Indicator for Meteorological Drought Tracking (ERA5)

This Factsheet provides a description of the “Indicator for Meteorological drought tracking (ERA5)” as implemented at the European Drought Observatory (EDO) of the Copernicus Emergency Management Service (https://emergency.copernicus.eu/). It is used for the spatio-temporal delineation of meteorological drought events. The indicator is computed every ten days, using the Standardized Precipitation Index (SPI) accumulated over a 3 months period (SPI-3), derived from the ERA5 reanalysis for the global climate and weather of the European Centre for Medium-Range Weather Forecasts (ECMWF). An example of the indicator is shown in Figure 1.

Variables	Temporal scale	Spatial scale	Coverage
Precipitation	Dekad (10 days)	0.25 degree (~25 km)	World

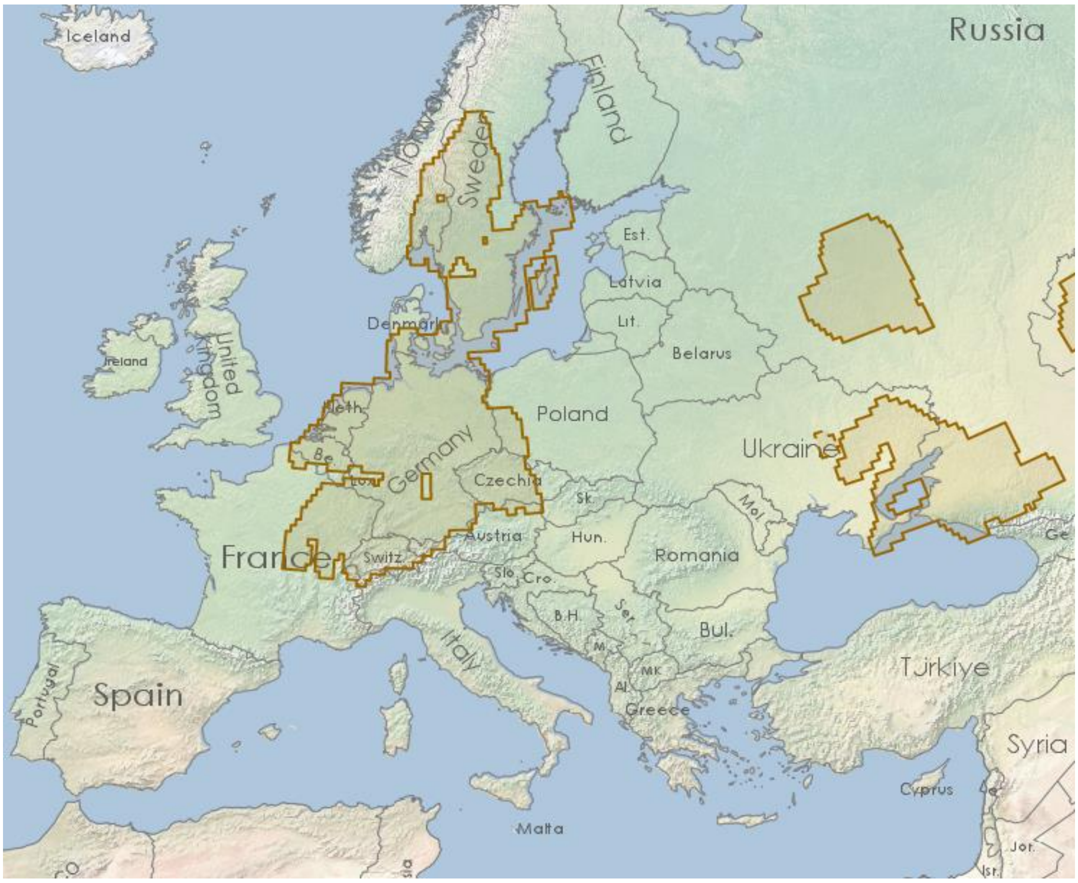


***Figure 1**: Snapshot example of the Indicator for Meteorological Drought Tracking.*

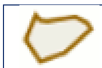
1. Brief overview of the indicator

The Indicator for Meteorological Drought Tracking provides a clear spatio-temporal identification of persistent low-precipitation conditions at the global scale and at near real-time. The indicator is based on the Standardized Precipitation Index (SPI) for 3-months accumulation periods (i.e. SPI-3). The SPI indicator is derived from the ERA5 fifth generation reanalysis for the global climate and weather of the ECMWF, with baseline 1991-2020. Drought events are identified by means of a three-dimensional density-based clustering algorithm (DBSCAN). The technical details describing the methods for the computation of the indicator can be found in Cammalleri et al. (2023).

2. What the indicator shows

The Indicator for Meteorological Drought Tracking provides the outline and the duration and total spatial extent of drought clusters. Areas subject to drought conditions are identified based on the Standardised Precipitation Index accumulation period of 3 months (SPI-3), and drought clusters are identified by means of a spatio-temporal DBSCAN algorithm, where clusters allow for spatial and temporal non-contiguity of multiple patches forming a drought event.
Different outlines indicate the status of the clusters: dashed for provisional events, full for consolidated ones, as shown in Table 1. Notice that the provisional status is a mere graphical indication of drought clusters that may likely change backwards, with following updates, and it does not indicate a real feature of the drought.

Table 1*: Legend for the status of drought clusters*

	Consolidated events: unlikely to be updated backwards in extension and duration.
	Provisional: the cluster may change significantly and backwards with further updates.

3. How the indicator is calculated

The Indicator for Meteorological Drought Tracking is computed following the methods described in Cammalleri et al. (2023). The Standardized Precipitation Index (McKee et al., 1993) at 3 months accumulation (SPI-3) is adopted since it is a common choice to characterize short- and medium-term meteorological drought conditions (WMO, 2012). Precipitation data from the ECMWF (European Centre for Medium-range Weather Forecasts) 5th generation reanalysis (ERA5, Herbasch et al., 2020) were used to compute the global SPI-3 maps at 0.25 degree spatial resolution from 1981 onwards, for roughly 10-day intervals (i.e. dekads: 3 SPI values per month, see Cammalleri et al., 2021). SPI-3 values are computed using a fitted gamma distribution by means of the Generalized Additive Model in the Location, Scale and Shape (GAMLSS, Stasinopoulos & Rigby, 2007). Cells and periods with more than 10 precipitation values lower than 0.01 mm in the baseline are masked out, as SPI values are not suitable for such dry areas (i.e. deserts). The SPI baseline is built on the precipitation time series 1991-2020.

Drought clustering is based on a generalization of the contiguous drought areas approach (CDA, Andreadis et al., 2005), following a weighted three-dimensional density-based spatial clustering of applications with noise (DBSCAN, Ester et al., 1996). A three-dimensional data cube (longitude, latitude and time) is analysed by searching in a three-dimensional neighbour space a minimum data density to define a cluster. A weighing factor is associated to each data cell in order to control the capability of each cell to form a cluster, and a minimum cluster size is introduce to remove noise. The equation for the weighting factor function is shown in Eq.1, below:

$$1 - \frac{1}{1 + \left(\frac{SPI3}{k}\right)^{e}} \tag{1}$$

Where ***k*** is a parameter that controls the centre value of the weighting logistic function and ***e*** is a parameter that controls the steepness of the logistic weighting function.

The weighting factor combined with the spatio-temporal DBSCAN methodology is implemented through a set of six parameters, which increases the capability of the methodology to adapt to different drought definitions (Cammalleri & Toreti, 2023), listed below:

- ***L***: the size of the search window in space used to detect neighbouring drought cells (value used L = 3, corresponds to a 3 × 3 search window in space);
- ***R***: the size of the search window in time, which may differ from the one in space to account for possible spatio-temporal asymmetry (value used R = 3).
- ***p***: the fraction of the cells within the search window that must be under drought to define a core cell (value used p = 0, corresponds to a single cell in the surrounding to define a cluster);
- ***A***: minimum size of a two-dimensional spatial cluster to filter noise (value used A = 200).
- ***k***: centre value of the weighting logistic function (value used k = 1.70);
- ***e***: steepness of the growing curve of the logistic weighting function (value used e = 8);

In Figure 2, an example is shown on how different values of ***k*** and ***e*** (displayed as ***w_lim*** and ***w_exp***, respectively) result in different configurations of the logistic weighting function, while the black line highlights the implemented parameterization. Figure 2 also displays an example of the application of the function.

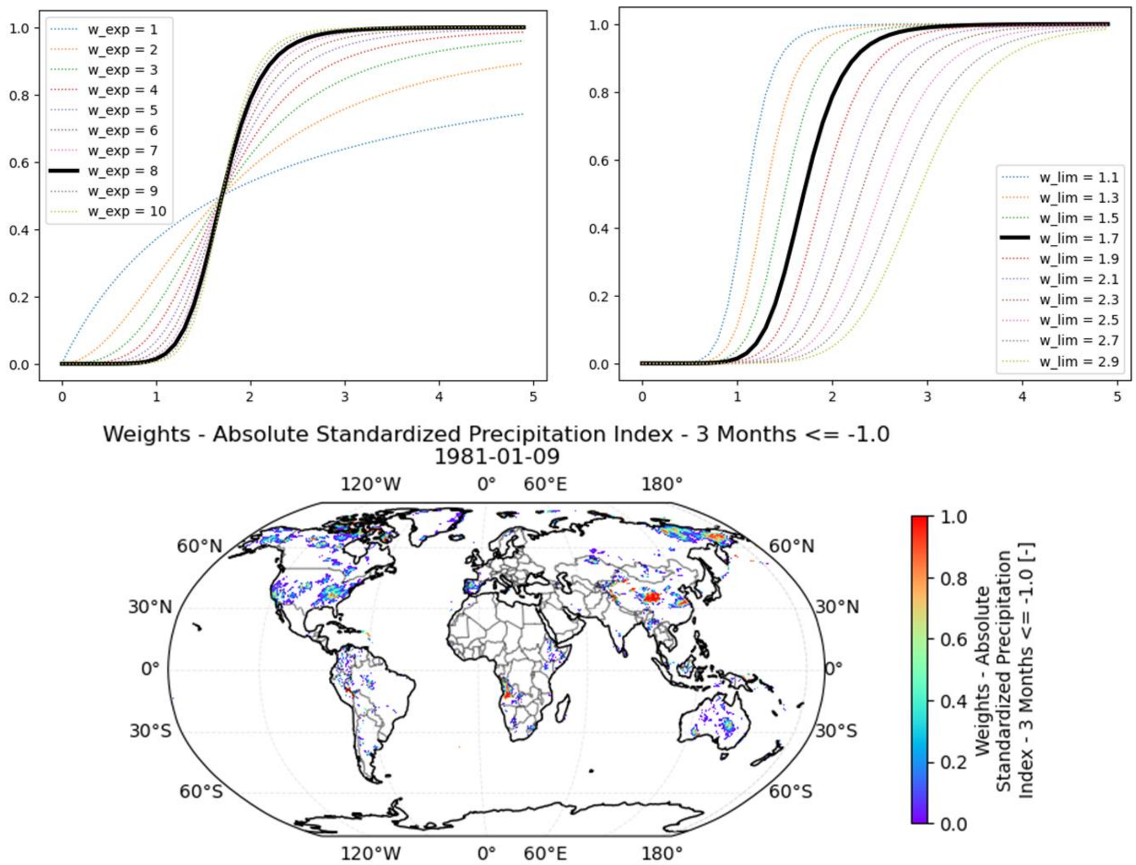


*Figure 2: Example of the logistic weighting function. On the upper left, the different shapes of the function when keeping **e=1.70** and varying **k** values from 1 to 10. On the upper right, the different shapes of the function when keeping **k=8** and varying **e** from 1.1 to 2.9. On the bottom part, an example of the application of the weighting function for SPI-3 in dekad 1 to 10 of January 1981.*

4. How to use the indicator

The indicator can be used to identify regions where drought events appear, expand, move, and to track their paths and extent in near real time. This allows, for instance, to overlap with other biophysical indicators, for aggregation purposes, to attribute drought impacts, to analyze drought dynamics (including predictability) and ultimately to inform drought risk evaluation.

5. Strengths and weaknesses of the indicator

Strengths:

- Clear delineation, both in time and in space, of drought events.
- Provision of near real-time information regarding the extension and duration of drought events at the global scale.

Weaknesses:

- A range of different degrees of clustering can be obtained using different model settings and parameterization, meaning that a same parameterization at the global scale can likely result in overestimation/underestimation of drought events in certain areas.

References

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