j is limited to the days within the months April to September.

RR_winterhalf:

$$f(\mathrm{RR}) = \sum_{j=1}^{n} \mathrm{RR}_j \tag{51}$$

where j is limited to the days within the months October to March.

Radiation-based climate indicators

These indicators utilize sunshine duration as input variables to quantify solar radiation. Specifically, the two key input variables used are SA for daily absolute sunshine duration in hours, and SR for daily relative sunshine duration, expressed as a fraction.

SAmean: The mean daily absolute sunshine duration over a specified period:

$$f(\mathrm{SA}) = \frac{1}{n} \sum_{t=1}^{n} \mathrm{SA}_t \tag{52}$$

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SRmean: The mean daily relative sunshine duration over a specified period:

$$f(\mathrm{SR}) = \frac{1}{n}\sum_{t=1}^{n} \mathrm{SR}_t \tag{53}$$

Humidity-based climate indicators

The input variables used are ET0 for daily reference evapotranspiration in mm, and SPEI as the Standardized Precipitation Evaporation Index [38] for 30, 90 and 365 days (SPEI30, SPEI90 and SPEI365), respectively.

ET0mean: The the average daily reference evapotranspiration over a specified period, calculated as:

$$f(\mathrm{ET0}) = \frac{1}{n}\sum_{t=1}^{n} \mathrm{ET0}_t \tag{54}$$

ET0_seasonality: The seasonality of ET0 quantifies the variability of reference evapotranspiration across months within a specified period. It is calculated in two steps:

$$f(\mathrm{ET0}_{mon}) = \sqrt{\frac{1}{n_{mon}}\sum_{t=1}^{n_{mon}} \left(\mathrm{ET0}_t - \overline{\mathrm{ET0}_{mon}}\right)^2} = \sigma_{\mathrm{ET0},mon} \tag{55}$$

where $\overline{\mathrm{ET0}_{mon}}$ is the monthly mean, and $\sigma_{\mathrm{ET0},mon}$ is the monthly standard deviation of ET0.
The final indicator is derived by averaging the monthly standard deviations over all months in the aggregation period:

$$f(\mathrm{ET0}) = \frac{1}{n_{months}}\sum_{j=1}^{n_{months}} \sigma_{\mathrm{ET0},j} \tag{56}$$

SPEI30mean: The average value of the SPEI calculated over a 30-day period within a specified time frame:

$$f(\mathrm{SPEI30}) = \frac{1}{n}\sum_{t=1}^{n} \mathrm{SPEI30}_t \tag{57}$$

SPEI90mean: Similar to Equation 57, but with SPEI90 instead of SPEI30.

SPEI365mean: Similar to Equation 57, but with SPEI365 instead of SPEI30.

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SPEI90_th-2: The count of days within a specified period where the SPEI for a 90-day window falls below a threshold of −2:

$$f(\text{SPEI90}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if SPEI90} < c \\ 0, & \text{otherwise.} \end{cases} \tag{58}$$

where $c = -2$ mm.

SPEI90_th-1: Similar to Equation 58, but with $c = -1$.

SPEI90_th+1: The count of days within a specified period where the SPEI for a 90-day window exceeds a threshold of 1:

$$f(\text{SPEI90}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if SPEI90} > c \\ 0, & \text{otherwise.} \end{cases} \tag{59}$$

where $c = 1$ mm.

SPEI90_th+2: Similar to Equation 59, but with $c = 2$.

Snow-based climate indicators

The input variables are:

- SDE - daily total height of snow (snow depth) in m,
- SF - daily amount of fresh snow (snowfall) in m,
- SWE_tot - daily total snow water equivalent in $\mathrm{kg\,m^{-2}}$,
- SWE_fr - daily fresh amount of available total snow water equivalent in $\mathrm{kg\,m^{-2}}$,
- snowmelt - daily amount of melted snow in $\mathrm{kgm^{-2}}$,
- runoff - daily total surface runoff from rain and snowmelt in m.

HS_Q95: The 95th percentile of SDE.

HSfr_Q95: The 95th percentile of SF.

SWE_Q95: The 95th percentile of SWE_tot.

SWEfr_Q95: The 95th percentile of SWE_fr.

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NSD_72h: The maximum 3-day fresh snow depth ('new snow depth within 72 hours') within a specified period, calculated as:

$$f(\mathrm{SF}) = \max(\mathrm{SF}_{3t}) \tag{60}$$

where SF_{3t} denotes the 3-day SF, calculated using a 3-day running window.

SCD01: The count of days within a specified period where the daily snow depth exceeds 1 cm, calculated as:

$$f(\mathrm{SDE}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if SDE} > c \\ 0, & \text{otherwise.} \end{cases} \tag{61}$$

where $c = 1$ cm.

SCD10: Similar to Equation 61, but with $c = 10$.

runoff_Q95: The 95th percentile of runoff.

snowmelt_Q95: The 95th percentile of snowmelt.

HN1_SD: The count of days within a specified period where the daily fresh snow depth exceeds 1 cm, calculated as:

$$f(\mathrm{SF}) = \sum_{t=1}^{n} \begin{cases} 1, & \text{if SF} > c \\ 0, & \text{otherwise.} \end{cases} \tag{62}$$

where $c = 1$ cm.

HN5_SD: Similar to Equation 62, but with $c = 5$ cm.

HN10_SD: Similar to Equation 62, but with $c = 10$ cm.

HN20_SD: Similar to Equation 62, but with $c = 20$ cm.

Climate indicators based on multiple input variables

SHMI: The summer heat moisture index is defined as the ratio of the maximum monthly average temperature (TG_{mon}) to the mean precipitation during summer months (June, July, August; RR_{JJA}), calculated as:

$$f(\mathrm{TG}, \mathrm{RR}) = \frac{\max(\mathrm{TG}_{mon})}{\mathrm{RR}_{JJA}} \tag{63}$$

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`ET0_Qcold`: The mean reference evapotranspiration in the coldest quarter, calculated as:

$$f(\mathrm{ET0}) = \frac{1}{n}\sum_{j=1}^{n}\mathrm{ET0}_j \tag{64}$$

where j is limited to the days within the season where

$$\mathrm{season} = \arg\min(\mathrm{TG}_{sea}) \tag{65}$$

with TG_{sea} denoting the seasonal average temperature.

`ET0_Qdry`: The mean reference evapotranspiration in the driest quarter, calculated as:

$$f(\mathrm{ET0}) = \frac{1}{n}\sum_{j=1}^{n}\mathrm{ET0}_j \tag{66}$$

where j is limited to the days within the season where

$$\mathrm{season} = \arg\min(\mathrm{RR}_{sea}) \tag{67}$$

with RR_{sea} denoting the seasonal total accumulated precipitation.

`ET0_Qwarm`: The mean reference evapotranspiration in the warmest quarter, calculated as:

$$f(\mathrm{ET0}) = \frac{1}{n}\sum_{j=1}^{n}\mathrm{ET0}_j \tag{68}$$

where j is limited to the days within the season where

$$\mathrm{season} = \arg\max(\mathrm{TG}_{sea}) \tag{69}$$

with TG_{sea} denoting the seasonal average temperature.

`ET0_Qwet`: The mean reference evapotranspiration in the wettest quarter, calculated as:

$$f(\mathrm{ET0}) = \frac{1}{n}\sum_{j=1}^{n}\mathrm{ET0}_j \tag{70}$$

where j is limited to the days within the season where

$$\mathrm{season} = \arg\max(\mathrm{RR}_{sea}) \tag{71}$$

with RR_{sea} denoting the seasonal total accumulated precipitation.

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BIO08: The mean temperature of the wettest quarter, calculated as:

$$f(\mathrm{TG}) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{TG}_j \tag{72}$$

where j is limited to the days within the season where

$$\text{season} = \arg\max(\mathrm{RR}_{sea}) \tag{73}$$

with RR_{sea} denoting the seasonal total accumulated precipitation.

BIO09: The mean temperature of the driest quarter, calculated as:

$$f(\mathrm{TG}) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{TG}_j \tag{74}$$

where j is limited to the days within the season where

$$\text{season} = \arg\min(\mathrm{RR}_{sea}) \tag{75}$$

with RR_{sea} denoting the seasonal total accumulated precipitation.

BIO18: The total precipitation during the warmest quarter, calculated as:

$$f(\mathrm{RR}) = \sum_{j=1}^{n} \mathrm{RR}_j \tag{76}$$

where j is limited to the days within the season where

$$\text{season} = \arg\max(\mathrm{TG}_{sea}) \tag{77}$$

with TG_{sea} denoting the seasonal average temperature.

BIO19: The total precipitation during the coldest quarter, calculated as:

$$f(\mathrm{RR}) = \sum_{j=1}^{n} \mathrm{RR}_j \tag{78}$$

where j is limited to the days within the season where

$$\text{season} = \arg\min(\mathrm{TG}_{sea}) \tag{79}$$

with TG_{sea} denoting the seasonal average temperature.

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