https://doi.org/10.5194/egusphere-2025-6173
Preprint. Discussion started: 26 January 2026

Local weather scenarios for soil and crop models: a simple generator based on historic data sampling

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Abstract. Weather scenarios are for example required to model future agricultural production and the development of soil properties under climate change. These scenarios should realistically depict regional weather conditions at a daily resolution for the expected climate development. In this technical note, we present the LocalWeatherSampler (LWS) for generating mid-term weather scenarios (20-30 years) for specific regions or locations based on historically recorded weather data. It is demonstrated for an example site in Germany. The core idea is to define wet or dry years and to increase their abundance in future years via a random sampling from history. A temperature trend based on common climate projections can be added afterwards. For the definition of dry/wet years, two different methods are implemented. The historical weather data can be either divided manually into a pool of wet (or dry) years or based on the Standardized Precipitation Index (SPI). By varying the threshold value for wet (dry) years and their probability of appearance within the scenario, the framework allows for the generation of scenarios tailored to specific requirements, such as sequences characterized by extremely dry years or by moderately dry years, as well as extremely wet future sequences. This approach is designed to test or analyze future scenarios of precipitation regimes and temperature trends using models that require realistic daily weather data, such as soil, crop, or hydrological models.

https://doi.org/10.5194/egusphere-2025-6173
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Graphical abstract

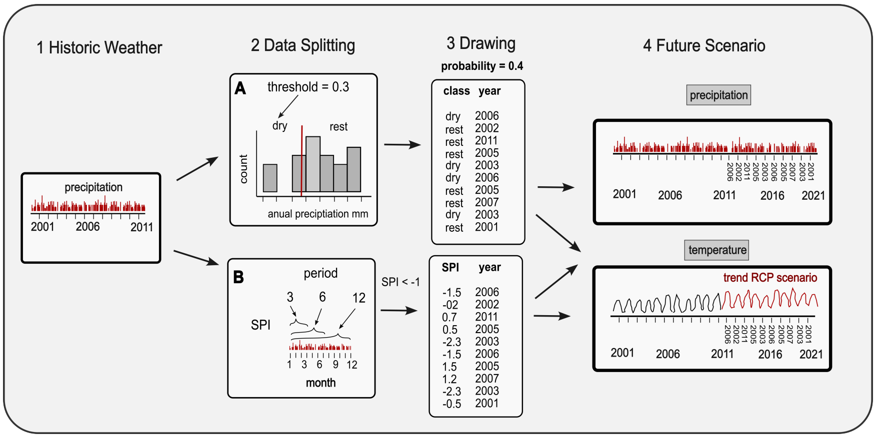

Figure 1. Overview of the LocalWeatherSampler and the conceptualization

1 Introduction

In agricultural modeling, the simulation of crop growth, water dynamics, and soil processes strongly depends on weather data with at least daily resolution that capture variations in water availability, temperature, and radiation. A major challenge in modeling weather-dependent processes lies in the representation of daily precipitation patterns under future climate scenarios. Representative Concentration Pathways (RCP) scenarios from the Intergovernmental Panel on Climate Change (IPCC) are often used to calculate future scenarios. They consider socio-economic developments in relation to CO_2 emissions and predict different climate developments under these assumptions (Pedersen et al., 2022). For Germany, the German Weather Service (DWD) provides RCP projections for the next 30 years (https://www.dwd.de/DE/klimaumwelt/klimaatlas/klimaatlas_node.html), which are available upon request. Climate models are primarily designed to provide long-term development of average temperature and precipitation. However, if these long-term climate simulations are downscaled to local daily weather events, they often fail to reproduce realistic precipitation patterns, including extreme events. This is mainly because averaging is performed over spatial and temporal scales that are significantly larger than the characteristic scales of weather events and thus not usable for site-specific modeling of hydrological processes. Typically, this averaging generates biases like an excessive number of days with light rainfall (the "drizzle effect"), it underestimates the frequency and intensity of intense rainfall events, and does not capture the expected change in seasonal timing and distribution of precipitation (Maity et al., 2019). Although combining climate models with stochastic weather generators for statistical downscaling is a common strategy to address scale mismatches and refine spatial resolution, this approach is not without significant methodological and practical limitations (Wilks, 2012). There is a huge variety of weather generators that follow different concepts and show different strengths and weaknesses in generating random precipitation events. Some issues weather generators are facing are: they underestimate

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Preprint. Discussion started: 26 January 2026

interannual and low-frequency climate variability, tend to underestimate heavy precipitation and extreme events, some fail to reproduce long dry or wet spells, need long calibration records, and can become very complex (Ailliot et al., 2015; Chen and Brissette, 2014). To ensure that the sequence of weather phenomena is depicted realistically and that interrelationships between weather variables are consistent, a promising approach for generating realistic local weather scenarios could be to build upon historical weather data for the given location. The historical data can be scaled to include predicted future trends in average temperature and total amount of precipitation. These data are site-specific and represent the prevailing weather conditions. This approach is followed by the STARS weather sampler (Orlowsky et al., 2008), where historical weather records are segmented into time slices of characteristic weather phases and resampled then following given trends. This method provides good scenarios for different climate trends given that the difference between historic and predicted climate is not too pronounced (Bülow et al., 2019). Based on these ideas, we have simplified the statistical procedure and set the sampling procedure focusing on precipitation regimes and integrated the approach as a R (R Core Team, 2024) routine.

In this technical note, we present the LocalWeatherSampler (LWS) an approach to generate realistic, user-defined weather scenarios for specific regions or locations. It is based on historic weather data recorded at a local weather station. Future weather at daily resolution is compiled according to a user-defined probability distribution for dry and wet phases. The temperature data obtained in this way are scaled to reflect the expected average trends. This kind of scenario generation is mainly intended for risk assessment or uncertainty analysis studies, but also for model applications that consider the long-term dynamics of weather-dependent processes, such as soil models or crop models. These models can then be used to explore specific precipitation regimes. The presented weather sampler produces weather scenarios for Germany, but the approach can be applied to every other country if the necessary data is available.

2 Methodological approach

2.1 Preparation of historic data

The required data includes daily precipitation [mm] and daily mean-, min- & max air temperature [K] and can easily be retrieved from typical weather stations. In Germany, these data are provided by the DWD for a dense network of weather stations (https://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/).

As first step, the historical data sequence is retrieved from a weather station, starting from the most current date. The total length of the historic sequence can influence the quality of the generated scenarios. With an increasing length the local variability can be represented more realistically.

The weather data should be checked for consistency and data gaps. Otherwise, data gaps can be interpreted as drought since rain events are missing.

In the next step, the period for which to generate a future weather sequence is specified. For this period, entire years from the past are linked in sequence to ensure realistic weather patterns. However, the scenario can start at any day during the actual year where a certain disruption in the meteorological variables is to be expected. For the following years, the frequency of dry or wet years can be adjusted as described below.

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2.2 Data splitting using thresholds

The general idea is to divide the historical weather data according to annual precipitation into a pool of dry years and a pool of the remaining years. Based on that, different future scenarios can be generated with a defined abundance of droughts or rainy seasons. Two approaches can be used to identify dry years, one based on percentiles of the distribution of annual precipitation, the other is based on the Standardized Precipitation Index (SPI).

2.2.1 Using percentiles

The historic weather data provides the distribution of annual precipitation x_i [mm] with $i = 1, 2...n$ for a period of n years. For robust results, we recommend using historical data that are at least as long as the future sequence. For this period, the percentiles $p(T)$, i.e. the fraction of years where the precipitation is smaller than a threshold value T, is given by:

$$p(T) = \frac{1}{n}\sum_{i=1}^{n} S(T) \tag{1}$$

where S(T) is the indicator function

$$S(T) = \begin{cases} 1 & \text{if } x_i \leq T \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Dry years can now be identified according to the choice of the percentile $p(T)$ and the corresponding threshold value for annual precipitation T in that all years with x_i < T are declared as dry and the others as wet. As an example, with the percentile $p(T) = 0.3$ the driest 30% of the historic years are identified as 'dry' years. (see Figure 1 (2A)).

In principle, the method can be applied to characterize both aridity and wetness by choosing the percentile. For example, selecting a 0.7 percentile assigns the 70% of years with the lowest precipitation to the dry category. By subsequently reducing the sampling frequency from these 70%, the relative share of wet years in the generated future sequences increases.

2.2.2 Using SPI

The second method uses the Standardized Precipitation Index (SPI) to analyze the historical data for dry or wet periods of different length. This is done by comparing the observed precipitation to its long-term average at a given location. The calculation of the SPI requires a historic weather sequence of at least 30 years (Moreira et al., 2015).

A gamma probability distribution is fitted to the cumulative precipitation data observed during fixed time intervals k. The length of the intervals can be optimized for the given application and is typically in the range of k = 3, 6, or 12 months. The obtained distribution is then transformed to the standard normal distribution with zero mean and variance one. This function reflects the SPI value and represents the standard deviation with negative values for below-average precipitation and vice versa. Values between -1 and 1 indicate near normal conditions. The more negative or positive the SPI value, the more pronounced the severity of drought or wetness (see table 1). The R package 'SPEI' provides the function to calculate SPI values for weather data (Beguería and Vicente-Serrano, 2014).

The computation of the SPI index should be based on the historic records of monthly precipitation for at least 30 years (missing data need to be filled appropriately). It is calculated along the following steps: (i) for a given time scale k calculate the accumulated precipitation for each month j within the historic record

$$X_j^k = \sum_{j-k+1}^{j} x_j, \tag{3}$$

with x_j the total precipitation in month j.

(ii) fit a gamma distribution F(X) to the resulting monthly series; (iii) compute the non-exceedance probability for each cumulative precipitation value; (iv) transform these probabilities to the standard normal distribution to obtain the SPI values. As an example for $k = 12$, the SPI for December of a given year reflects the relative precipitation deficit or excess of this year in relation to the entire historic period (Moreira et al., 2015).

Table 1. Common classification of SPI values (McKee et al., 1993).

Class	SPI values
Extremely wet	2.0 $<$ SPI
Very wet	1.5 $<$ SPI $\leq$ 2.0
Moderately wet	1.0 $<$ SPI $\leq$ 1.5
Normal precipitation	-1.0 $<$ SPI $\leq$ 1.0
Moderately dry	-1.5 $<$ SPI $\leq$ -1.0
Very dry	-2.0 $<$ SPI $\leq$ -1.5
Extremely dry	SPI $\leq$ -2.0

With that, we can use SPI thresholds to identify dry or wet years. The use of SPI thresholds can be especially attractive for agricultural applications, as it allows focusing on relevant periods or identifying those with particularly long dry or wet spells.

2.3 Design of future scenarios

After classifying dry or wet years using the percentile or the SPI approach, a fixed probability p_1 can be set to control the frequency of dry years and $p_2 = 1 - p_1$ the probability of drawing from wet years for the future scenario of n years. Thus, the expectation of dry years within the scenario is $n_{\text{dry}} = n * p_1$ and the expectation of wet years is $n_{\text{wet}} = n * p_2$. The consecutive years are randomly drawn from the dry and wet years with probabilities p_1 and p_2, respectively, and the drawn years are returned to the pool (see Figure 1 (3)). The dates of the sampled sequence will be overwritten by a future date sequence starting from the most current date of historic weather.

With the proposed approach, the aridity or wetness of the future scenario can be controlled by two parameters. First, the choice of the threshold to separate dry and wet years (i.e. the percentile $p(T)$ or the threshold SPI), which determines the severity of dry and wet spells, and second, the proportion of dry and wet years within the scenario, which determines the long-term probability of such dry and wet spells.

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2.4 Adding temperature trends

Following the precipitation-based sampling of future scenarios, temperature values are corrected in accordance with projected trends from RCP scenarios. To achieve this, the geographic coordinates of the respective weather station are used to extract local temperature trends available for the period 2030–2060. Thereby, different RCP scenarios can be chosen, such as RCP 1.5 or RCP 8.5. The corresponding temperature increase for the next 30 years ΔT_{30} is then used to calculate the daily (i.e. linear) trend for the future temperature T_f, which is added to the temperature of the sampled historic temperature T_h for each day:

$$T_f = T_h + N_d \frac{\Delta T_{30}}{(30 * 365)}, \tag{4}$$

where N_d is the number of days from the actual day into the future. This is done for the mean-, min & max air temperature. In case, no RCP scenario files are available, the trend can also be set manually.

2.5 Implementation

The LWS is implemented in R (R Core Team, 2024) and is freely available via the Zenodo archive (European Organization For Nuclear Research and OpenAIRE, 2013) at the following link: https://doi.org/10.5281/zenodo.17511186. The uploaded scripts include one script with the function to generate climate scenarios and a script that executes an example scenario. A CSV file with weather data is required with air temperature in K and precipitation and can be accessed by the DWD for German weather stations. The following R packages are used: data.table v. 1.16.0 (Barrett et al., 2024), ncdf4 v. 1.23 (Pierce, 2024), SPEI v. 1.8.1 (Beguería and Vicente-Serrano, 2014), tidyverse v. 2.0.0 (Wickham et al., 2019), zoo v. 1.8.12 (Zeileis and Grothendieck, 2005).

3 Example scenarios

For the following example, we created a wet scenario and a dry scenario by choosing a SPI >= 1 with a time interval of k = 12 months to consider long wet spell periods (for the dry scenario SPI <= -1, respectively). The probability of drawing for the wet scenario was set to $p1$ = 0.4 and for the dry scenario to 0.6. We used historical precipitation data of the DWD weather station in Müncheberg (latitude = 52.5176, longitude = 14.1232), and extracted the temperature trend from an ensemble RCP8.5 scenario for the given coordinates (accessed: https://www.dwd.de/DE/klimaumwelt/klimaatlas/klimaatlas_node.html). If no RCP scenarios are available the trend for mean, minimum and maximum temperature can be set manually. We used 30 years (1993-2022) of historical data to create a future scenario of also 30 years (2023-2052). The LWS results are compared with the results of a single model run of an ensemble of bias-adjusted regional climate model simulation based on EURO-CORDEX (EUR-11 MOHC HadGEM2-ES rcp85 r1i1p1 GERICS-REMO2015 v1-GERICS-ISIMIP3BASD) (Menz, 2023). The model run uses the RCP8.5 scenario and has been bias-corrected and downscaled using the ISIMIP3BASD method (Lange, 2019).

As outlined in the introduction, climate model runs can exhibit a "drizzle-down effect", meaning that precipitation is distributed too evenly across the year and without distinct dry periods. The EURO-CORDEX simulation produces substantially

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longer and frequent wet spells, including sequences of up to 13 consecutive weeks with daily precipitation, see table 2. The annual totals of precipitation also differ noticeable. The 30-year historic mean was 547.9 mm, while EURO-CORDEX historic yields 1077.6 mm and EURO-CORDEX future 1094.9 mm. In comparison, the dry scenario produces 483.1 mm, and the wet scenario 635.7 mm of mean anual precipitation. Figure 2 displays the frequency distribution of monthly precipitation over 30 years for the past and future scenarios. The overall distribution of rainfall events is comparable in the historic, dry, and wet scenarios, apart from slight shifts toward higher amounts in the wet scenario and lower amounts in the dry scenario. In contrast, the EURO-CORDEX model run exhibits a fundamentally different precipitation pattern, with a higher frequency of high precipitation months while low precipitation months with precipitation < 10 mm are almost absent.

Table 2. Counts of consecutive daily rain events for 30 years (N = 10956 days) aggregated in weeks (week 1 means 1-7 days of consecutive daily rain, week 2 means 8-14 days of consecutive daily rain, etc).

week	historic	dry scenario	wet scenario	EURO-CORDEX historic	EURO-CORDEX future
1	1801	1796	1803	946	813
2	69	60	43	220	227
3	6	7	16	66	87
4	0	0	0	41	47
5	0	0	0	12	16
6	0	0	0	7	10
7	0	0	0	5	3
8	0	0	0	2	2
9	0	0	0	1	2
10	0	0	0	1	0
11	0	0	0	0	0
12	0	0	0	0	1
13	0	0	0	1	0

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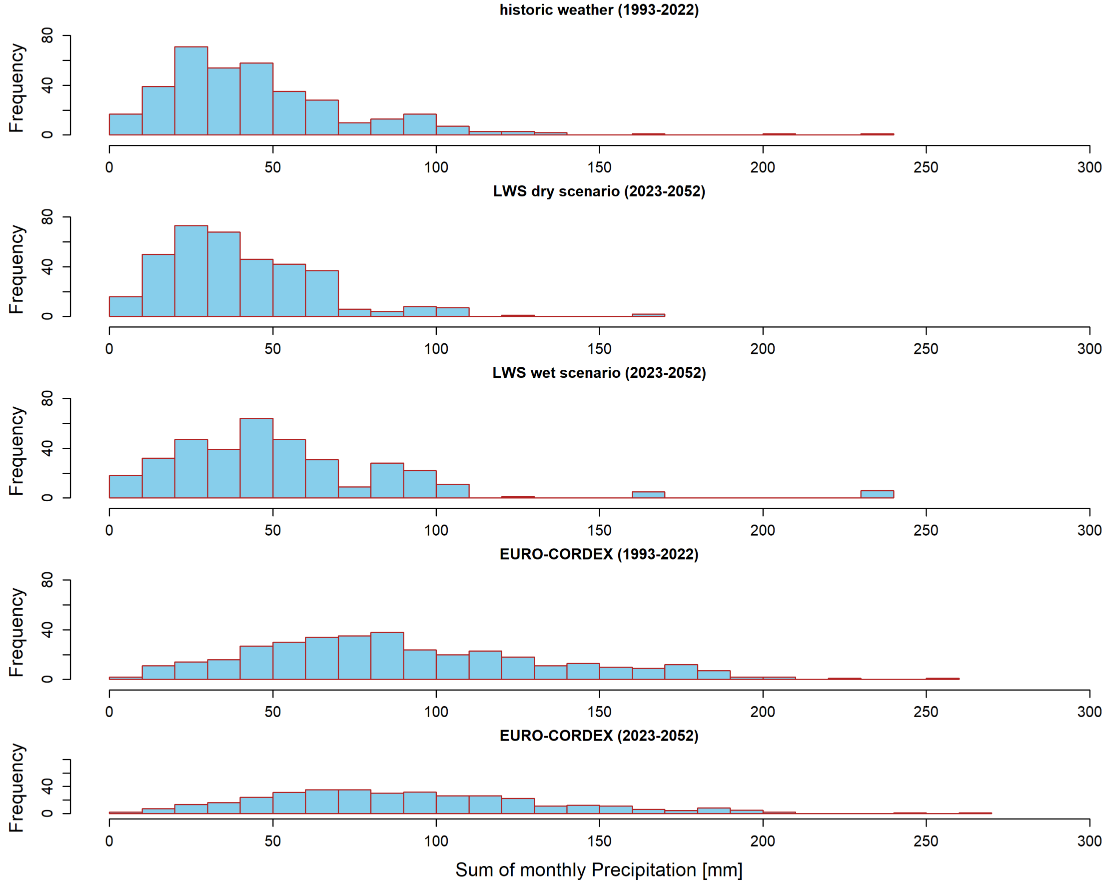

Figure 2. Frequency distribution of monthly precipitation for 30 years, for historic, EURO-CORDEX model run for the past and future, dry and wet scenario generated with the LWS.

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4 Discussion & conclusion

The presented method is designed to provide realistic weather scenarios at a daily resolution, and not to predict the most likely future weather conditions. Such realistic scenarios are highly required for modeling agricultural systems, including crop growth together with soil carbon and nutrient dynamics. There are mechanistic models available (BODIUM (König et al., 2023), APSIM (Holzworth et al., 2014), Expert-N (Engel and Priesack, 1993), LandscapeDNDC (Haas et al., 2013)) that have the potential to predict the impact of a changing climate and future agricultural management strategies on agricultural production and soil functions, which rely on such weather scenarios. This enables very practical questions to be addressed. For example, farmers would like to know how sensitive a planned crop rotation will be with respect to expected weather changes, or how this sensitivity can be mitigated by appropriate measures such as different tillage practices or different crop rotations. Such questions can indeed be addressed by models. However, they require realistic weather scenarios, which are hardly available at the moment.

The presented approach is designed to have daily weather patterns that can be manipulated in terms of aridity and wetness. Importantly, the resulting scenarios incorporate precipitation amounts and distributions that are consistent with the conditions observed historically and are representative for the respective location. Except for the transition between the last day of one year and the first day of the subsequent year, the scenarios follow locally observed sequences of weather phenomena. Since the transition between two consecutive years falls within the dormant season, this inconsistency is regarded negligible. The approach generates realistic daily precipitation data, to which a linear temperature trend is added. Although this approach captures long-term warming patterns, it may be less accurate than simulations based on fully coupled climate models, including long-term phenomena like the El Niño cycle. However, interannual weather patterns may change towards longer dry spells (Van der Wiel et al., 2023) or more frequent extreme events (Chang et al., 2025), these pattern changes might not be adequately reflected in the available historical data, since only observed weather can be used to generate the scenario. Yet the proposed framework provides a simple tool to generate scenarios tailored to specific requirements, such as sequences characterized by extremely dry years or by moderately dry years, as well as extremely wet future sequences. Moreover, the approach is easily transferable to other regions and allows for fast, straightforward calculations without the need for complex bias-correction procedures or Markov chain models. Thus, the presented approach can be a useful tool for scenario analysis of long-term models, such as crop or soil models, which require weather data of daily resolution. An example for the application of the LWS is BODIUM 4 FARMERS (https://bodium4farmers.de), which is an online model where framers can evaluate soil functions under selected management and climate scenarios .

Code and data availability. The technical implementation in R with an executable example can be obtained from the Zenodo archive (European Organization For Nuclear Research and OpenAIRE, 2013) under the license CC-BY-4.0 via the link: https://doi.org/10.5281/zenodo.17511186. The meteorological data can be obtained from the DWD: https://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/.

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Author contributions. All authors elaborated the algorithmic concept; AG implemented the codes and prepared the manuscript. All authors reviewed and edited the manuscript.

Competing interests. The authors declare that they have no conflicts of interest.

Acknowledgements. We thank Nora Leps from DAS-Basisdienstes „Klima und Wasser“ for providing data support and climate projections. We also thank Christoph Menz of the Potsdam Institute for Climate Impact Research for providing us with the code and all relevant information for the STARS 3.0 weather generator. The climate forecast data of the CORDEX-EUR11 runs were provided by Luis Samaniego of the Helmholtz Centre of Environmental Research - UFZ. AI tool have been used for spell checking. This work was funded by the German Federal Ministry of Research, Technology and Space (BMFTR) in the framework of the funding measure “Soil as a Sustainable Resource for the Bioeconomy – BonaRes”, project “BonaRes (Module B): BonaRes Centre for Soil Research, subproject A” (grant 031B1064A).

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