




SPEI: A Python package for calculating and visualizing drought indices

Martin A. Vonk ^{1,2}

¹ Department of Water Management, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, South Holland, The Netherlands ² Artesia B.V., Schoonhoven, South Holland, The Netherlands

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Summary

SPEI is a Python package for calculating drought indices from time series. Popular Python packages such as Pandas ([McKinney, 2010](#)), SciPy ([Virtanen et al., 2020](#)), and Matplotlib ([Hunter, 2007](#)) are used for handling the time series, statistics, and visualization respectively. This makes the calculation and visualization of drought indices straightforward and flexible.

Statement of need

Water is a vital natural resource, but freshwater availability is increasingly threatened by droughts linked to climate change and human activities. Drought refers to a water deficit relative to normal conditions ([Sheffield & Wood, 2011](#)). Both the definition of drought and the baseline for what constitutes “normal” conditions vary depending on the context and objective of a given analysis ([Dracup et al., 1980](#)). As a result, many drought indices have been developed to quantify drought characteristics. Each index quantifies a drought’s severity, location, timing, and duration, helping to track and predict its impact.

Standardized drought indices

The most common drought indices are standardized indices, which fit a time series to a probability distribution and convert it into a Z-score of the standardized normal distribution. For meteorological droughts, widely used indices include the Standardized Precipitation Index (SPI) ([Lloyd-Hughes & Saunders, 2002](#); [McKee et al., 1993](#); [Svoboda et al., 2012](#)) and the Standardized Precipitation Evaporation Index (SPEI) ([Vicente-Serrano et al., 2010](#)); the latter index is also the name of the SPEI package. Hydrological droughts are often measured using the Standardized Groundwater Index (SGI) ([Bloomfield & Marchant, 2013](#)) and the Standardized Streamflow Index (SSFI or SSI) ([Vicente-Serrano et al., 2012](#)). For agricultural droughts, the Standardized Soil Moisture Index (SSMI) ([Sheffield et al., 2004](#)) can be used. All of these standardized indices are explicitly supported by the SPEI package, though any other standardized drought index can also be computed using the same methodology.

Computation

Standardized indices are commonly calculated from a time series of at least 30 years ([McKee et al., 1993](#)). Rolling sums or averages are computed over typical time scales (generally 1, 3, 6, 12, 24, or 48 months)¹, and a continuous probability distribution is fitted to each.

¹A month is not an unambiguous time unit, varying between 28 and 31 days, which adds complexity to computations. The package handles this internally using Pandas to ensure consistent time aggregation.

Alternatively, non-parametric methods like normal-scores transforms or kernel density estimates can be used. The probability of each value is then converted to a Z-score using the inverse normal distribution, yielding a standardized index with a mean of zero and standard deviation of one.

Implementation

The SPEI package is built on Pandas (McKinney, 2010; The pandas development team, 2025), which in turn relies heavily on NumPy (Harris et al., 2020). It uses pandas.Series with a DatetimeIndex, enabling powerful time series methods such as resample and rolling. Probability density functions are provided via the SciPy stats module (Virtanen et al., 2020). Literature offers general guidance for what distribution to use for each standardized index; e.g., a gamma distribution for SPI (Thom, 1966) and a fisk (log-logistic) distribution for SPEI (Vicente-Serrano et al., 2010). However, with the SciPy package, users are free to experiment with any of the 200+ univariate continuous distributions available. Each distribution has a fit method for maximum likelihood estimation on the data.

Example

As an example, the Standardized Precipitation Evaporation Index is computed using a dataset with daily precipitation and potential evaporation from the Royal Netherlands Meteorological Institute (KNMI), shown in Figure 1a. The SPEI uses the precipitation surplus (precipitation minus potential evaporation), which is aggregated monthly for this example and shown in Figure 1b.

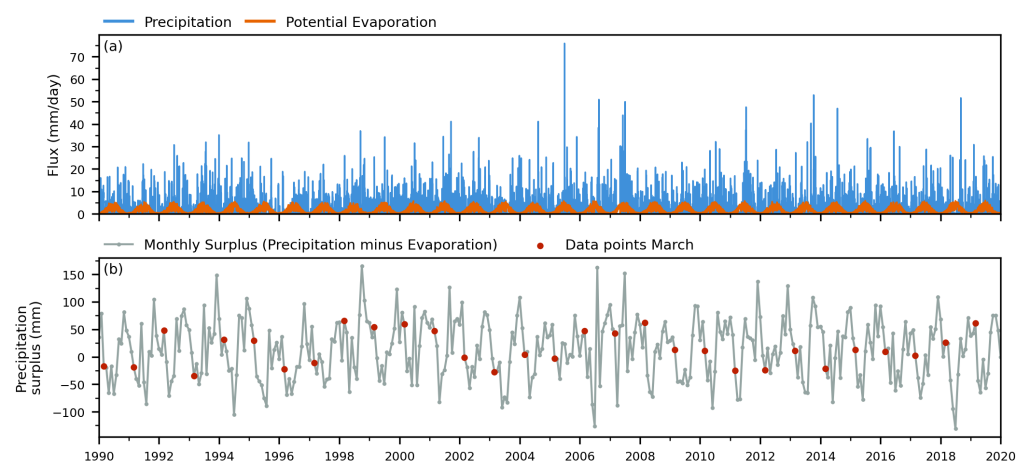


Figure 1: Example meteorological time series

The Python code to compute the SPEI-1 (-1 indicating a one month time scale) with a fisk distribution is as follows:

```
# load packages
import pandas as pd
import scipy.stats as sps
import spei as si

# load daily time series
meteo: pd.DataFrame = pd.read_csv(
    "meteo.csv",
    index_col="datetime",
```

```

    parse_dates=["datetime"],
)
prec: pd.Series = meteo["precipitation"]
evap: pd.Series = meteo["pot_evaporation"]

# compute monthly precipitation surplus
surplus: pd.Series = (prec - evap).resample("MS").sum() # MS: month-start

# compute SPEI-1
spei1: pd.Series = si.spei(
    series=surplus,
    dist=sps.fisk,
    timescale=1, # unit: frequency of the data (months in this case)
)

```

The standardization process is illustrated in Figure 2. The empirical cumulative density function of the surplus in March (red dots, matching Figure 1b) with the fitted fisk distribution are shown in Figure 2a. The fitted probability for each red dot is plotted in Figure 2b (blue dots) and converted to a Z-score using a standardized normal distribution (purple line). The black dashed line traces this procedure for a 31 mm surplus from March 1994, near the 69th percentile, corresponding to a Z-score of around 0.4925.

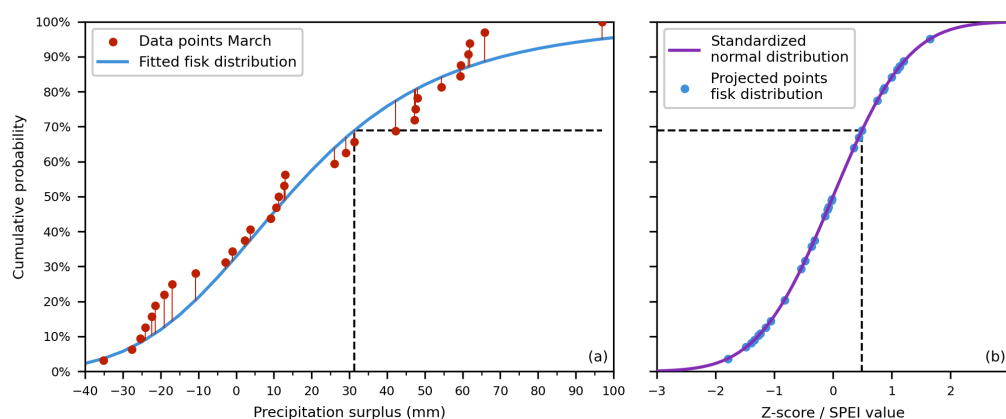


Figure 2: Example equiprobability transformation for the precipitation surplus in March. Figure adapted from Edwards & McKee (1997).

Application of this procedure for all data points and months results in the standardized index, SPEI-1, as shown in Figure 3. The background filling and categories (based on McKee et al., 1993) in Figure 3 allow for the interpretation of drought (and wet) periods. The SPEI package has additional options to allow for other time scales, time series frequencies (e.g., daily), and fit window options to ensure valid distribution fit.

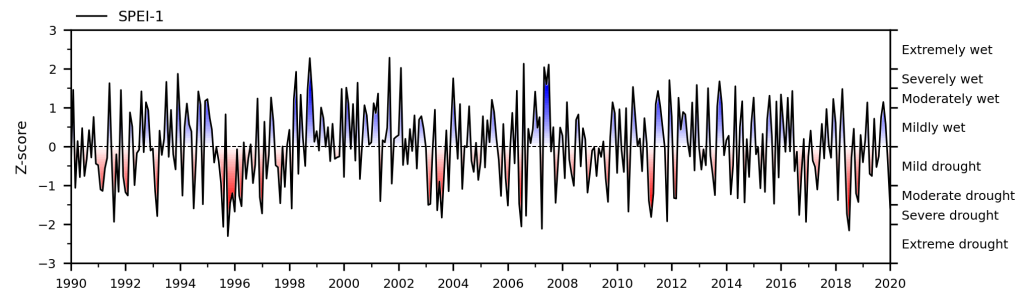


Figure 3: Resulting SPEI-1 from the monthly precipitation surplus

Threshold

Drought characteristics can also be derived from time series using a threshold level. This defines at what level a drought starts and quantifies the deficit. The threshold can be either fixed or variable. A variable threshold, as shown in [Figure 4](#) for part of the series of [Figure 1b](#), is typically derived from percentiles of the time series or from a fitted probability density function ([van Loon, 2015](#)).

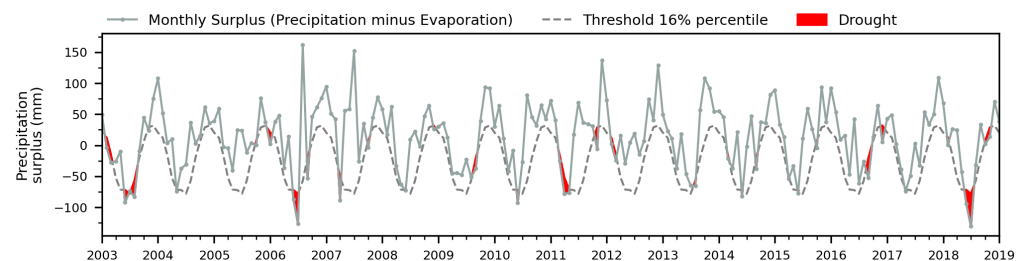


Figure 4: Visualization of drought based on a variable threshold level

Heatmap

When multiple time scales are used, standardized drought indices can be visualized in a single graph to reveal whether a drought persists over time and to identify the build-up to multi-year droughts ([van Mourik et al., 2025](#)). For hydrological droughts, this persistence relates to the system's storage capacity and response time (e.g., [Bloomfield & Marchant, 2013](#)). The SPEI heatmap ([Figure 5](#)) illustrates this across six time scales (1, 3, 6, 9, 12, and 24 months), clearly highlighting the 1995–1998 multi-year drought as a large red zone.

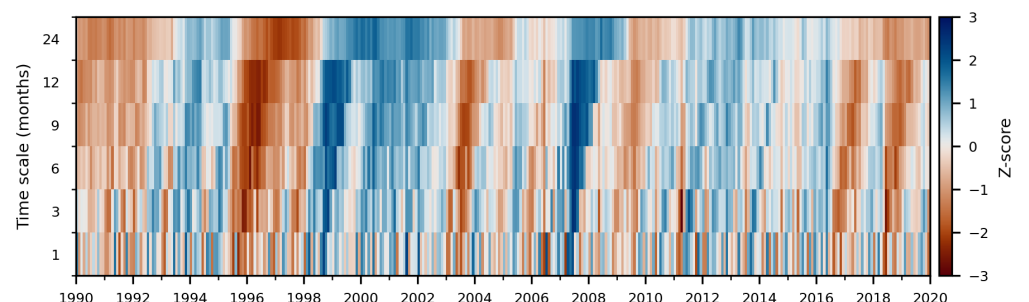


Figure 5: Visualization of the SPEI as a heatmap with different time scales

Other drought indices in the SPEI package

Several other drought indices from the literature are also supported by the SPEI package, briefly outlined below.

Rainfall anomaly index

The Rainfall Anomaly Index (RAI) is a relative drought index that quantifies deviations from historical precipitation without fitting a distribution (van Rooy, 1965). The package also includes the Modified RAI (mRAI), which adds a scaling factor for local conditions. (Hänsel et al., 2016).

Climdex

Climdex is an online platform providing indices for heat, cold, precipitation, and drought changes over time (Alexander et al., 2025), with several of its precipitation indices available in the SPEI package.

Precipitation deficit

The KNMI defines drought during the growing season using the precipitation deficit (potential evaporation minus precipitation). The package includes five functions (after Witte et al., 2025) to calculate this absolute drought index, primarily for the Netherlands but adaptable to other regions by adjusting the keyword arguments.

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