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Searching for the optimal drought index and time scale combination to detect drought: a case study from the lower Jinsha River Basin, China

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Abstract. Drought indices based on precipitation are commonly used to identify and characterize droughts. Due to the general complexity of droughts, comparison of index-identified events with droughts rely typically on model simulations of the complete hydrological system (e.g., soil humidity or river discharges), entailing potentially significant uncertainties.

The present study explores the potential of using precipitation based indices to reproduce observed droughts in the lower part of the Jinsha River Basin, proposing an innovative approach for a catchment-wide drought detection and characterization. Two new indicators, namely the Overall Drought Extension (ODE) and the Overall Drought Intensity (ODI), have been developed. These indicators aim at identifying and characterizing drought events at basin scale, using results from four meteorological drought indices (Standardized Precipitation Index, SPI; Rainfall Anomaly Index, RAI; Percent of Normal precipitation, PN; Deciles, DEC) calculated at different locations of the basin and for different time scales. Collected historical information on drought events is used to contrast results obtained with the indicators.

This method has been successfully applied to the lower Jinsha River Basin, in China, a region prone to frequent and severe droughts. Historical drought events occurred from 1960 to 2014 have been compiled and catalogued from different sources, in a challenging process. The analysis of the newly developed indicators shows a good agreement with the recorded historical drought at basin scale. It has been found that the combinations of index and time scale that best reproduces observed events are the SPI-12 and PN-12 for long droughts (1 year or more) and the RAI-6, PN-6 and DEC-6 for shorter or more consecutive events.

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1 Introduction

Drought is a natural phenomenon that results from persistent lower precipitations than what is considered as normal. It generally affects larger areas than other hazards and more people than any other natural catastrophe (Keyantash and Dracup, 2002; Wilhite, 2000).

In China, droughts represent the most severe natural threat for socioeconomic development and ecosystems (Mei and Yang, 2014). Drought events occur in the Jinsha River Basin (JRB) and surrounding regions with high frequency. They affect a wide range of areas and cause huge losses in agriculture (He et al., 2013). The clustering of severe and sustained droughts in southwest China during the last decade has resulted in tremendous losses, including crop failure, lack of drinking water, ecosystem degradation, health problems, and even deaths (Wang et al., 2015).

To reduce and anticipate such drought impacts, a comprehensive characterization of the phenomenon is essential to which effective and accurate analysis of hydrometeorological data is a key input. Drought indices are useful for tracking droughts and providing quantitative assessment of the severity, location, timing and duration of such events (World Meteorological Organization and Global Water Partnership, 2016), but also for real-time monitoring (Niemeyer, 2008), risk analysis (Hayes et al., 2004) and drought early warning (Kogan, 2000).

Some organizations and agencies already rely on the use of indices in their decision-making processes, thus enhancing proactive drought management policies (Wilhite, 2000). That is the case of the U.S. Drought Monitor (USDM, 2017), an index-based drought map that policymakers use in discussions of drought and in allocating drought relief. Other platforms such as the European Drought Observatory (Joint Research Centre, 2017), the China's National Climate Change (Department of Climate Change, National Development and Reform Commission, 2017) or the experimental African Drought Monitor (Land Surface Hydrology Group - Princeton University, 2017) also use this approach for the assessment, diagnosing and forecasting of droughts.

The choice of the index should be based on the type of drought (meteorological, agricultural, hydrological or socio-economical), the climate regime, as well as the regions affected. The present study focuses on the use of meteorological indices for this characterization, in particular: the Standardized Precipitation Index (SPI, McKee et al., 1993a, 1995), the Rainfall Anomaly Index (RAI, Van Rooy, 1965), the Percent of Normal precipitation (PN, Barua et al., 2011) and the Deciles (DEC, Gibbs and Maher, 1967). Main advantages of meteorological indices are the ease of use, the limited need of data and the capacity to an early detection of drought events. Extensive literature and calculation tools are widely accessible (World Meteorological Organization and Global Water Partnership, 2016). The four above-mentioned indices only rely on precipitation data; temperature and river discharge data are often not exploitable, potential evapotranspiration data are nonexistent at most meteorological stations, and soil characteristics information is hardly appraisable.

To fill the lack of specific drought-related information, most studies assess the performance of drought indices against results from hydrological soil water models (Halwatura et al., 2016; Hao and AghaKouchak, 2013; Trambauer et al., 2014; Vasiliades et al., 2011; Wanders et al., 2010). However, the performance of this type of studies is depending on the accuracy

of the models. Their limitations and uncertainties represent an important drawback and should be addressed (Mishra and Singh, 2011). An alternative that often requires a more exhaustive work is the compilation of historical records of drought events from different sources. Consequently, their duration, the water scarcity levels and the drought impacts on population and agriculture can be estimated and then integrated into the analysis. This allows identifying other types of droughts such as socio-economical droughts that are hard to assess with hydrological models.

Regarding their spatial resolution, the available drought indices may be based on local measurements (Zhou et al., 2012) and index calculations are usually applied to stations or cells of gridded precipitation datasets; overall spatial patterns at catchment or sub-catchment scales being thus hardly captured. As stated above, droughts affect large areas whose limits are often vaguely demarcated. Besides, water resources are part of a more complex interrelated network that links the source to the point of consumption, where isolated rainfall deficiencies do not imply necessarily a shortage of water availability or even a drought event. This leads to the convenience of relying on overall indicators capable of capturing in a unique value the effect of the rainfall deficiency at a regional level.

The objective of this study is to capitalize on the collection of drought events that the authors have registered in the lower part of the JRB since 1960 to evaluate and calibrate two indicators capable of identifying drought occurrence and characterizing their intensity at catchment scale. These new indicators are based on commonly used meteorological drought indices for particular time scales.

2 Investigation area and data

The JRB is a sensitive zone in terms of water resources, food security, ecosystem management and human well-being where glacier and climatic variability greatly influence the water regimes and availability. Originating from the southern glacier at Jianggendiru peak, highest point of the Geladaindong Snowy Mountain in the middle of the Tanggula Mountains, the JRB constitutes the upper part of the Yangtze River Basin. It is located between 24°28′ N–35°46′ N longitude and 90°23′ E–104°37′ E latitude in southwestern China, with a catchment area of 473 200km^2 (Fig. 1). The total length of the river is 3 500 km from the Yibin city, with a total fall of 5 100 m. This part of the Yangtze River accounts for 55.5 % of its length and 95 % of its total fall.

The lower part of JRB is a hot-dry valley region characterized by a southwest monsoon climate. The hydrologic regime is characterized by a pronounced seasonal cycle with an annual average precipitation of 600–800 mm/year. Dry season (November to April) precipitation accounts for 10 % to 22 % of the annual precipitation. Evaporation is 10 to 20 times of precipitation during dry season, which could be the major reason for the frequent occurrence of winter drought or winter–spring droughts in lower JRB (Mei and Yang, 2014; Yang et al., 2013). Droughts occurring in the lower JRB and surrounding areas affect a wide range of areas, causing huge losses in agriculture (Wu et al., 2011): more than 4 million people and 3 million livestock face drinking water shortage, and more than 1 million hm^2 of cultivated area are susceptible to

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be affected by severe droughts and water shortages, with expected direct economic losses of hundreds of million USD (Wu, 1999).

Figure 1 shows the division of the JRB in three parts (Upper, Middle and Lower), and the location of the meteorological stations used. This study focuses on the analysis of drought events in the lower JRB. The data needed in this study have been obtained from the China Meteorological Data Service Center (China Meteorological Administration, 2017), which is responsible for primary quality control. The monthly precipitation data of 29 meteorological stations within or around JRB, recorded from 1960 to 2014, have been collected and processed. More than 50 years of continuous data are thus available, except for the Batang and Yuanmou stations where only 46 years are available. The spatial distribution of the stations and the quality of the records enable its use for this study.

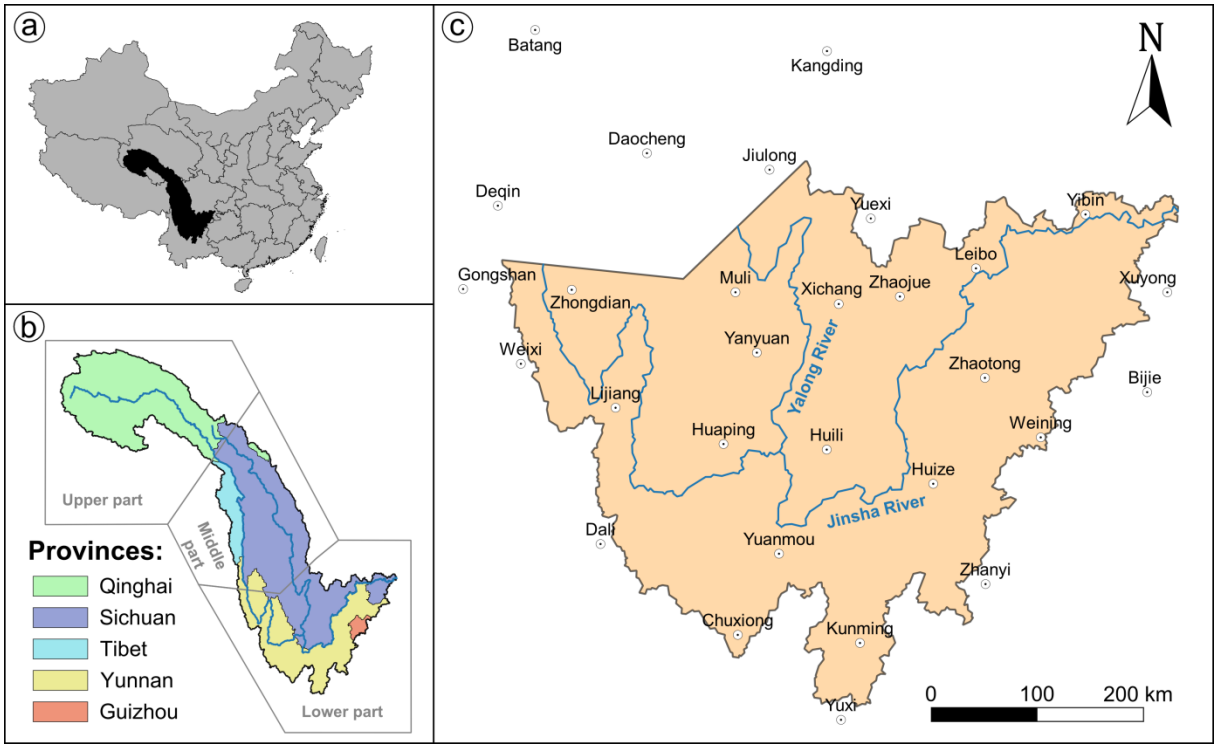

Figure 1. a) Location of the JRB in China; b) subdivision of the JRB for this study; c) overview of the lower JRB with the location of the 29 meteorological stations.

3 Catalogue of historical droughts

Historical drought events have been recorded since 1960. The information required for the identification and characterization of major droughts in the lower JRB has been compiled from different sources, including scientific literature, inventories, governmental reports and yearbooks, newspaper and internet. The collection of information focused on the affected area, the

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start date of the drought events, their duration, their spatial and temporal distribution, their severity and impacts on the population and agriculture, their damage and financial losses.

A web-based event registration platform and database (GEOTEST AG, 2017) has been developed to provide a standardized analytical framework with a quantitative description of the drought characteristics. All available information on extreme or disaster events has been compiled within the platform, giving a valuable description of each recorded event and allowing a comparison of them. Table 1 summarizes the main available information for the registered drought events within the lower JRB.

For the last 20 years, detailed information is available regarding all drought events. Before 1980, much less information about droughts in the lower JRB is available. Moreover, detailed information prior to 1960 could not be found.

Compiling and harmonizing the information from different data sources is a challenge, as the different information sources often provide only partial information for one event, for example only for one county and not the entire affected area. For some events, the data harmonizing process even revealed differences in the information issued from different sources.

In total, 13 major drought episodes have been registered from 1960 until 2014. However, this data set is probably not complete, as non-documented events likely have occurred. A clustering of severe and sustained droughts in the JRB has been observed from 2009 to 2014. Another period with high drought activity and severity can be detected between 1980 and 1990. Although the droughts identified from 2009 until 2014 were extremely serious, this was not the worst period in the long-term because the drought episodes that occurred around 1940 were of similar intensity and duration (Wang and Chen, 2012).

The use of meteorological indices allows analyzing the influence of precipitation on the identification of droughts in the lower JRB. However, the documentation also reveals that the registered droughts often occur during periods with temperatures above average.

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Table 1. Catalogue of historical drought collected for the lower JRB (DJF=December-January-February, MAM=March-April-May, JJA=June-July-August, SON=September-October-November).

ID	Year	Seasons	Affected area	Reference	Other indicators	Impacts
I	1962–1963	SON, DJF, MAM, JJA	Yunnan, southern part of Sichuan	He, 2010	Precipitation deficit of 50 % from November 1962 to April 1963.	Drinking water shortage for 900 000 people. Impacts on 3 700 km^2 agricultural land.
II	1978–1979	DJF, MAM, JJA	Yunnan	Liu, 2012		Impacts on 7 000 km^2 agricultural land, poor harvest, crop loss.
III	1981–1982	DJF, MAM, JJA	Sichuan, northern Yunnan	He, 2010		Drinking water shortage for 2 million people or 3 million people and 2 million livestock.
IV	1987	exact duration unknown	Mainly Yunnan			Impacts on 6 000 km^2 agricultural land, poor harvest, crop loss.
V	1992	MAM, JJA, SON	Yunnan, southern Sichuan	He, 2010	Maximum precipitation deficit: 50–80 %.	Drinking water shortage for 2 million people and 1 million livestock. Impacts on 9 300 km^2 agricultural land.
VI	1998–1999	DJF, MAM	Mainly Yunnan	He, 2010	Temperatures in Yunnan province 2–3 °C higher than long-term average. Dayao County: 150 days without rain.	8 000 km^2 damaged agricultural area.
VII	2000–2001	DJF, MAM	Sichuan, Yunnan	WCB, 2001	Temperatures in Yunnan province 2–3 °C higher than long-term average. The cities of Dali, Baoshan, Dehong, Chuxiong, Lincang have almost no rainfall during the whole winter.	Drinking water shortage for 3 million people and 2 million livestock. Impacts on 5 800 km^2 agricultural land.
VIII	2005	MAM, JJA	Large parts of Yunnan	Yang et al., 2012; Liu Yu et al., 2007	High temperatures; in April to early June, the temperature is 1 °C above the same period of history in most parts of Yunnan province. Precipitation deficit of 20–80% in May-June November. 56 days without precipitation.	Drinking water shortage for 6 million people and 4 million livestock. Impacts on 15 200 km^2 agricultural land, poor harvest.
IX	2009–2010	SON, DJF, MAM	Parts of Yunnan, Sichuan and Guizhou	Yang et al., 2012;Wang et al., 2015	Precipitation deficit. 119 days without precipitation. Average temperature anomaly of plus 1 °C.	Drinking water shortage for 21 million people and 11 million livestock. Impacts on 43 500 km^2 agricultural land, poor harvest.
X	2011	MAM, JJA, SON	Large areas in southwest China	Yang et al., 2012; Wang et al., 2015	Temperatures 0.4–1.1 °C higher than normal. From June to September 2011, persistent high temperature weather conditions. Precipitation deficit of 20–60 %.	Drinking water shortage for 12 million people and 9 million livestock. Impacts on 19 000 km^2 agricultural land. Cargo shipping has been suspended.
XI	2011–2012	DJF, MAM	Large areas in southwest China	Wang et al., 2013	Precipitation deficit.	Drinking water shortage for 2.4 million people and 1.6 million livestock. Impacts on 6 500 km^2 agricultural land.
XII	2012–2013	Oct-Apr	Southwest China	Guha-Sapir et al., n.d.; Hu Xueping et al., 2015	From October to April 0.5 °C higher temperatures than normal, in February 2.5 °C higher than long-term average. Jan-Feb: precipitation deficit of 45–55 %.	More than 3 million people and about 2 million large livestock had drinking water shortage with varying degrees. 323 small rivers and 331 small reservoirs dried up. 23 300 km^2 agricultural area affected (whereof 15 500 km^2 forest).
XIII	2014	DJF, MAM	Central Yunnan and south Sichuan	Duan et al., 2015	Spring temperatures 2–4 °C higher than historic values in SW China. Spring precipitation in central Yunnan and south Sichuan province was 50–90 % less than average of the same period.	Drinking water shortage for 1.6 million people in Yunnan province. 106 rivers and 76 reservoirs dried up.

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4 Meteorological drought indices

Four different commonly used meteorological drought indices have been applied in this study: the Standardized Precipitation Index, the Rainfall Anomaly Index, the Percent of Normal precipitation and the Deciles. Their definition basically rests upon the comparison of precipitation values with normal value (the definition of "normality" may vary from one index to another), resulting in a single number. This allows characterizing drought conditions and thus facilitating its interpretation and use in strategic planning and operational applications (Tigkas et al., 2013).

This comparison must be month or season specific. For the index calculation of January 2000, the precipitation of this month should be compared to the normal precipitation extracted taking into account only the Januaries from a reference period. The same applies when calculating the index for the time window January-February-March 2000: the sum precipitation for these 3 months will be compared to the sum of precipitation of all the groups of January-February-March registered in the reference period.

4.1 Standardized Precipitation Index (SPI)

The widely used Standardized Precipitation Index (SPI) was formulated by McKee et al. (1993a, 1995) to quantify the precipitation deficit from long-term recording and for multiple time scales.

Long-term record of precipitation values is fitted to a probability distribution which is then transformed into a standard normal distribution, of which mean and variance are 0 and 1, respectively (Edwards and McKee, 1997). The data sets are most commonly adjusted to the Gamma function (McKee et al., 1993a; Sönmez et al., 2005; Tsakiris et al., 2007) although some studies show better adjustments to other functions (Akbari et al., 2015).

A classification of drought conditions based on the SPI values was established by McKee et al. (1993a) to define drought intensities and is presented in Table 2. Positive SPI values indicate greater than normal precipitation, and negative values indicate less than normal precipitation.

Table 2. Classification of drought conditions according to the SPI values.

SPI	Classification
≥ 2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
–0.99 to 0.99	Near normal
–1.49 to –1.0	Moderately dry
–1.99 to –1.5	Severely dry
≤ –2.0	Extremely dry

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As mentioned earlier, the SPI was designed to quantify precipitation deficit for multiple time scales or moving time windows (World Meteorological Organization, 2012). These time scales reflect the drought impacts on different water resources that are needed by decision-makers:

- 3-month SPI: reflects short- and medium-term moisture conditions and provides a seasonal estimation of precipitation.
- 6-month SPI: indicates seasonal to medium-term trends in precipitation and may be very effective in showing the precipitation anomaly over distinct seasons. Information from a 6-month SPI may also be associated with anomalous streamflow and reservoir levels, depending on the region and time of year.
- 12-month up to 24-month SPI: reflects long-term precipitation patterns and is usually tied to streamflow, reservoir levels, and even groundwater levels at longer time scales.

4.2 Rainfall Anomaly Index (RAI)

The Rainfall anomaly Index (RAI) was developed by Van Rooy (1965). The RAI indices are computed by comparing the average precipitation over a given time window with the mean of the ten highest (for positive anomalies) and the ten lowest (for negative anomalies) precipitation records. Despite its simplicity, this index requires series of complete data to be calculated.

The RAI values are classified (Van Rooy, 1965) as shown in Table 3. Olukayode Oladipo (1985) found that differences between the RAI and the more complicated indices of Palmer Drought Index (Palmer, 1965) and Bhalme and Mooly Drought Index (Bhalme and Mooley, 1980) were negligible.

Table 3. Classification of the period according to the values of the RAI.

RAI	Classification
≥ 3.00	Extremely wet
2.00 to 2.99	Very wet
1.00 to 1.99	Moderately wet
0.50 to 0.99	Slightly wet
–0.49 to 0.49	Near normal
–0.99 to –0.50	Slightly dry
–1.99 to –1.00	Moderately dry
–2.99 to –2.00	Very dry
≤ –3.00	Extremely dry

4.3 Percent of Normal precipitation (PN)

The percent of normal precipitation (PN) is one of the simplest measurements of precipitation value for a location. It is calculated by dividing precipitation during a given time window by normal precipitation of that same time window over the

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reference period (typically considered to be a 30-year average). For PN values over 100%, the precipitation is higher than the average precipitation (and vice versa): the higher PN value, the wetter the considered month is.

The main advantage of this index is its simplicity and transparency, which makes it practical to communicate drought levels to the public (Keyantash and Dracup, 2002). Analyses using PN are very effective when used for a single region and/or a specific season.

Even if no threshold ranges have been widely established in the technical literature for the PN, some studies (Barua et al., 2011; Morid et al., 2006) propose a classification similar to the SPI. For this study, the classification proposed by Barua et al. (2011) has been adopted (Table 4).

Table 4. Classification of drought conditions according to the PN values.

PN	Classification
180% or more of normal rainfall	Extremely wet
161% to 180% of normal rainfall	Very wet
121% to 160% of normal rainfall	Moderately wet
81% to 120% of normal rainfall	Near normal
41% to 80% of normal rainfall	Moderately dry
21% to 40% of normal rainfall	Severely dry
20% or less of normal rainfall	Extremely dry

4.4 Deciles (DEC)

Another drought-monitoring technique consists in dividing the monthly precipitation data into deciles (DEC). This method, developed by Gibbs and Maher (1967), was selected as the meteorological measurement of drought for the Australian Drought Watch System (Lee, 1979; Sivakumar et al., 2010) because it is relatively simple to calculate and requires less data and fewer assumptions than the Palmer Drought Severity Index (Smith et al., 1993). The procedures have also been adopted by the World Meteorological Organization to monitor drought on a worldwide scale (World Meteorological Organization, 1985).

The threshold ranges of deciles used to classify drought conditions are presented in Table 5 (Gibbs and Maher, 1967).

Table 5. Classification of drought conditions according to the values of the deciles.

DEC	Percent	Classification
Deciles 1–2	lowest 20%	Much below normal
Deciles 3–4	next lowest 20%	Below normal
Deciles 5–6	middle 20%	Near normal
Deciles 7–8	next highest 20%	Above normal
Deciles 9–10	highest 20%	Much above normal

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5 Approach for the identification of drought events at basin scale

An indicator (or indicators) capable to adequately characterize historical droughts must be able to capture the following characteristics:

- The beginning and the end of the event, which defines its duration.
- The drought intensity, derived from the index value.
- The geographical area affected by the drought.

The following guidelines specify the approach proposed in this study to characterize drought events at basin scale based on precipitation data available at each station and how to contrast these results with the catalogued historical events.

First, following the previous definitions (Sect. 4), precipitation data are used to calculate the four above-described meteorological drought indices (SPI, PN, RAI and DEC) for each station and for different time scale (1-, 3-, 6-, 12-, 24- and 48-month). Then, according to the criteria presented below, these values are used to detect potential drought events at a given station and at a given time. In order to aggregate results from all stations of the basin, two new indicators are proposed in this study: the Overall Drought Extension (ODE) and Overall Drought Intensity (ODI). The results of these new indicators will then be contrasted with historical recorded events to define the best combination of index and time scale used for the definition of the ODE and ODI new indicators.

5.1 Use of indices to detect droughts at station scale

According to McKee et al. (1993), a drought event occurs at the station level any time the SPI is continuously negative and the SPI reaches a value of –1.0 or less, which corresponds to moderately dry condition (Table 2) or drier. The drought begins when the SPI first falls below zero (mean of the normalized precipitation) and ends with the positive value of SPI following a value of –1.0 or less. The drought magnitude is the positive sum of the SPI for each month during the drought event. The intensity of a drought is defined as the magnitude of this event divided by its duration.

Figure 2 shows an example of the SPI-6, SPI-12 and SPI-24 series calculated at the Chuxiong station. Drought periods are colored in orange and the lower threshold that defines their occurrence in red. The influence of the time scale on the number and duration of detected droughts is clearly apparent.

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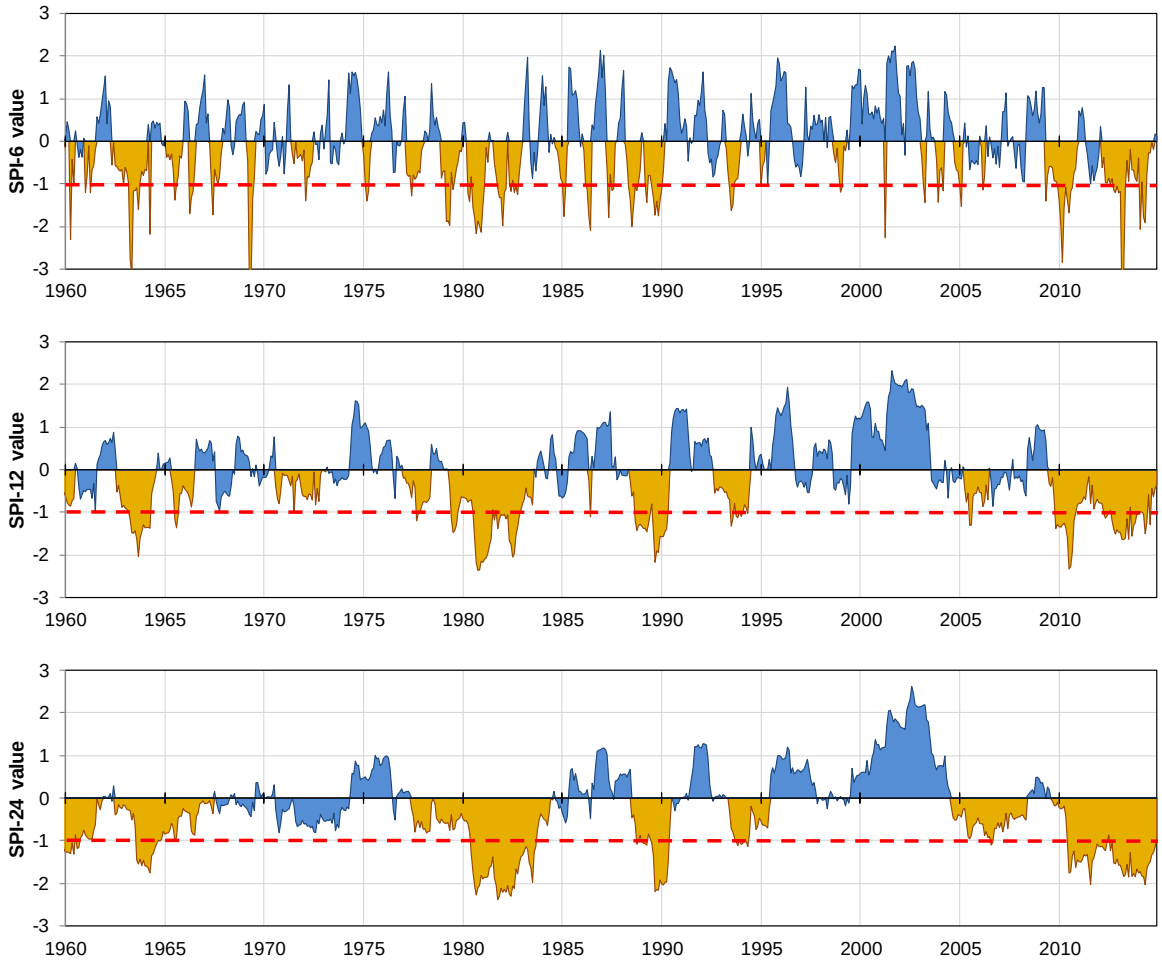

Figure 2. Example of the SPI-6, SPI-12 and SPI-24 series at the Chuxiong station, indicating drought periods in orange (lower threshold in red).

In the present study, the above-mentioned principles used to detect drought events based on the SPI classification (McKee et al., 1993b) have been standardized to be applicable to the other three indices (PN, RAI and DEC) as follows:

- A drought event occurs any time the index is continuously below its normal value and reaches the moderately dry condition class.
- The drought is considered to begin when the index first falls below its normal value.
- The drought ends when the index exceeds its normal value.

Table 6 summarizes the thresholds for each index that specify the drought event's start and end criteria, which correspond respectively to the limit of the moderately dry class and to the index normal value. Although the "normal value" of DEC would be 50% (which corresponds to the median of the precipitation records), in this study the drought end criterion

suggested for this index is 60%, which is the limit between near and above normal conditions (Jain et al., 2015; Tsakiris et al., 2007).

Table 6. Values of the thresholds defining the start and the end of the drought events, for each index.

Index	Start (moderately dry condition)	End (normal value)
SPI	–1	0
RAI	–1	0
PN	80	100
DEC	40%	60%

5.2 Identification of drought occurrence

As stated above, when analyzing directly a meteorological index, results only concern each station surroundings without capturing the patterns of neighboring areas. However, available historical records refer to regional droughts characterized by larger areas that cover several stations.

In order to consider the basin as a whole in the definition of drought occurrence, duration and intensity, the resulting indices must be consistently extended to the entire area and then combined in overall indicators. For that purpose, a regular grid divides the lower JRB into a 400x300 cells raster (400 rows and 300 columns) that, after trimming off the areas sticking out the basin boundaries, possesses 44 133 cells. Index values have been calculated at each grid cell by applying the Inverse Distance Weighting (IDW) spatial interpolation from the values available at the stations.

For this study, it is considered that a basin-wide event is ongoing when a substantial part of the basin is under drought conditions. It is therefore necessary to identify the portion of the territory for which the calculated index indicates a drought. An indicator to detect drought occurrence at basin scale has been set up based on the criteria described above to identify an event considering the index values (Fig. 2).

Based on the interpolation of the index, drought events are detected for each time step and at each grid cell of the described raster. This allows defining a new indicator, named here Overall Drought Extension (ODE). It is expressed as the percentage of the lower JRB suffering a drought by calculating the number of cells indicating a drought at a precise date (N_drought) divided by the total number of cells of the raster (in this case, N_TOTAL=44 133) as shown in Eq. (1).

$$ODE = \frac{N\_drought}{N\_TOTAL} \cdot 100 \,, \qquad (1)$$

The ODE ranges from 0% (when no drought is occurring at any point of the basin) to 100% (when the entire basin is suffering an event). It highlights the coverage of a drought, allowing a direct comparison between registered historical information and calculated results. Moreover, it helps defining the temporal component of droughts as it states the beginning and the end of an event. However, it does not take into account its intensity.

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5.3 Characterization of drought intensities

Regarding the intensity of the droughts, in this study a complementary new indicator is proposed to integrate the intensities computed at every grid cell. The Overall Drought Intensity (ODI) is defined as the average index value across the cells under drought conditions at a precise date, as shown in Eq. (2).

$$ODI = \frac{\sum_{i=1}^{N\_drought}(Index_i)}{N\_TOTAL}, \quad (2)$$

The ODI expresses the average severity in the drought-affected part of the basin. It gives information about the meteorological stress level of the areas being effectively affected by a drought. Moreover, this indicator may help completing the collected historical records for little information regarding the magnitude of the events has been found.

From indications of Table 2, Table 3, Table 4 and Table 5, lower values of this indicator denote drier conditions. Not defined values occur when no cells are under drought conditions.

On purpose, only cells under drought conditions have been considered for the definition of this indicator. If the ODI was calculated as an average value for the entire basin (as adopted for instance in Trambauer et al. (2014)) higher (or lower) indicator values in a part of the basin may compensate lower (or higher, respectively) indicator values in the rest of the basin, offering an overall value close to normal precipitation. Therefore, the ODI must always be used together with the ODE: whenever a drought has been detected with the ODE, its overall intensity may be assessed with the corresponding value of the ODI.

5.4 Evaluating indicator-based results with catalogued historical events

In order to support the choice of an index and time scale combination for the definition of the ODE and ODI, an assessment of the quality of the forecasts performed with the different variants is recommended. The hypothesis followed in this study is that drought events (i.e., the forecasts) correspond to the cases when the ODE value exceeds a given threshold, which indicates a certain area is affected by an event. These forecasts have to be then contrasted with the occurrence of recorded droughts (i.e., the observations).

Different scores for verifying dichotomous forecasts (occurrence vs. no occurrence) exist: the Peirce skill score, PSS (Hanssen and Kuipers, 1965; Murphy and Daan, 1985; Peirce, 1884); the Heidke skill score, HSS (Heidke, 1926); the Gilbert's skill score, GSS (Schaefer, 1990); or the odds ratio skill score, ORSS (Stephenson, 2000). As recommended by Candogan Yossef et al. (2012), the PSS is used in this study. For its calculation, the Miss Rate (M) and the False Alarm Rate (F) are defined in Eq. (3) and Eq. (4) respectively:

$$M = \frac{c}{a+c}, \quad (3)$$

$$F = \frac{b}{b+d}, \quad (4)$$

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where a, b, c and d represent the number of cases for each possible forecast outcome: hit, false alarm, miss and correct rejection, respectively (Table 7). The Miss Rate (M) indicates how many of the observed events are not forecasted (related to the Type 1 errors) while the False Alarm Rate (F) is the proportion of non-occurrences that are incorrectly forecasted (Jolliffe and Stephenson, 2003).

The PSS is expressed as shown in Eq. (5):

$$PSS = 1 - M - F \,, \tag{5}$$

The PSS ranges from –1 to +1: perfect forecasts receive a score of one, random forecasts receive a score of zero, and negative values indicate less skill than a random prediction. A suitable combination of the index and time scale will then lead to higher PSS values.

Table 7. Contingency table of the comparison between forecasts and observations.

		Observation	
		Yes	**No**
Forecast	**Yes**	a (hit)	b (false alarm)
	No	c (miss)	d (correct rejection)

However, high values of the PSS score may be obtained purely by chance, especially when using only a small number of forecasts. This could lead to overestimate the goodness of a combination of index and time scale. A statistical test should then be applied to check if the calculated PSS values are significantly different from zero, at least at a 95% confidence. Assuming independence of the Miss and False Alarm rates, the standard error in the Peirce skill score is simply the square root of the sum of the squared standard errors in the Miss and False Alarm rates (Stephenson, 2000), as expressed in Eq. (6):

$$SE_{PSS} = \sqrt{(SE_M)^2 + (SE_F)^2} \,, \tag{6}$$

where the standard errors in estimated Miss (SE_M) or False Alarm (SE_F) rates can be extracted from Thornes and Stephenson (2001). If the $PSS \pm 1.96 \cdot SE_{PSS}$ interval does not include zero, then the null of random forecast can be rejected at a 95% confidence level.

6 Results and discussion

Following the previous approach, the series of the SPI, PN, RAI and DEC indices have been calculated for different time scales (1-, 3-, 6-, 12-, 24- and 48-month) for the period 1960–2014. First computed at the 29 stations, these indices have then been extrapolated to the rest of the lower JRB. Figure 3 shows the example of the Standardized Precipitation Index for a 12-

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month time scale (SPI-12) calculated in August 2013 and spatially distributed at the entire lower JRB. Blue colors indicate wet conditions while brown colors represent regions under drier conditions.

According to the criteria proposed in Table 6, detected drought events have been identified based on these values. Then, the ODE and ODI indicators have been calculated for the lower JRB. The resulting ODE and ODI series are represented in Fig. 4 and Fig. 5 as well as in Appendix A, highlighting the recorded historical droughts in orange.

The objective is to establish a combination of time scale and index that offers an optimum identification of historical droughts. As stated before, the main criteria used to contrast the performance of the forecasts is that a drought event is supposed to happen when the ODE value exceeds a threshold that is to be defined for each combination. The combination finally retained should maximize the number of hits and minimize the misses between the forecasts and the observed events.

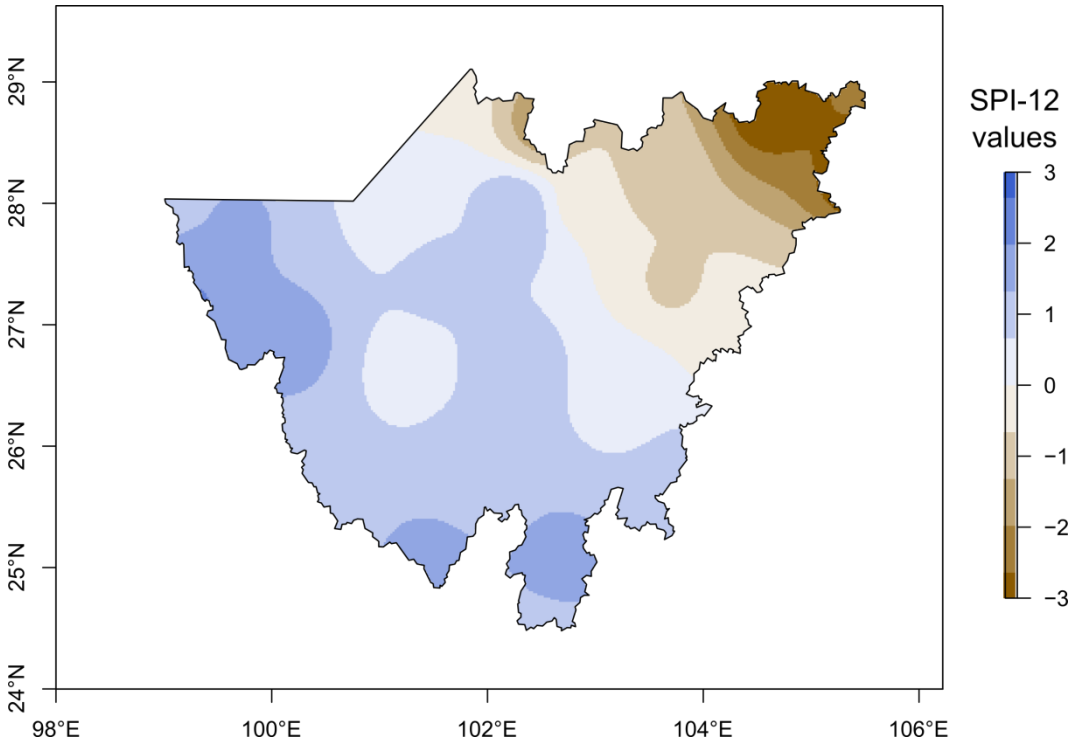

Figure 3. Extrapolated SPI-12 values in August 2013 for the entire lower JRB.

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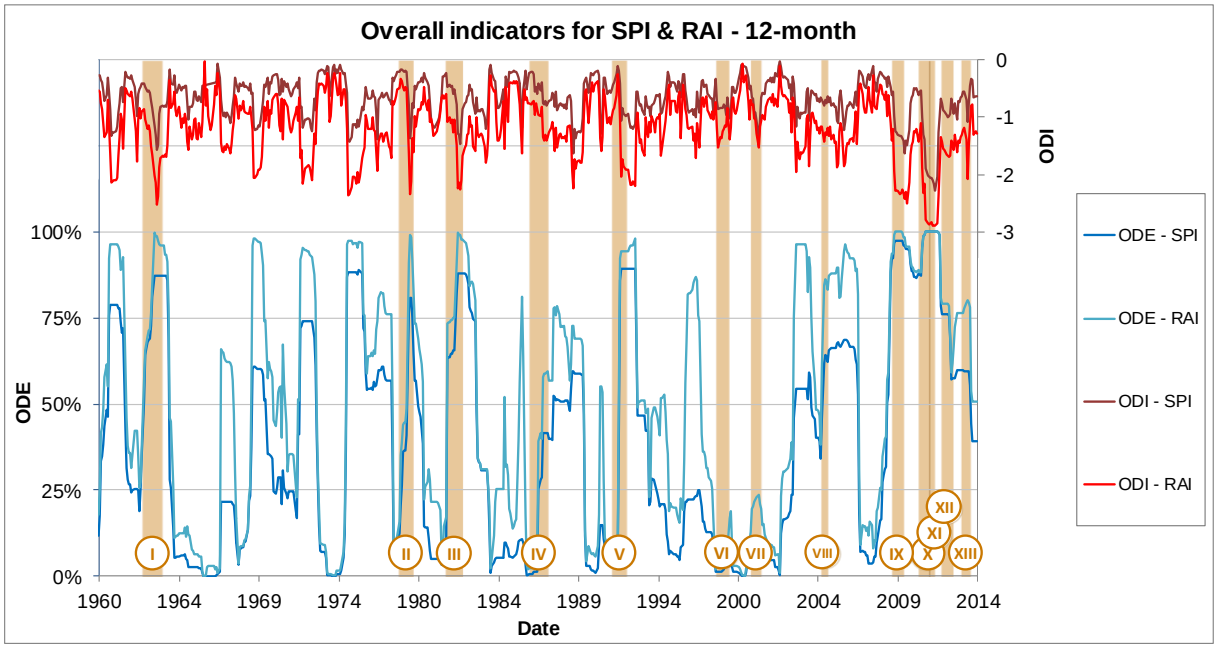

Figure 4. ODE and ODI values using the 12-month time scales of SPI and RAI indices, compared with the 13 detected historical droughts (in orange).

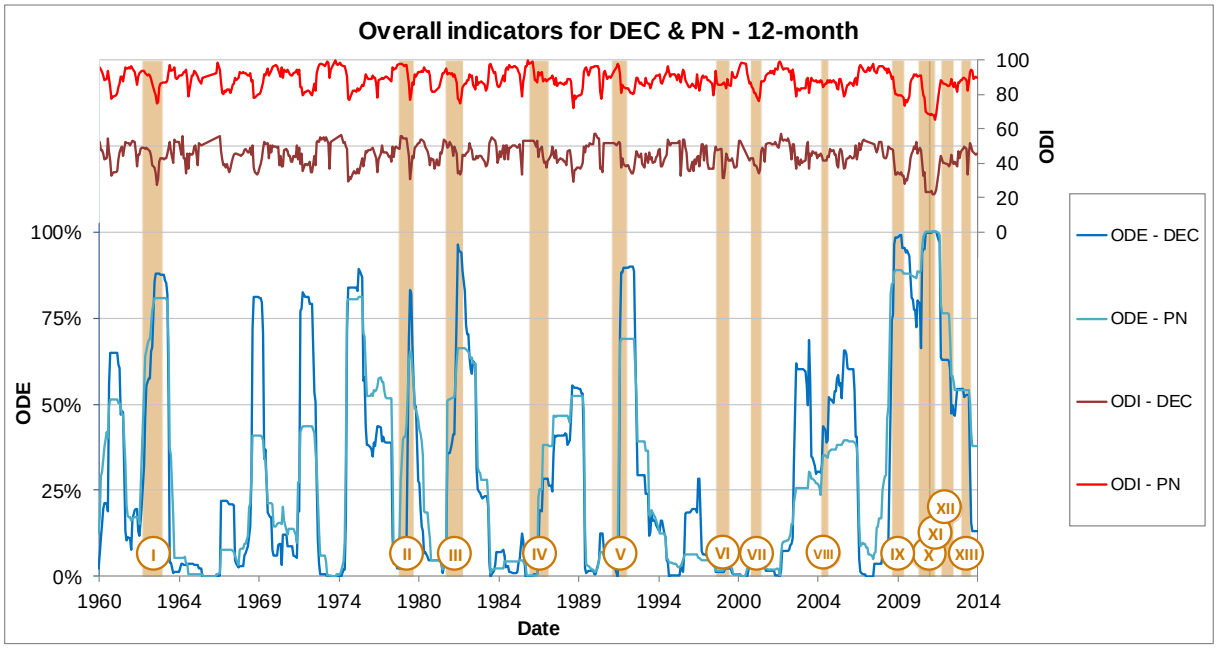

Figure 5. ODE and ODI values using the 12-month time scales of DEC and PN indices, compared with the 13 detected historical droughts (in orange).

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The 1-month scale overall indices show rapid fluctuations that correspond with short periods of precipitation deficiency not captured in the catalogue of historical droughts. This is mainly due to punctual large rainfall events having an important influence in the indices which may indicate that the drought had ceased when it is not the case (Barua et al., 2011). The use of this time scale is not recommended for drought monitoring since long drought events are hardly identified. The opposite effect occurs when using the 48-month scale. The inertia of the rainfall shortage tendencies may mask shorter droughts and overestimate their durations. Since most of the episodes last one year or less (Table 1), they are hardly detected using the 48-month scale. The droughts occurred from 2009 to 2014 (droughts IX to XIII) illustrate this phenomenon: even if five different droughts have been catalogued, a unique one is detected using the 48-month scale, according to the ODE time series. Therefore, using the 1- and 48-month scales do not provide any substantial information about the occurrence and duration of the droughts and have been excluded from the performance analysis.

For the rest of the time scales (3-, 6-, 12- and 24-month), the ODE thresholds indicating the occurrence of a drought are required. Based on the resulting ODE series, a set of thresholds has been manually estimated (Table 8) to match as many observed events as possible. According to these thresholds, the PSS is calculated for each index and time scale combination (Table 9) along with its 95% confidence interval, which allows verifying whether the score is significantly different from zero, as described in Sect. 5.4. Graphic results are presented in Fig. 6.

Table 8. Thresholds estimated for the ODE indicating the occurrence of a drought.

Index	Time scale			
	3-month	**6-month**	**12-month**	**24-month**
SPI	75%	75%	65%	50%
RAI	95%	85%	75%	75%
PN	95%	85%	60%	25%
DEC	75%	75%	75%	60%

Table 9. Peirce skill score values for each combination of index and time scale, with 95% confidence intervals.

Index	Time scale			
	3-month	**6-month**	**12-month**	**24-month**
SPI	0.34 ± 0.18	0.23 ± 0.18	0.38 ± 0.18	0.17 ± 0.18
RAI	0.3 ± 0.16	0.4 ± 0.14	0.25 ± 0.18	0.17 ± 0.18
PN	0.37 ± 0.17	0.44 ± 0.16	0.45 ± 0.16	0.32 ± 0.16
DEC	0.29 ± 0.18	0.38 ± 0.18	0.32 ± 0.17	0.25 ± 0.18

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Figure 6. Graphic representation of the PSS results, with the black error bars representing the 95% confidence interval (±1.96 standard errors).

Most of the 95% confidence intervals of the PSS do not include zero, disproving that skill scores could have identified drought events by chance sampling fluctuations. On the contrary, for the SPI and RAI at 24-month, results cannot assert that skill scores are significantly different from zero and thus these two combinations should not be considered.

In general, the 6- and 12-month time scales shows a better performance on detecting historical droughts, in particular when using the PN index. It is worth noting that the confidence intervals obtained are in general relatively wide, which is mainly due to the few events used as the basis for the PSS evaluation. An additional analysis of the ODE series is thus required to assess the performance of each combination in the detection of droughts.

Attending to the 12-month ODE series (Fig. 4 and Fig. 5), it is important to highlight some relevant aspects:

- All ODE series have peaks corresponding to the drought events I, II, III and V.
- The drought event IV is captured by an increase of the ODE values. This increase is shifted forward, starting in the middle of the drought event IV and having its peak around 1990 (around 3 years later than specified in the catalogue). Nevertheless, as indicated in the catalogue of droughts (Table 1) the exact start date and duration of this event are unknown and could have occurred later.
- Although event VIII has an estimated duration of 3 months, ODE and ODI results consistently show a drought occurring in two phases (two consecutive increases of their values), covering a period of 1.5 and 2.5 years respectively. Event VIII seems to correspond to the second of these phases. Again, the exact period of this drought is not well defined as indicated in the catalogue, leaving room for a longer duration of the real episode.

- Among the four different meteorological indices, the RAI presents the higher variability which may lead to inconsistencies with the catalogued droughts. A clear example is the false positives detected in 1997 that does not correspond with any recorded event.
- In general, the SPI and the DEC indices are quite correlated, identifying most of the recorded droughts. The PN index behaves similarly, although it tends to underestimate the ODE values in relation to the SPI and the DEC.
- Three droughts of increasing magnitude are consistently detected between event I (1962) and II (1979) even if no droughts have been chronicled (false alarms). This may correspond to the above-mentioned scarcity of reliable information on droughts prior to 1980.
- While two episodes are reported in 1999 (event VI) and in 2001 (event VII), no ODE has captured them. However, the SPI-based ODI shows a significant decrease corresponding to event VII, which may indicate a not wide but intense drought.
- As mentioned above, during the period 2009–2014, five consecutive events (IX, X, XI, XII and XIII) have been reported. Using the 12-month series a certain spotting of these events can be achieved, although it tends to aggregate them in one or two unique episodes.

For the 6-month time scale (Fig. A5 and Fig. A6 of Appendix A):

- The IX, X, XI, XII and XIII droughts are well captured by the use of the 6-month timescale. As shown in Fig. A5 and Fig. A6, the different events during this period (2009–2014) match with the consecutive increases in the ODE values for all the indices (DEC, PN, RAI, SPI).
- However, the series of ODE suggest false positive detections: more drought events than the observed are calculated. An overestimation of the influence of short periods of rainfall scarcity may be masking the true duration of the droughts.

In general, the 1-, 3-, 24- and 48-month time scales do not reproduce the observed events and their use is not recommended. According to both the ODE series and the forecast verification carried out with the PSS, it seems that the best combination for the identification of long droughts (one year or more) is the SPI or the PN indices at a 12-month time scale, and the RAI, the PN or the DEC at a 6-month scale for shorter or more consecutive events (e.g., events IX to XIII). However, the risk of false positives must be addressed carefully, especially for 6-month scales.

Despite the performance shown by the proposed overall indicator ODE to detect droughts, some considerations are recommended. In particular, the choice of meteorological indices as a basis for the calculation of the ODE and ODI can lead to some errors when assessing drought occurrence. It has been proved that not all indices are equally capable of identifying droughts in this particular region. The variability of temperature, for instance, may have an important impact on the crop water availability and then in the assessment of agricultural droughts, although it has not been taken into account. Besides, changes in the regulation infrastructures such as reservoirs have a growing influence on water supply. Hence, meteorological indices are not fully capable to capture the impacts on water scarcity and should be complemented with other types of

indices, such as agricultural or hydrological. The same approach proposed in this study is recommended using different indices, such as hydrological or agricultural, in order to better capture the complex drought processes.

The performance assessment of the ODE indicator to detect droughts relies basically on the comparison with the historical events catalogued in this study. The search and compilation of this information from different data sources, often scarce and ambiguous, represents a challenge. Different information sources often provide only partial information for one episode, and for some events the differences in the available information complicate the harmonization of data. As a result, the accuracy of the collected information may impact on the applicability of the developed methodology.

7 Conclusions

This study aims at defining overall drought indicators representing the drought status within the entire lower JRB investigation area. This represents a tool for drought monitoring and risk management purposes at basin scale. It is based on established meteorological indices for the identification of droughts and a newly developed method for a catchment-wide drought assessment and characterization, which is compared to historical drought events of the lower JRB.

The information used for the identification and characterization of major historic droughts has been compiled from different sources. A total of 13 major droughts between 1960 and 2014 have been identified in the lower JRB and have been catalogued using a web-based registration platform, allowing a comparison of the different events.

Drought indices typically assess local water deficits while available historical records usually refer to regional droughts. To overcome this problem, two new indicators, the Overall Drought Extension (ODE) and the Overall Drought Intensity (ODI), have been developed to characterize the occurrence and intensity of an event within a specific investigation area. These new indicators are based on four common meteorological indices at different time scales between 1 and 48 months: the Standardized Precipitation Index (SPI), the Rainfall Anomaly Index (RAI), the Percent of Normal precipitation (PN) and the Deciles index (DEC). These indices only rely on precipitation data, which facilitates their applicability.

The performance of the ODE at detecting droughts has been assessed by contrasting the results of this new indicator with historical recorded events, offering promising results. It seems that the best combinations of index and time scale are the SPI-12 and the PN-12 to identify long droughts (1 year or more) and the RAI-6, PN-6 and DEC-6 for shorter or more consecutive events. Moreover, for each combination, an ODE threshold has been defined as a trigger to detect the occurrence of a drought in the lower JRB: 65% for the SPI-12, 60% for the PN-12, 85% for the RAI-6, 85% for the PN-6 and 75% for the DEC-6.

Considering the challenge that the compilation of historical drought information supposes and the identified limitations, this is a good method for the monitoring of drought episodes within an entire catchment. The definition of drought indicators at basin scale and the use of historical collected information represent the main innovative aspects of this study. Since meteorological droughts are the first stage in the progression of subsequent agricultural or hydrological droughts, this methodology could be used to activate a management response facing a drought event, which starts at a specific threshold

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value. Additionally, this methodology can be used to complete lacking information on droughts' duration, geographical extension or intensity.

8 Appendix A: series of ODE and ODI indicators

The series of the Overall Drought Extension (ODE) and the Overall Drought Intensity (ODI) have also been calculated for the 1-, 3-, 6-, 24 and 48-month time scales. Graphic results are presented in Fig. A1 to Fig. A10 below.

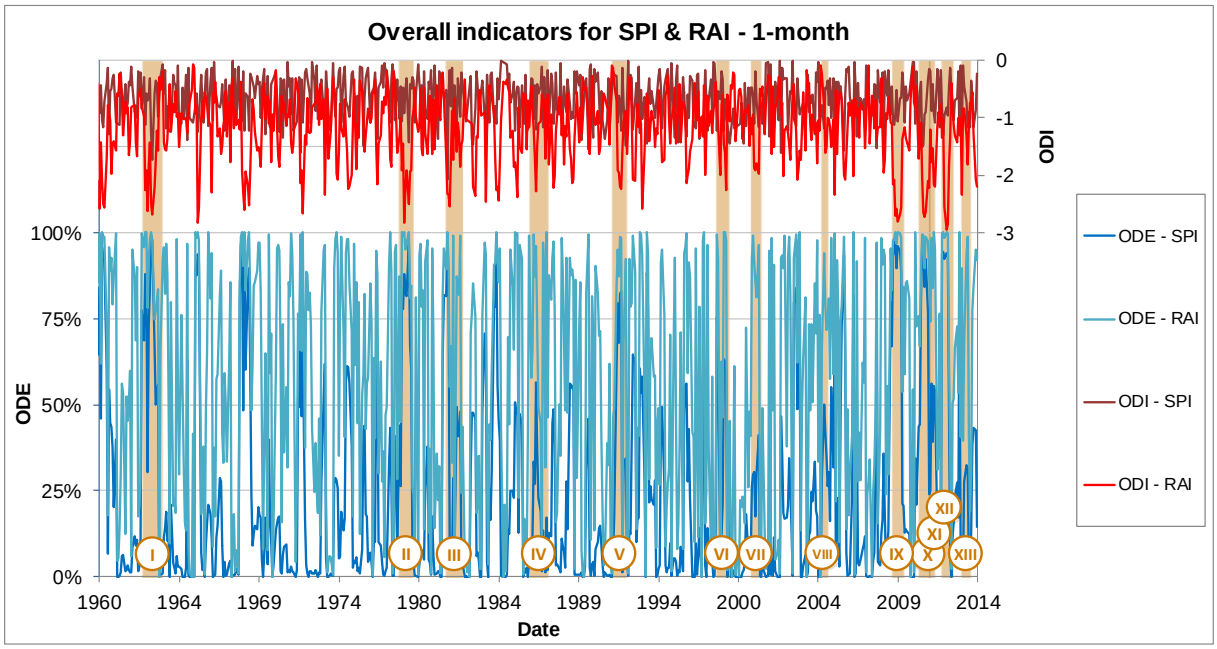

Figure A1. ODE and ODI values using the 1-month time scales of SPI and RAI indices, compared with the 13 detected historical droughts (in orange).

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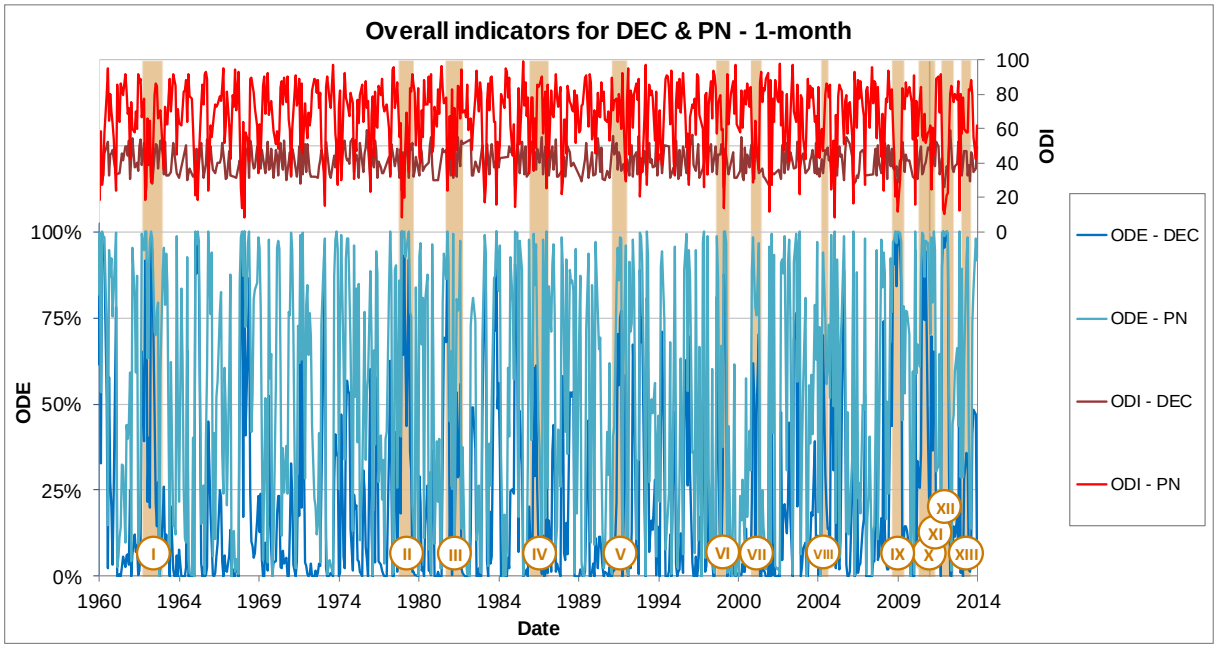

Figure A2. ODE and ODI values using the 1-month time scales of DEC and PN indices, compared with the 13 detected historical droughts (in orange).

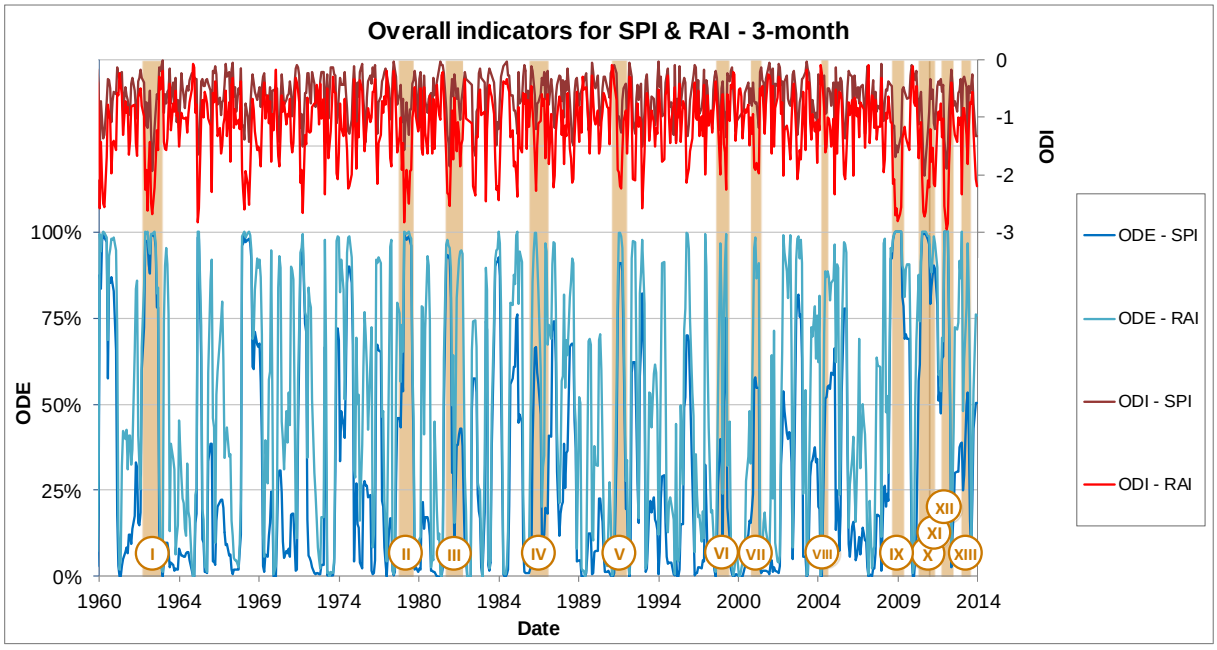

Figure A3. ODE and ODI values using the 3-month time scales of SPI and RAI indices, compared with the 13 detected historical droughts (in orange).

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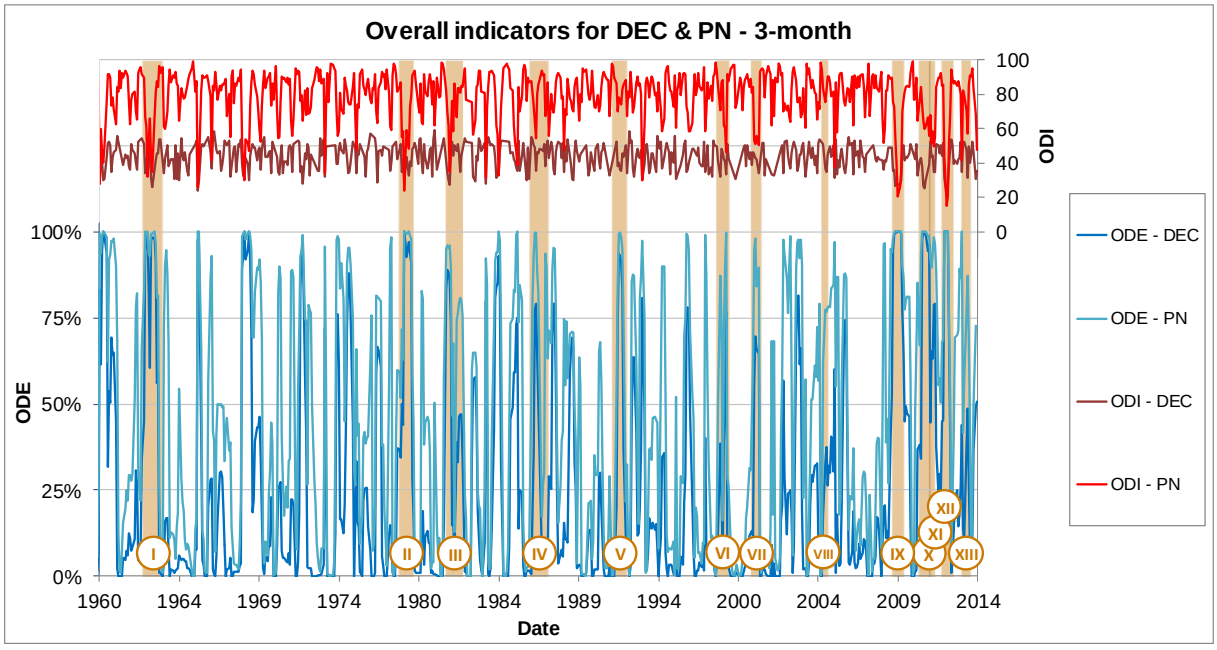

Figure A4. ODE and ODI values using the 3-month time scales of DEC and PN indices, compared with the 13 detected historical droughts (in orange).

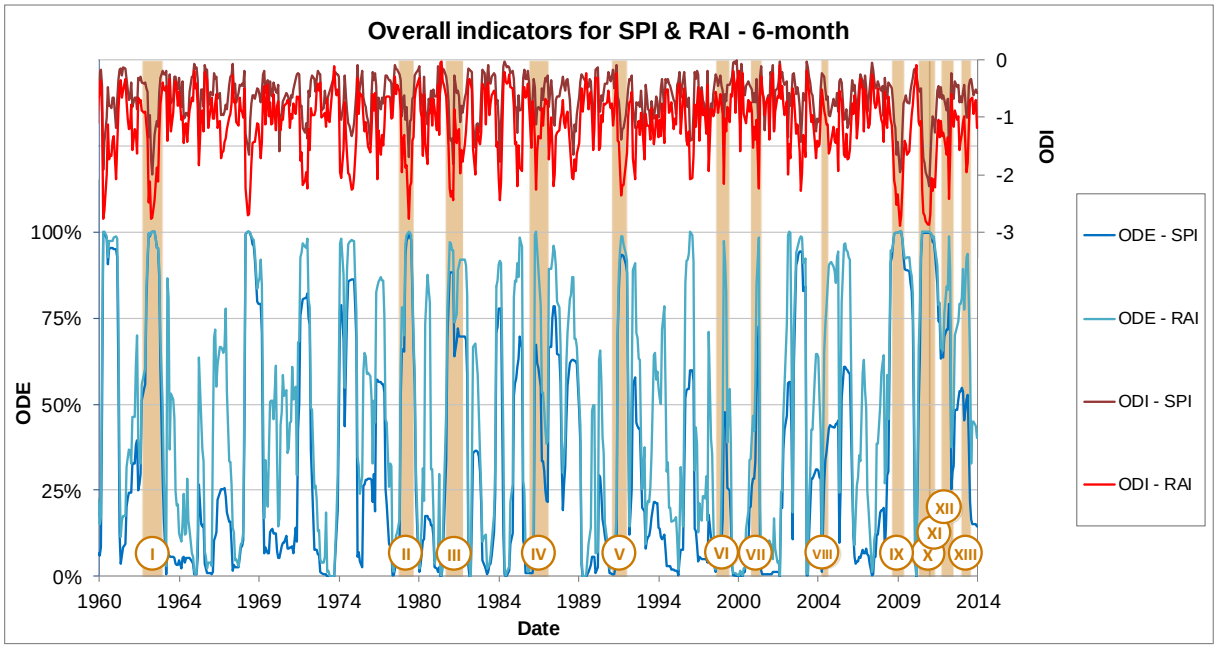

Figure A5. ODE and ODI values using the 6-month time scales of SPI and RAI indices, compared with the 13 detected historical droughts (in orange).

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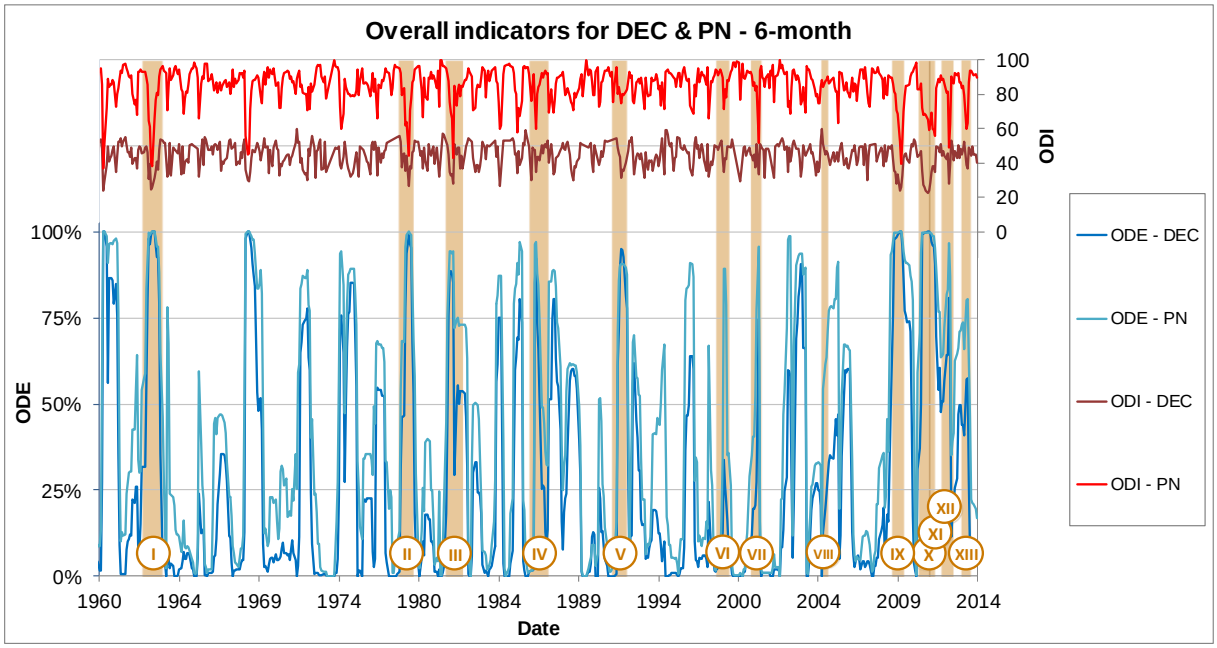

Figure A6. ODE and ODI values using the 6-month time scales of DEC and PN indices, compared with the 13 detected historical droughts (in orange).

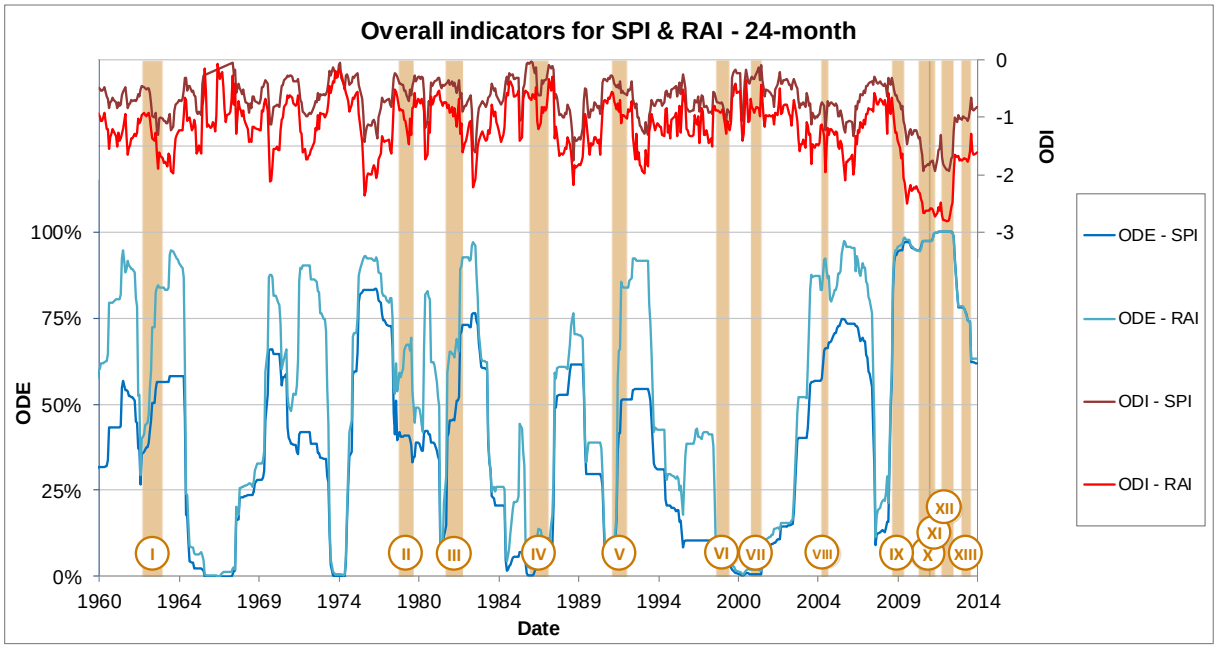

Figure A7. ODE and ODI values using the 24-month time scales of SPI and RAI indices, compared with the 13 detected historical droughts (in orange).

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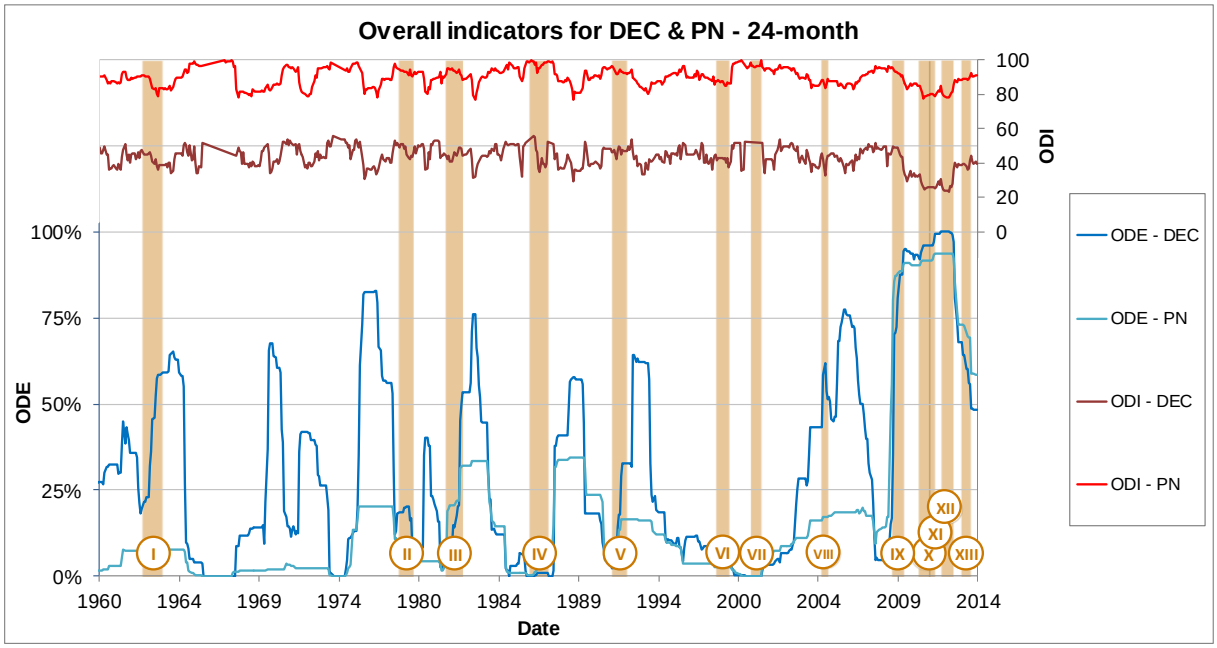

Figure A8. ODE and ODI values using the 24-month time scales of DEC and PN indices, compared with the 13 detected historical droughts (in orange).

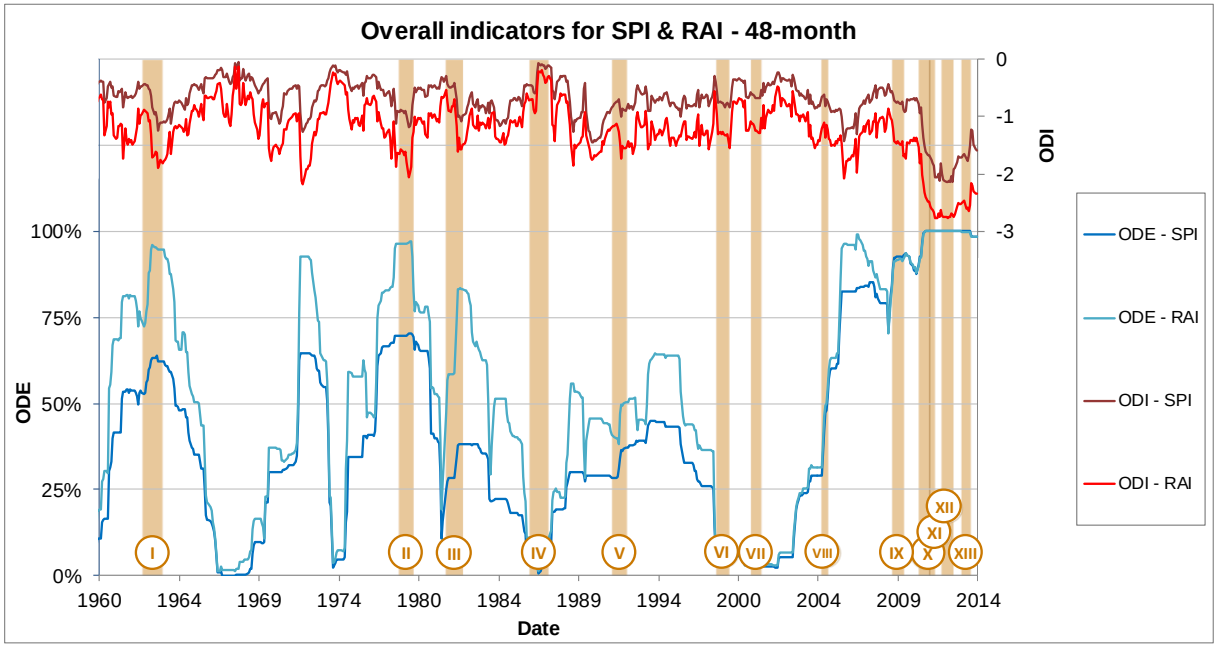

Figure A9. ODE and ODI values using the 48-month time scales of SPI and RAI indices, compared with the 13 detected historical droughts (in orange).

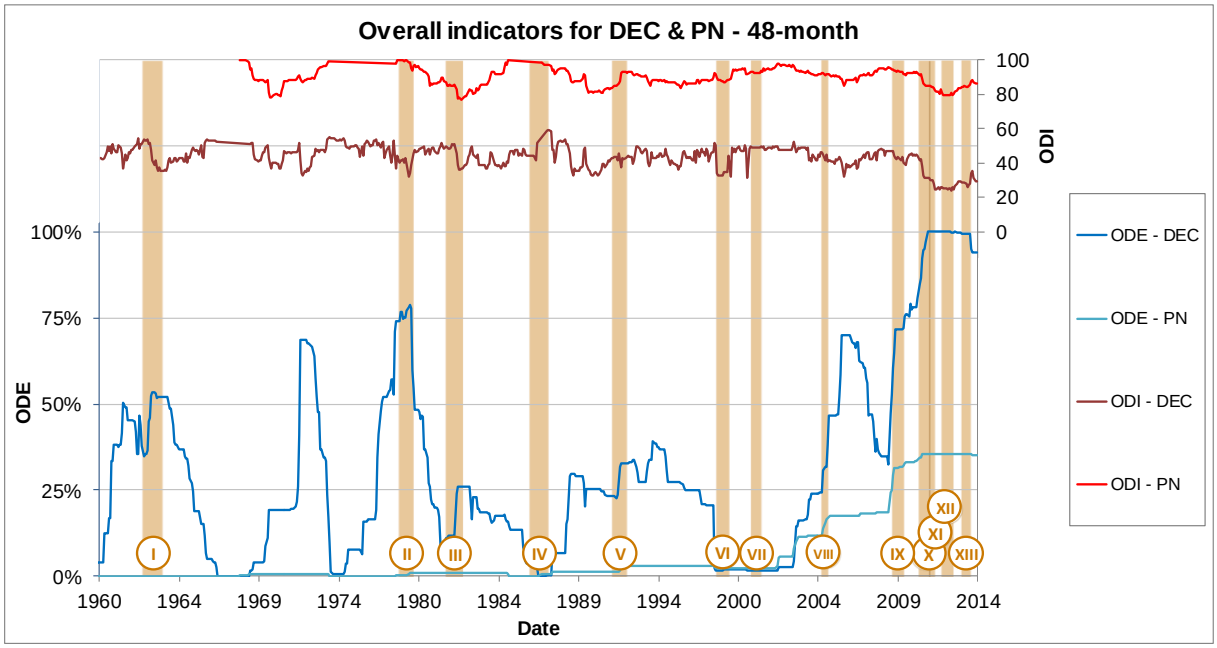

Figure A10. ODE and ODI values using the 48-month time scales of DEC and PN indices, compared with the 13 detected historical droughts (in orange).

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