hydrology

Technical Note

Incorporating aSPI and eRDI in Drought Indices Calculator (DrinC) Software for Agricultural Drought Characterisation and Monitoring

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Abstract: The agricultural sector is vulnerable to extreme phenomena such as droughts, particularly in arid and semi-arid environments and in regions where water infrastructure is limited. Devising preparedness plans, including means for efficient monitoring and timely identification of drought events, is essential for informed decision making on drought mitigation and water management, especially for the water-dependant agricultural sector. This paper presents the incorporation of two new drought indices, designed for agricultural drought identification, in Drought Indices Calculator (DrinC) software. These indices, namely the Agricultural Standardized Precipitation Index (aSPI) and the Effective Reconnaissance Drought Index (eRDI), require commonly available meteorological data, while they employ the concept of effective precipitation, taking into account the amount of water that contributes productively to plant development. The design principles of DrinC software leading to the proper use of the indices for agricultural drought assessment, including the selection of appropriate reference periods, calculation time steps and other related issues, are presented and discussed. The incorporation of aSPI and eRDI in DrinC enhances the applicability of the software towards timely agricultural drought characterisation and analysis, through a straightforward and comprehensible approach, particularly useful for operational purposes.

Keywords: drought monitoring; vegetation–agricultural drought; hydroinformatics; decision support systems; agricultural standardised precipitation index (aSPI); effective reconnaissance drought index (eRDI); effective precipitation; hydrological extremes

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1. Introduction

Drought is a natural hazard with direct and significant impacts on agriculture. Especially under arid or semi-arid conditions, drought effects are more intense [1], while prolonged droughts can cause serious food security issues [2–4]. Drought is typically classified into types, which are based on specific attributes of the phenomenon. Meteorological drought is related to the physical drivers, i.e., the variation of meteorological parameters such as precipitation and temperature, leading to a drought episode. Other types of droughts are the hydrological drought, expressing the effects of drought on water resources, and the agricultural (or vegetation-agricultural) drought, describing the impacts of the phenomenon on plant development. Due to the slow onset of drought, its characteristics (severity, duration and areal extent) cannot be easily assessed. Nonetheless, the accurate and timely identification of a drought event is essential for implementing efficiently drought management plans and relief measures.

Agricultural drought characterisation is not a simple task, considering the complexity of vegetation types, including the diverse susceptibility and tolerance of plants to drought events under different climates, soil types, cultivation techniques, etc. Agricultural drought severity can be assessed by quantifying the impact of the phenomenon on vegetation, taking into account parameters related to plant development, crop yield and others. However, the direct implementation of the above is practically difficult, due to the complexity of the analysis, the involved uncertainties and the variety of factors, apart from drought, that may also affect the soil-plant-atmosphere system. Therefore, the most common approach is to aggregate hydroclimatic fluxes and/or land surface characteristics, for quantifying the triggering variables of agricultural drought [5]. This can be achieved by employing drought indices, commonly used for drought characterisation, which can provide a quantitative measure of drought intensity [6–9].

Currently, there are several indices suitable for agricultural drought identification [10]. Many of them are based on soil moisture, since this is one of the key parameters directly associated to vegetation stress due to water deficiency, such as the widely used Palmer Drought Severity Index, PDSI [11] and many others, e.g., [12–15]. During the recent years, several satellite-based indices have also been developed, using vegetation properties, soil moisture measurements through remote sensing approaches, etc. [16,17]. However, many of the above indices may be complex and/or data demanding, thus their use in operational applications may be limited.

On the other hand, indices based on meteorological data (precipitation, evapotranspiration) have been proven to be efficient in agricultural drought identification, e.g., [18–21]. Furthermore, such indices are usually preferred due to their simple structure and to the fact that the required input data are easily obtainable.

The calculation of drought indices can be facilitated by software tools currently available, e.g., [22–24]. The design and the available modules in such software may vary, though it is important to be customizable to fit the specific needs of different case studies, while the outcomes must be clearly interpretable for allowing objective and transparent decision making.

The Drought Indices Calculator (DrinC) software was developed towards the above principles, providing means for drought analysis based on drought indices for research and operational purposes [25,26]. DrinC is a stand-alone software, freely available online (https://drought-software.com, accessed on 29 April 2022) and it is currently used in more than 145 countries in a wide range of drought-related studies and applications, e.g., [27–52].

Two drought indices specifically developed for agricultural drought identification have been incorporated in DrinC software (version 1.7), aiming at enhancing its potential for agricultural drought analyses. These indices, namely the Agricultural Standardized Precipitation Index (aSPI) [53] and the Effective Reconnaissance Drought Index (eRDI) [54,55], are modifications of two broadly used drought indices, the Standardized Precipitation Index (SPI) [56] and the Reconnaissance Drought Index (RDI) [57], respectively. Both aforementioned modifications aimed at retaining the simple structure and low data requirements of the original indices, while providing more robust conceptual base towards the characterisation of agricultural drought conditions and the assessment of drought impacts on vegetation.

As already mentioned, agricultural drought characterization has different goals and principles than meteorological drought. However, the similarities that aSPI and eRDI share with their corresponding original indices, including the fact that they use only meteorological input data, might create confusion regarding their proper assessment approach for agricultural drought identification. Therefore, it is crucial for DrinC software to include distinguishable components, which can be suitably adjusted according to the objectives of each drought characterisation study. Furthermore, it is important to identify the reasons leading to the selection of these adjustments in order to avoid misconducted analyses and consequent misinterpretations of the outcomes.

To this end, the paper presents the aforementioned design principles that have been used for incorporating aSPI and eRDI in DrinC software including the adjustable components which emphasise the key points of agricultural drought analysis. The major issues which are illustrated in detail are the selection of suitable reference periods and calculation steps, while specific justifications are presented regarding their proper use in agricultural drought characterisation and monitoring. The presented update of the software aims at providing researchers and stakeholders with means for conducting straightforward, transparent and sound analyses for timely agricultural drought identification, towards informed decision making and efficient water resources management for mitigating the anticipated drought impacts.

2. Basic Notions

The characterization of agricultural drought is focusing on the conditions affecting the development of vegetation, which is linked to the specific system under study. For instance, drought impacts may vary, depending on the considered plant species, the water deficits during critical growth stages, etc. Therefore, agricultural drought analysis should be based on properly adjustable tools, according to the properties of the system of interest.

The aSPI and eRDI indices intend to build on the advantages of the SPI and RDI, while being customizable and more sensitive to the factors affecting agricultural drought [53–55]. To this end, the parameter of total precipitation has been replaced in both indices with the effective precipitation, i.e., the portion of total precipitation that can be used productively by the plants. This is achieved by employing empirical methods, which are solely using monthly precipitation data to estimate the corresponding effective precipitation.

Additionally, eRDI is also using potential evapotranspiration, formulating its initial value α_e as the ratio of the cumulative effective precipitation (P_e) to the cumulative potential evapotranspiration (PET), for a specified reference period of k months:

$$\alpha_{e(k)} = \frac{\sum_{j=1}^{j=k} P_{ej}}{\sum_{j=1}^{j=k} PET_j} \tag{1}$$

The calculation of the indices is based on a standardisation process, in which the initial timeseries (P_e and α_e for aSPI and eRDI, respectively) is fitted into a suitable distribution which is then transformed into normal distribution, producing the final standardised values of each index. Details regarding the theoretical base of the indices can be found at Tigkas et al. [53,55].

The main advantages of the indices, apart from the simple structure and the low data requirements, are their ability to provide comprehensible outcomes even for non-experts, that correspond to specific drought classes (Table 1), while they are not location-specific, since their results can be spatially comparable.

Table 1. Drought classes based on aSPI or eRDI values.

aSPI or eRDI Value	Category
$\geq$2.00	Extremely wet
1.50 to 1.99	Severely wet
1.00 to 1.49	Moderately wet
0.50 to 0.99	Mildly wet
−0.49 to 0.49	Normal
−0.50 to −0.99	Mild drought
−1.00 to −1.49	Moderate drought
−1.50 to −1.99	Severe drought
$\leq$−2	Extreme drought

The aSPI and the eRDI can be used to study the impacts of drought on farming crops, but also natural ecosystems, in order to investigate the response of vegetation growth to drought. Recent studies have shown that these indices are suitable for such purposes, providing similar or more accurate outcomes regarding agricultural drought characterisation compared to the original indices [53,55,58–62]. To this end, the reference periods can be adjusted according to the vegetation type under investigation, for interpreting efficiently its response to drought.

3. Implementation of aSPI and eRDI in DrinC Software

3.1. Software Design for Assessing Agricultural Drought

The agricultural drought characterisation process in DrinC software includes three main stages: (a) data management and input parameters; (b) selection of appropriate reference periods and time step; (c) drought indices calculation. The design of the software aims at producing, through a straightforward approach with customizable options, concrete and clearly interpretable outcomes regarding agricultural drought conditions. The above are performed through the graphical user interface of the software (Figure 1).

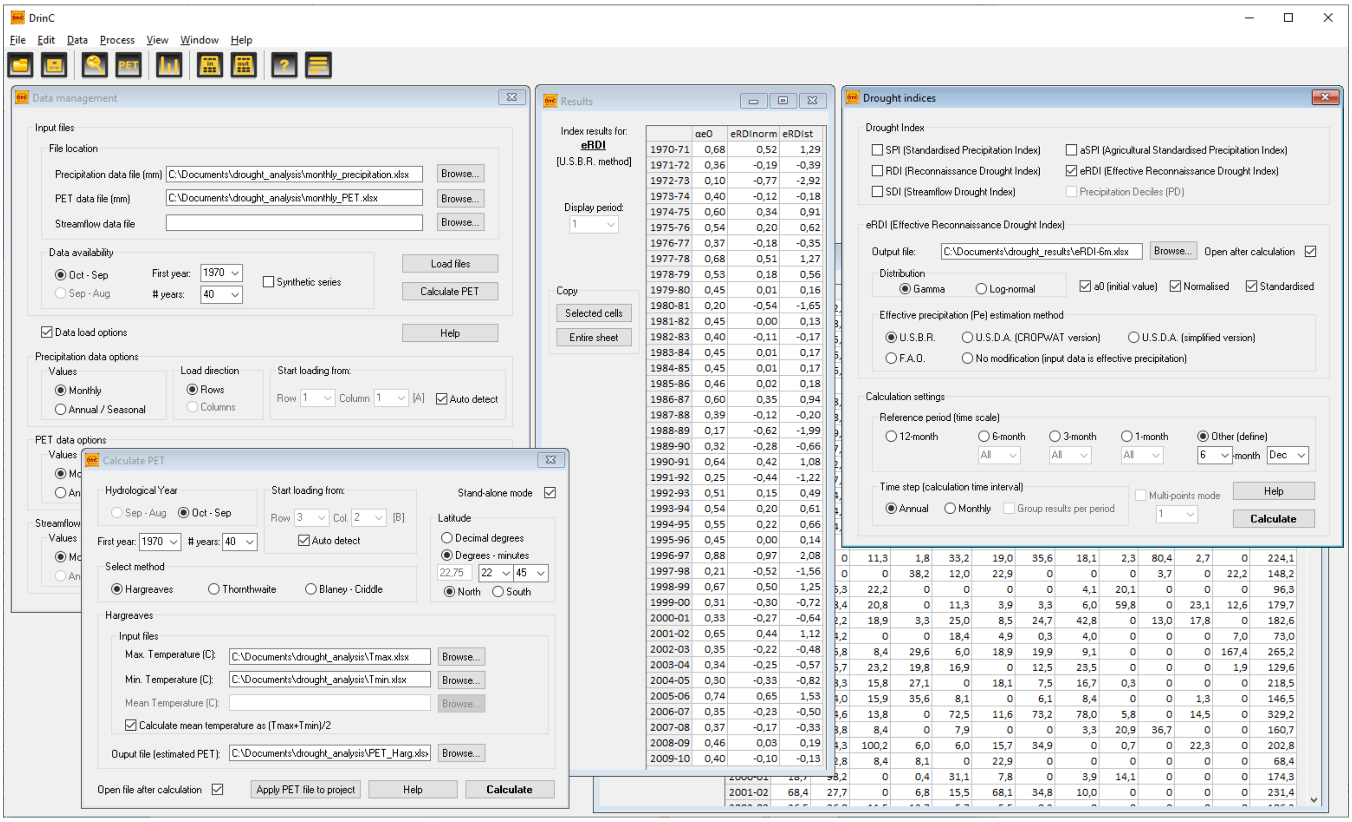

Figure 1. The graphical user interface of DrinC software.

In the next sections, each of the above stages is described in detail, along with the principles for the suitable adjustments to fit the objectives of drought analysis cases. In brief, in the first stage the required input data for each index are presented, along with the description of the available effective precipitation estimation methods and the module for assessing potential evapotranspiration with temperature-based methods. The second stage presents the principles for selecting the appropriate reference period and time step, depending on the aims of the agricultural drought characterisation or monitoring study. The third stage describes the calculation procedure for both indices and the interpretation of their outcomes. A schematic representation of the overall process is shown in Figure 2.

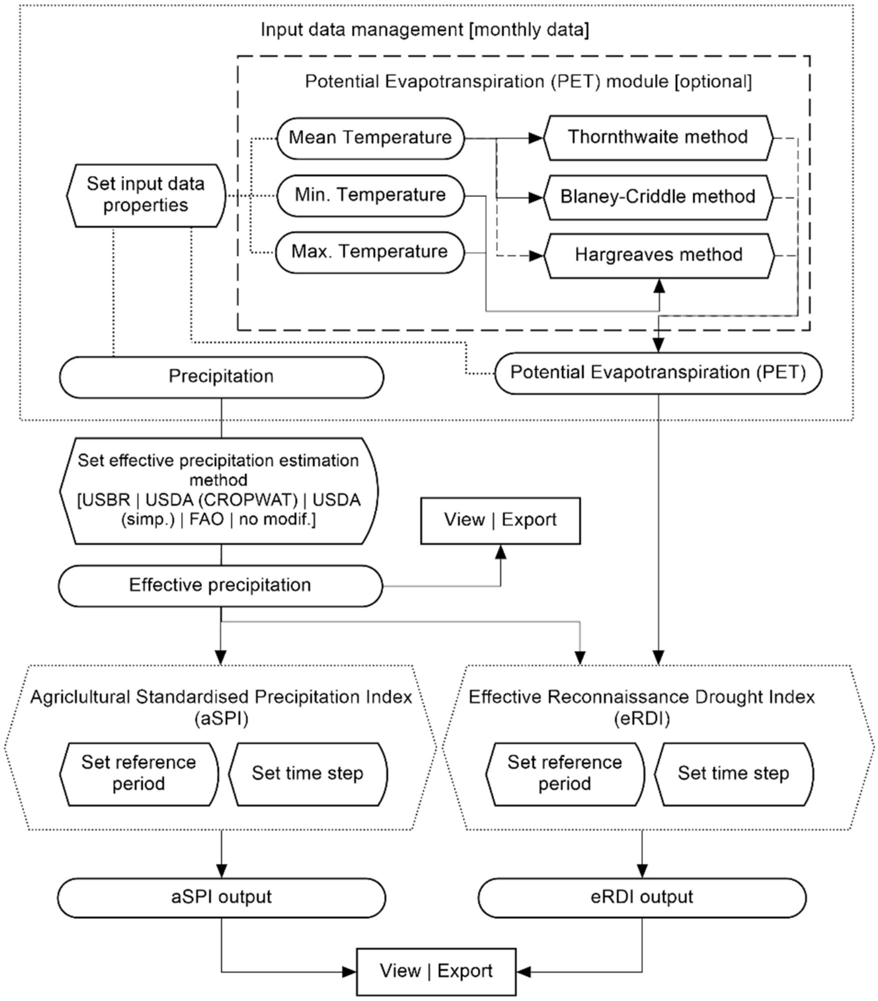

Figure 2. Schematic overview of the assessment process of aSPI and eRDI in DrinC software.

3.2. Data Management and Input Parameters

The required data for both aSPI and eRDI is monthly precipitation, while eRDI requires also monthly PET. Annual or seasonal data (cumulative values of precipitation and/or PET) can be also used; however, in such a case, the results will refer only to the specific accumulated input periods. Data may be imported using various file formats (MS Excel files, delimited text files, etc.).

The estimation of P_e based on precipitation data is performed through empirical methods. Four alternative methods are incorporated in DrinC:

- *U.S. Bureau of Reclamation (USBR) method:* In this method, P_e is estimated through the use of precipitation classes, as presented in Table 2 [63].

Table 2. Effective precipitation estimates, based on total monthly precipitation classes.

Total Monthly Precipitation Value (mm)	Effective Precipitation Class (%)
0.0–25.4	90–100
25.4–50.8	85–95
50.8–76.2	75–90
76.2–101.6	50–80
101.6–127.0	30–60
127.0–152.4	10–40
>152.4	0–10

- *Soil Conservation Service/U.S. Department of Agriculture–CROPWAT version (USDA-SCS CROPWAT) method:* This is an approach used in CROPWAT software, based on the USDA SCS [64] method, using only total precipitation (P) for estimating P_e according to the following formulae [64]:

$$P_e = \begin{cases} P\frac{(125-0.2P)}{125} & for\ P \leq 250 \text{ mm} \\ 0.1P + 125 & for\ P > 250 \text{ mm} \end{cases} \quad (2)$$

- *Soil Conservation Service/U.S. Department of Agriculture–simplified version (USDA-SCS simp.) method:* A simplified version of the USDA SCS [64] method, using only precipitation data and assuming constant the other parameters of the model [53].
- *U.N. Food and Agriculture Organization (FAO) method:* A simple empirical approach that has been proposed by FAO, using the following equations [65]:

$$P_e = \begin{cases} 0.6P - 10 & for\ P < 75 \text{ mm} \\ 0.8P - 25 & for\ P \geq 75 \text{ mm} \end{cases} \quad (3)$$

It is noted that the first three methods have very similar response for total monthly precipitation up to 110 mm, which is the usual case for arid and semi-arid regions. The FAO method follows a different pattern, with lower effective precipitation estimates for the same amount of total monthly precipitation. Overall, the aforementioned methods are mostly considered suitable for arid and semi-arid conditions, while their use in humid environments may have limited credibility. Furthermore, the FAO method can be applied mainly in plain areas, with maximum slope of 4–5% [53].

Obviously, the software also includes the option to import directly effective precipitation data, in which case no further processing is performed for this parameter.

Regarding the estimation of PET, a relevant module is available in DrinC incorporating three temperature-based methods (Hargreaves, Blaney-Criddle and Thornthwaite), which are appropriate for RDI calculation [66,67]. The required input for these methods is monthly temperature data and specifically:

- monthly averages of maximum and minimum temperature values for Hargreaves method;
- monthly average of mean temperature values for Blaney-Criddle and Thornthwaite methods (optionally for Hargreaves method).

Additionally, the latitude of the meteorological station must be set (Figure 3). Nevertheless, PET data estimated by other appropriate methods (e.g., FAO Penman-Monteith) can be also imported directly in the software. This is quite useful, considering the uncertainties of PET estimates depending on the adopted method [68,69] and the characteristics of the surface above which the meteorological attributes are measured [70].

3.3. Selection of Reference Periods and Time Step

An important decision for proper agricultural drought analysis is the selection of the reference period and the calculation time step, which must be suitable for the purpose of each study or application. The reference period (or time scale) determines the time (months) for which the respective input parameters are accumulated, while the index outcome corresponds to the conditions of the specific period. The time step (or calculation time interval; usually monthly or annual) refers to the calculation interval between subsequent reference periods.

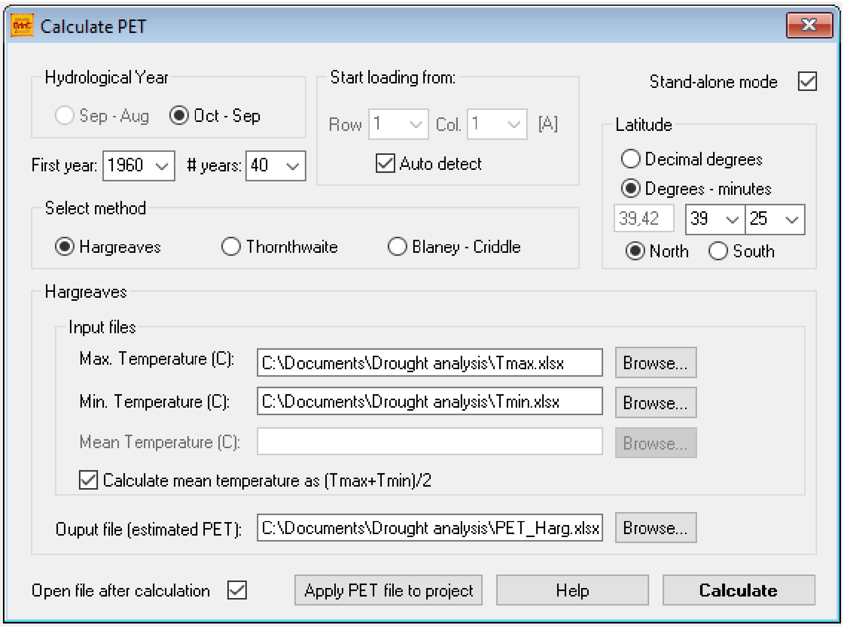

Figure 3. The PET calculation module of DrinC software.

The selection of the appropriate reference periods and time step for aSPI and eRDI may be different from what applies to the original indices (SPI and RDI), due to the distinctive nature of vegetation-agricultural drought. For instance, the typical approach for assessing meteorological drought using SPI is by selecting a specific time scale (e.g., 12-month) which is calculated for a monthly time step. This produces a 'rolling' timeseries of the index (one value per month), representing the prevailing conditions for the corresponding reference period (e.g., the past 12 months) in the study area.

However, in agricultural drought characterisation, the focus of the investigation is on the potential impacts of drought on agricultural or natural systems. Therefore, depending on the objectives of the analysis, emphasis should be given to cultivation periods of the considered crops, growth periods of vegetation in natural ecosystems (e.g., forests), as well as development stages, during which specific plants may be more susceptible to drought conditions. It is noted that for the dry seasons of the year under arid or semi-arid conditions, a high percentage of zero values is expected in precipitation timeseries, which may cause difficulties in the calculation of the indices, if short reference periods (e.g., 1- or 3-month) are selected.

Indicatively, for a typical winter wheat crop under Mediterranean conditions, the cultivation period initiates in November, while the harvesting usually takes place in June. A suitable reference period to identify drought conditions for such a case would be the entire 8-month cultivation period November–June. In addition, shorter reference periods could be also considered, such as the 3-month February–April period, focusing on critical development stages of the crop (e.g., tillering, anthesis), in which water stress may have considerable effects on yield [71–73].

The selection of the appropriate calculation time step is important for focusing on the aim of drought analysis and avoiding the production of excessive information that may be disorientating, especially in decision making process. To this end, the annual time step is recommended for evaluating the vegetation response to drought conditions, while the monthly time step is more appropriate for real time drought monitoring.

Another efficient approach for agricultural drought monitoring, reflecting possible cumulative effects of water deficits during crop development, is the use of progressively incrementing reference periods (e.g., 3-, 4-, 5-month), starting always from the same month (e.g., the sowing month). A graphical example of this approach is presented in Figure 4. As shown by this figure, the cumulative water deficit for each month is illustrated more clearly through the use of progressive reference periods (from the beginning of the cropping season), instead of using a constant (in this case 3-month) reference period.

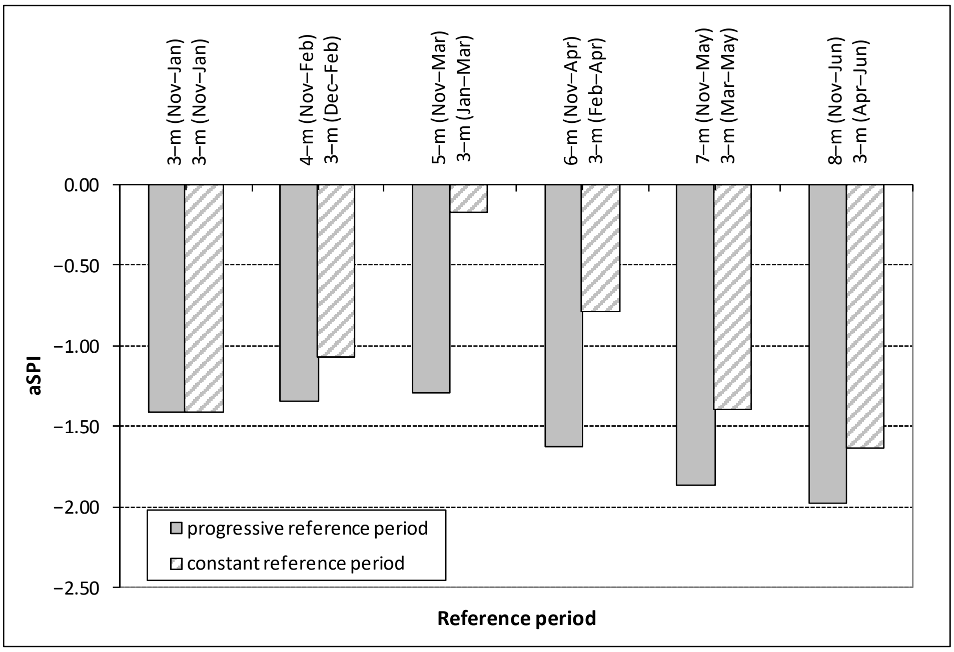

Figure 4. Drought monitoring with aSPI during cropping season (winter wheat crop), using constant and progressive reference periods for an indicative drought year (location: Alexandroupolis–Greece; hydrological year: 1984–1985).

3.4. Drought Indices Calculation

The calculation of aSPI and eRDI in DrinC is performed through the interface presented in Figure 5, in which the respective index is selected. The distributions that can be used for each drought index (*DI*) are log-normal and gamma, both considered suitable for the calculation of the indices.

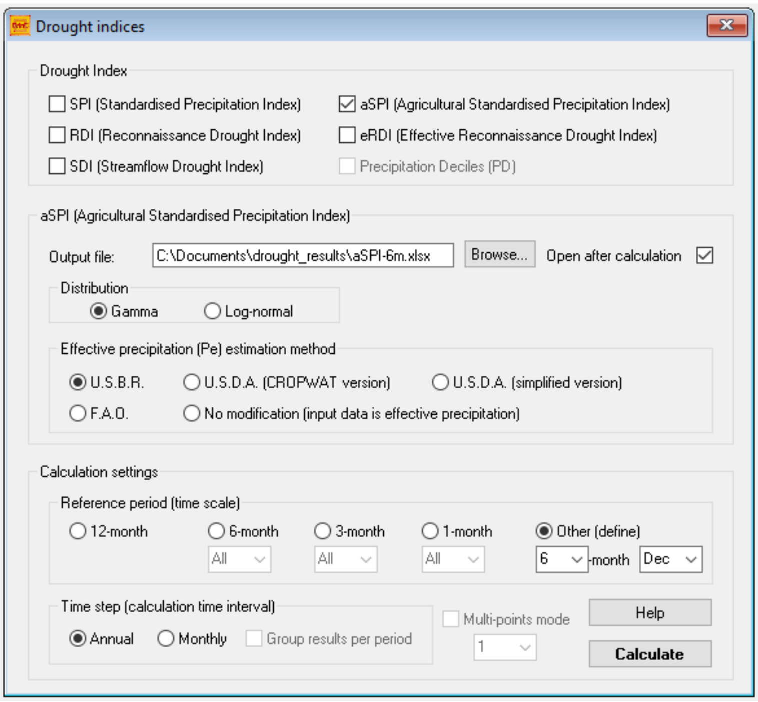

Figure 5. Drought indices calculation settings.

The log-normal distribution is based on the logarithmic data transformation:

$$y = \ln(x), \text{ for } x > 0 \tag{4}$$

in which x is the input variable for each DI, i.e., P_e for aSPI and α_e for eRDI, for the considered reference period.

The standardised timeseries of the DI is derived by:

$$DI_i = \frac{y_i - \overline{y}}{\hat{\sigma}_y} \tag{5}$$

in which $\overline{y}$ is the arithmetic mean and $\hat{\sigma}_y$ is the standard deviation.

It is noted that the above cannot be applied, if the accumulated effective precipitation for the selected reference period includes zero values ($x = 0$). This is a usual condition, if a short reference period is selected under arid or semi-arid conditions, in which case gamma distribution can be used, as follows.

In gamma distribution, the probability density function is:

$$g(x) = \frac{1}{\beta^{\gamma}\Gamma(\gamma)} x^{\gamma-1} e^{-x/\beta}, \text{ for } x \ > \ 0 \tag{6}$$

in which γ and β are shape and scale parameters, respectively, with $\gamma > 0$ and $\beta > 0$, and $\Gamma(\gamma)$ is the gamma function: $\int_0^{\infty} y^{\gamma-1} dy$.

The parameters γ and β can be estimated by:

$$\gamma = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \ \beta = \frac{\overline{X}}{\gamma} \tag{7}$$

in which $A = \ln(\overline{x}) - \frac{\sum \ln(x)}{n}$ and n is the length (years) of the timeseries.

The cumulative probability $G(x)$ is derived from Equation (6) as:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\gamma}\Gamma(\gamma)} \int_0^x x^{\gamma-1} e^{-x/\beta} dx \tag{8}$$

Letting $t = x/\beta$, Equation (8) becomes the incomplete gamma function:

$$G(x) = \frac{1}{\Gamma(\gamma)} \int_0^x t^{\gamma-1} e^{-t} dt \tag{9}$$

As already mentioned, the above is defined for $x > 0$; if $x = 0$, i.e., the cumulative effective precipitation for a selected period is zero, to estimate the zero-value probability (q) of x, the cumulative distribution function is:

$$H(x) = q + (1 - q)\ G(x) \tag{10}$$

The cumulative distribution function is transformed to normal distribution for the estimation of DI, using the following approximation [74]:

$$DI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \text{ for } 0 \ < \ Hx \ \leq \ 0.5 \tag{11}$$

in which $t = \sqrt{ln\left(\frac{1}{1-H(x)^2}\right)}$, while the values of the constants are:
$c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.43278$, $d_2 = 0.189269$ and $d_3 = 0.001308$.

Due to the probabilistic nature of the indices' calculation, the sufficient length of input data timeseries plays important role. Typically, a 30-year timeseries is considered adequate for a reliable analysis, while 50 to 60 years of available data would be ideal. However, in real-world applications it may be needed to conduct analyses with limited data availability (shorter timeseries). In such cases, it is critical to acknowledge the level of reliability due to the involved uncertainties of the analysis. To this end, major points that should be taken into account are the actual length of the timeseries, the quality of the available data and possible indications whether the range of the climatic conditions of the area is sufficiently represented by the dataset.

The calculated results can be directly exported from DrinC to MS Excel files, including drawn charts of the selected index. The drought severity level can be categorised according to Table 1, as indicatively presented in Figure 6, providing a direct visualisation of drought conditions.

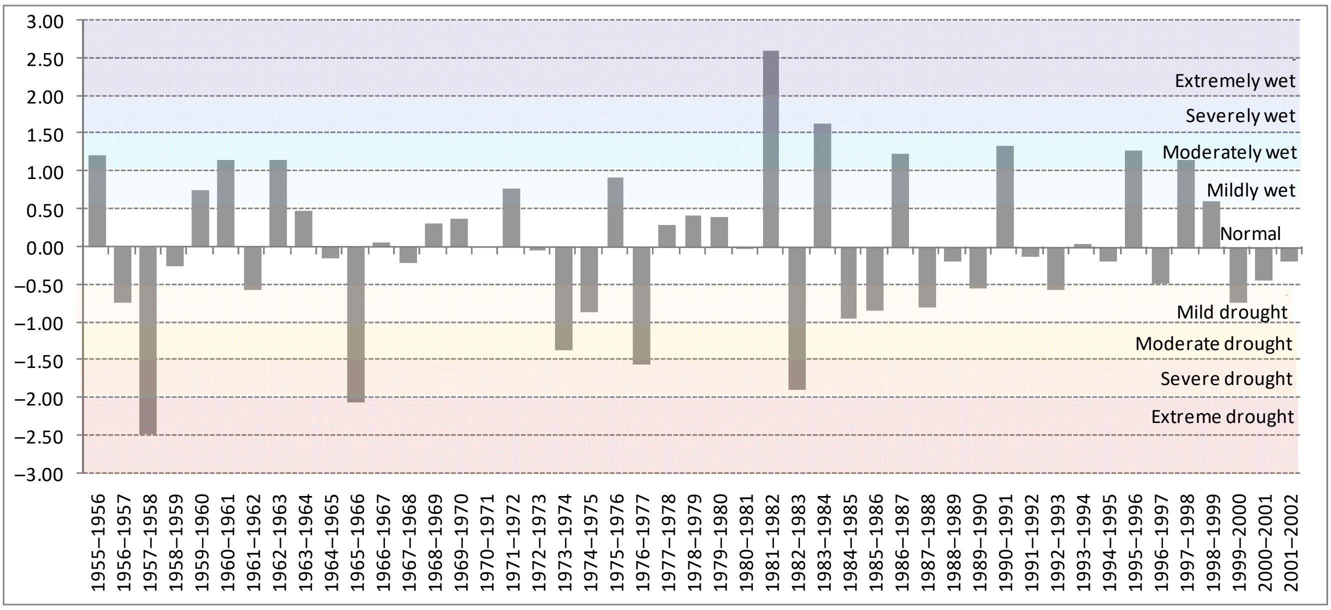

Figure 6. eRDI values (reference period: 6-month, December–May) with the corresponding drought severity classes (location: Larissa-Greece).

4. Concluding Remarks

In this paper, the incorporation in DrinC software of two new indices for agricultural drought identification, the Agricultural Standardised Precipitation Index (aSPI) and the Effective Reconnaissance Drought Index (eRDI), is presented. Previous studies have shown that the use of these indices provides a robust conceptual base for accurate agricultural drought identification and analysis [53,55,59–61]. Furthermore, the data requirements of both indices are low, including commonly available meteorological parameters, allowing their application even in data-scarce locations.

One of the principal goals of the paper is to clarify possible misconceptions and discuss the appropriate approaches regarding agricultural drought characterisation, which can be achieved through the use of DrinC software. Towards this objective, it is illustrated how the design of the software emphasises the key-points that must be properly adjusted for agricultural drought identification, according to the different types of analysis.

Additionally, the software includes modules for transforming input data (precipitation, temperature) to the parameters required for each index (effective precipitation, potential evapotranspiration), using suitable approaches for any study. In addition, the software allows the customisation of the calculation process, using different reference periods and calculation time steps, in order to fit best to any drought characterisation and monitoring purpose. One of the main advantages is the easy interpretation of the outcomes, using drought severity classes that facilitate the understanding of drought phenomenon by stakeholders and decision-makers, enhancing timely and efficient water management and mitigation of the anticipated drought effects on agriculture.

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Conflicts of Interest: The authors declare no conflict of interest.

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