

Article

Utilizing Different Drought Indices to Monitor Temporal Drought Risks in Lisbon, Portugal in the Context of Climate Change Effects

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Abstract

Drought is becoming more frequent and severe in many regions, particularly in Mediterranean climates, where water demand is increased by warming and changes in precipitation regimes. A long-term assessment of meteorological drought at the Lisbon climatological station is provided in this study using the Standardized Precipitation Index (SPI) and the Reconnaissance Drought Index (RDI) over the period 1864–2021. Monthly precipitation and temperature data are used to compute SPI and RDI at 3-, 6-, and 12-month time scales, so that short-, mid-, and long-term droughts and their temporal evolution can be characterized. RDI is evaluated with three widely used empirical potential evapotranspiration (PET) formulations—Hargreaves, Thornthwaite, and Blaney–Criddle—in order to examine how PET estimations influence drought classification. Given the absence of a physically based reference PET—such as FAO-56 Penman–Monteith—for this station, the focus is on the internal consistency of the PET methods. Furthermore, the Hargreaves formulation is retained as a representative empirical PET for subsequent SPI–RDI comparison. The results show broadly consistent standardized RDI behavior across PET methods; it is indicated that drought conditions are captured more comprehensively by RDI than by SPI because both precipitation deficits and enhanced evaporative demand are included. At the Lisbon station, the estimated average return periods for short-, mid-, and long-term droughts are 3.79, 7.31, and 7.92 years according to RDI, compared with 3.86, 5.69 and 10.88 years from SPI. Several severe drought episodes are identified, including the years 1907, 1922–1923, 1944–1945, 1976, 1981, 1992–1993, 2005, and 2018. While no formal attribution analysis is performed, the drought characteristics are interpreted in the context of observed long-term warming and documented rainfall variability in Lisbon. The findings provide a single-station benchmark of historical drought behavior, by which local water-resources management can be supported and which can serve as a basis for future multi-station and climate-projection-based studies in Portugal.



Academic Editor: Nir Y. Krakauer

Received: 13 May 2026

Revised: 29 June 2026

Accepted: 1 July 2026

Published: 7 July 2026

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Keywords: climate change; drought risk assessment; PET; RDI; SPI; Lisbon; Portugal

1. Introduction

Climate change is mainly attributed to human activities and the associated increase in greenhouse gas emissions, in addition to natural processes. Climate change has affected numerous components of the hydrologic cycle, such as temperature, wind, and precipitation patterns. Additionally, climate change has the potential to change hydrological regimes and increase the likelihood of extreme weather occurrences, including droughts and floods in several regions across the globe. In 2014, the average global air temperature increased by 0.85 °C and it is expected to increase by 1.0 °C above pre-industrial levels, with an estimated range between 0.8 °C and 1.2 °C. If global warming continues at its current pace, it may increase by 1.5 °C within the timeframe of 2030 to 2052. The global average temperature is expected to increase by 2.6 °C to 4.8 °C under the RCP 8.5 scenario, which signifies a high emission scenario, and by 0.3 °C to 1.7 °C under the RCP 2.6 scenario, representing a low emission scenario. The levels of uncertainty and the time series of forecasts indicate that the global average surface temperature is likely to rise in the future (IPCC, 2023) [1].

Drought is widely recognized as one of the most complex and destructive natural hazards due to its gradual onset, multidimensional nature, and extensive socio-economic and environmental impacts. Drought causes a lot of economic and environmental losses across all climatic regions annually. Previous studies indicated that global warming increases the possibility of drought and could increase the threat to human beings [2]. Therefore, using suitable drought indices could help in monitoring drought intensity. Drought is a natural phenomenon and can be classified into three main categories (meteorological, agricultural, hydrological) according to the effects it has on water resources. Drought is caused by below-average precipitation in a specific area, leading to prolonged water shortages in atmosphere (meteorological drought), soil (agricultural drought) as well as in surface and groundwater resources (hydrological drought). Understanding the spread of drought is essential for regions as it helps with effective water resources management and provides early warnings [2].

Drought indices are indicators that were created to characterize the various forms of droughts and to illustrate their fluctuations across different spatial and temporal scales on local, regional, and global levels. Over the years, several drought indices have been used to assess drought risks. Reconnaissance Drought Index (RDI) is a powerful tool for evaluating drought conditions at regional and local scales, measuring severity, duration, and spatial extent to support effective water management, agriculture, and drought preparedness [3]. Moreover, Standardized Precipitation Index (SPI) is commonly used because it requires less data [4]. RDI has proven effective in several countries and shows distinct trends in different climatic zones. However, challenges remain in evaluating the effect of different PET estimation methods on RDI values and understanding drought trends in specific vulnerable regions such as Lisbon, Portugal [5]. The Lisbon station was chosen in this study because of the increasing temperature and the decrease in precipitation in the region. Meteorological drought identification using RDI is less widespread than drought identification using SPI because RDI needs a larger range of meteorological data. Despite this fact, it has been used for regional drought assessment in several countries such as Greece [3], Cyprus [6], Portugal [7], and Italy [8] and Slovakia [9].

A number of studies have been conducted to assess the effectiveness of RDI compared to other drought indices such as SPI, Palmer Drought Severity Index (PDSI), and Standardized Precipitation Evapotranspiration Index (SPEI). Zarch et al. (2011) [10] examined

precipitation and potential evapotranspiration in Iran using the RDI. They compared their findings with SPI 3, 6, and 9 month timescales and identified similar results during drought conditions. Zarch et al. (2015) [11] calculated SPI and RDI over land areas excluding Antarctica at more than 4000 stations covers the period 1960–2009. They found good agreement between SPI and RDI in hyper-arid zones. In semi-arid zones, there is no noticeable trend in SPI, but RDI indicates more downward trends. However, in humid areas, SPI indicates increasing humidity, with RDI showing roughly equal percentages of increasing and decreasing trends. However, across all zones, RDI exhibits a greater percentage of decreasing trends compared to SPI.

Different drought indices have been applied in different regions to assess the risks of drought. Wable et al. (2019) [12] studied the performance of five drought indices in western India during the period 1985–2009. They found very high correlation between SPI and RDI at all timescales. Tigkas et al. (2017) [13] used RDI and eRDI for assessment of drought effects on agricultural system in Greece. The eRDI demonstrated a stronger correlation with the reduction in crop yield of winter wheat. Ortiz-Gómez et al. (2022) [14] detected eight evapotranspiration models to evaluate RDI and SPEI in central Mexico and stated that there are no statistically significant differences between RDI and SPEI. Nagy and Zeleňáková (2020) [15] analyzed the occurrence of drought by RDI and SDI during the year 1960–2015 in 13 stations located in the eastern part of Slovakia and detected a trend in drought index with the Mann–Kendall test.

Furthermore, Mohammed et al. (2021) [16] studied the spatial-temporal variability of meteorological drought and trends of its changes in Lakes' Region of Ethiopian Rift Valley during the year (1986–2019) by RDI. At many of stations they detected rising tendencies of drought events, which were detected generally during spring at annual timescales. Also, Thomas et al. (2016) [17] investigated meteorological drought in 13 districts located in central India. Mohamed et al. (2023) [18] examined monthly precipitation, as well as minimum and maximum temperatures in Tunisia from 1958 to 2020 to identify the trends with Mann–Kendall test and evaluate the spatial variability of meteorological drought. Ogunrinde et al. (2023) [19] examined the key features of prolonged seasonal hydrological drought by RDI across all agro-ecological zones in Nigeria covering the years from 1951 to 2100. Babre et al. (2022) [20] examined the spatial and temporal distribution of groundwater drought events over the period 1989–2018 in Estonia, Latvia and Lithuania by drought indices: SPI, SPEI, RDI, SRI and SSRI and SGI.

Moreover, Wubneh et al. (2023) [21] showed, with the RDI values, that the magnitude of drought increases from a scenario model of years 2020–2049 to another scenario model of years 2050–2079 in both time scales (RDI-6 and RDI-12) in Ethiopia. Öz et al. (2024) [22] made a comprehensive drought analysis using the SPI, SPEI and RDI methods applied for the data of 219 meteorological stations between 1991 and 2022 covering Turkey. The results of SPI, SPEI and RDI reveal that the severity of drought rises across the whole area. However, the short-term drought results revealed more frequent dry periods, while the long-term analyses show less frequent dry periods. In short-term drought analyses the three indices depicted different attention in increased drought severity while in long-term drought analyses, the stations on the north and west coasts, as well as in the east, show similar values in the examined indices.

Drought monitoring is an important factor in drought risk management. Ali et al., (2011) [23] used several geostatistical methods including Ordinary Kriging, Inverse Distance Weighted (IDW) and Thin Plate Smoothing Spline with different drought indices—SPI and Effective drought Index (EDI)—to assess the derivation of maps of drought indices at 27 climatic stations in the Boushehr province of Iran. The results indicated that Inverse IDW method with the power of two is more appropriate for spatial analysis of

SPI and Ordinary Kriging method is more appropriate for spatial analysis of EDI [23]. Benyoussef et al. (2024) [24] assessed the influence of climate change on Ghis–Nekor watershed over 38 years (1978–2016) in three stations using SPI, RDI, and DI. A key discovery of their study is the decrease in the annual rainfall from 2008, indicating a greater drought risk. The influence of PET calculation method on the RDI was analyzed by Vangelis et al. (2013) [25], Campos-Aranda (2020) [26], and Ortiz-Gómez et al. (2022) [14]. They concluded that the resulting RDI values are not significantly dependent on PET estimation method.

The Mediterranean countries such as Portugal are vulnerable to drought occurrences. Changes in daily rainfall and surface temperature in Lisbon (Portugal) were studied by Espinosa et al. (2022) [27] who analyzed trends and quantified their magnitude. They reported that the area under study experienced a temperature increase of 1.91 °C over the 1864–2021 timeframe. Additionally, it was noticed that extreme drought events have become more prevalent in the past six decades compared to other recorded period. Temporal variability of long-term rainfall trends in Portugal was studied by Portela et al. (2020) [28] during the years from 1910 to 2019. The study demonstrated a notable decrease in rainfall over Portugal during the past five decades.

Recently, other drought indices have been used. Silva et al. (2022) [29] assessed performance and applicability of drought index (particularly SPI, SPEI, PDSI, scPDSI) in mainland Portugal and found that droughts are more frequent and severe than wet periods, with SPI being the most sensitive index for early detection of extreme droughts, while PDSI, scPDSI and SPEI provide more reliable monitoring of medium-term and long-term drought conditions, highlighting the importance of using multiple indices together for comprehensive drought assessment and management. Páscoa et al. identified an expansion of climate change in the Iberian Peninsula, evidenced by increasing trends in drought occurrence [30]. Espinosa and Portela analyzed the long-term rainfall trends across mainland Portugal between 1919 and 2019 and explored connection to the North Atlantic Oscillation NAO, revealing a widespread decline in rainfall since the late 1960s that is strongly associated with increasingly positive NAO phases. Their results showed that winter and annual rainfall were negatively correlated with NAO indices and that declining rainfall has contributed to more frequent and severe regional droughts, suggesting that drought risk may continue to increase under persistent positive NAO conditions and ongoing climate change [31]. Some authors applied new models: Copula-Based Continuous Drought Probability Monitoring System CDPMS [32] or Log-Linear modeling [33] or Geostatistical Predictive Model [34] for prediction climatic or hydrological variables in Portugal. Soares et al. made regional climate projections under multi-scenarios for Portugal [35]. Parente et al., (2019) [36] assessed the drought regime for past climate conditions (1981–2017) in Portugal, using four drought indices, namely SPI, SPEI, RDI and VCI, and assessed the influence of drought in large wildfires occurrence. The results included characterization of drought number, duration, severity, intensity, extension, and inter-annual variability for different classes of severity and the space-time distribution of large wildfires in drought periods and affected areas. The main findings concluded that 67% of the study period was drought months and it is not clear which is the best index, but drought plays a vital role in occurrence of large wildfires in Portugal.

This study aims to tackle these challenges by investigating how empirical PET methods may influence RDI-based drought assessments in Lisbon's Mediterranean climate, using Drought Indices Calculator (DrinC) software version: 1.7 (97) for temporal drought analysis. Historical meteorological data of the Lisbon region for 157 years—the period from 1864 to 2021—were used for the rainfall trend analysis, evapotranspiration and drought indices calculations. Different droughts are calculated (short-term, mid-term and long-term) and compared using RDI and SPI. DrinC software is employed to compute PET, SPI and

RDI values, facilitating a comprehensive temporal assessment of drought. Through the comparison of these methods, the results of the current study could enhance the precision and dependability of drought monitoring, offering significant insights into the management of water resources and strategies for climate adaptation in the area.

2. Materials and Methods

The impacts of frequent droughts have been exacerbated in past decades due to climate change. The occurrence of droughts in the Lisbon region and their adverse impacts is particularly substantial for water management in this area. In this study, drought indices (RDI and SPI) are used for assessing the drought occurrence in this region, utilizing meteorological data over a span of 157 years, from 1864 to 2021.

2.1. Description of the Study Area

Drought is a regional hazard which appears when the rainfall concentrations shift below normal conditions in a certain area [37]. The current study area is Lisbon in the west of Portugal which experiences a Mediterranean climate. Lisbon is in the southwest of the Iberian Peninsula on the coast of the Atlantic Ocean, as seen in Figure 1 [27]. Lisbon serves as the capital and the largest city of Portugal, boasting an estimated population of 550,000 and covering an area of 100 km².



Figure 1. The study area location map.

2.2. Data Collection

The data used for calculating the drought indices (SPI and SPEI) were obtained from the Instituto Português do Mar e da Atmosfera (IPMA). The data correspond to the Lisboa/Geofísico station (ID: 535), located at an elevation of 77 m, latitude 38°43'9" N, and longitude 9°8'59" W. The dataset spans 157 years, from October 1864 to September 2021. The meteorological time series for precipitation and temperature are complete for the entire reference period. The raw data are publicly available through the IPMA long-term data series portal (<https://www.ipma.pt/en/index.html>, accessed on 20 January 2026). The core dataset used in this study, including the calculated drought indices, are publicly available in Espinosa and Portela (2026) [38].

2.3. Methodology

The methodology includes a number of steps. First, PET is calculated using three methods: Blaney-Criddle, Hargreaves and Thornthwaite. Then, drought is calculated using

two drought indices (SPI & RDI) and the results were compared. For RDI, three values can be calculated using meteorological data (temperature and precipitation) but SPI is simpler and depends only on the precipitation data. PET calculation methods, RDI and SPI are explained in the following subsections.

The basic steps for estimating SPI and RDI values can be described as follows:

1. Collect the monthly data from the meteorological station.
2. Calculate RDI and its various forms: initial value, normalized and standardized.
3. Analyze the influence of the PET mathematical method on RDI, as well as frequency of historical drought occurrence.
4. Calculate SPI and RDI for different timescales.

The individual steps of calculating methodology used in the current study are summarized in the chart diagram (see Figure 2).

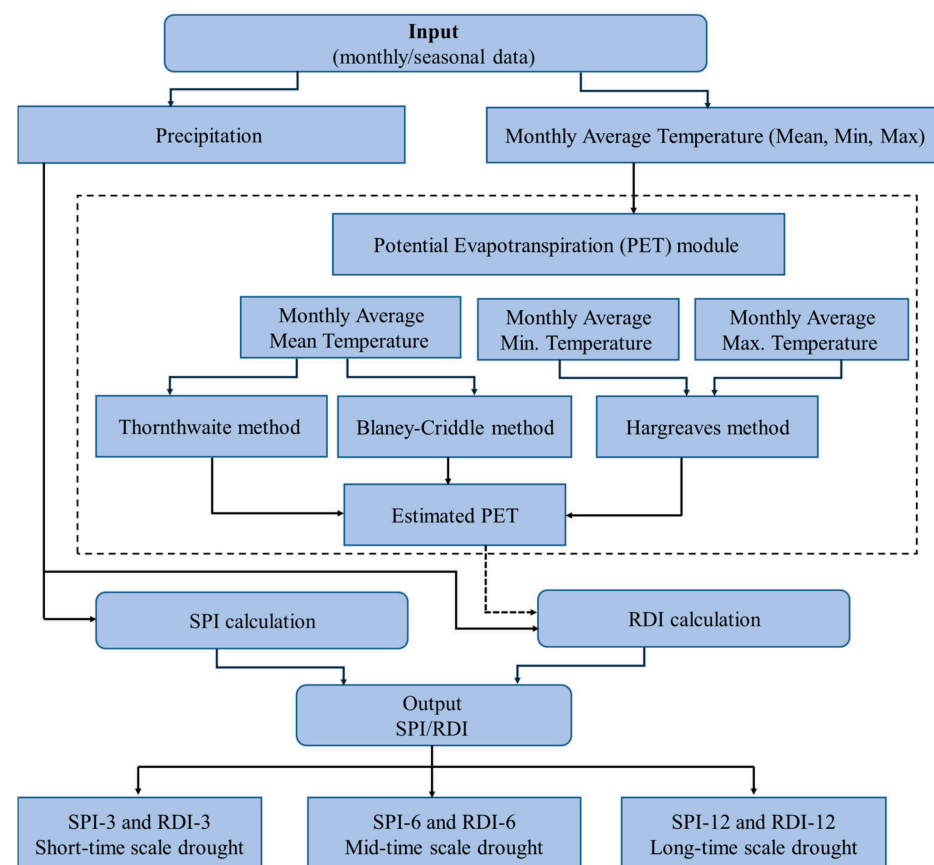


Figure 2. Chart diagram of methodology used in the current study.

2.3.1. Calculation of PET

The drought indices are determined based on the precipitation and PET using three methods; Blaney-Criddle, Hargreaves and Thornthwaite. The equations of the three methods are as follows [25]:

Blaney-Criddle Method

Blaney-Criddle equation is one of earliest equations for obtaining potential evapotranspiration based on the temperature. The method is broadly applied and can be written as follows [39]:

$$PET = k \times p \times (0.46 \times T_{mean} + 8.13) \quad (1)$$

where

T_{mean} is the mean temperature ($^{\circ}\text{C}$);

p is the percentage of the total daytime hours for period used to the total daytime hours of the year;

k is the monthly consumptive use coefficient that depends on the vegetation type, the location and the season.

The coefficient k changes for the vegetation growing season from 0.5 to 1.2.

The value of p is obtained by equation for specific latitude:

$$p = 100 \times \left(\frac{\sum_{i=d_1}^{d_2} N_i}{\sum_{i=1}^{365} N_i} \right) \quad (2)$$

where

N_i is the daytime hours of Julian day i ;

d_1 a d_2 are first and last Julian day of the month.

Hargreaves Method

Hargreaves method is another method to estimate the potential evapotranspiration, using the following equation [40]:

$$PET = 0.135 \times R_s \times (T_{mean} + 17.8) \quad (3)$$

where

R_s is the global solar radiation at the surface (mm/day);

T_{mean} is a mean temperature ($^{\circ}\text{C}$).

Thornthwaite Method

The Thornthwaite method estimates potential evapotranspiration using the following equation [41]:

$$PET = 16 \times \left(\frac{N}{12} \right) \times \left(\frac{m}{30} \right) \times \left(10 \times \frac{T_{mean}}{l} \right)^{\alpha} \quad (4)$$

In which

T_{mean} is a mean monthly temperature ($^{\circ}\text{C}$);

N is the mean monthly possible sunshine hours (h/day);

m is the number of days of each month.

α is a parameter that can be calculated using the following equation:

$$\alpha = 6.75 \times 10^{-7} \times l^3 - 7.71 \times 10^{-5} \times l^2 + 1.79 \times 10^{-2} \times l + 0.49 \quad (5)$$

where l is a heat value computed as summation of the 12 monthly values according to the following equation:

$$\sum_{i=1}^{12} \left(\frac{T_{mean}}{5} \right)^{1.514} \quad (6)$$

2.3.2. Calculation of Drought Indices Using DrinC

Drought Indices Calculator (DrinC) software is used to calculate RDI, SDI, SPI and the Precipitation Deciles. It is a user-friendly graphical interface program developed for Microsoft Windows, designed to be both simple and comprehensive. DrinC is available on website: <https://drought-software.com/>, (accessed on 10 January 2026). It provides tools for calculating a range of commonly used drought indices [42].

Reconnaissance Drought Index (RDI)

RDI has recently been employed to track meteorological droughts and to determine drought characteristics, including duration, severity, intensity, and inter-arrival time. Tsakiris et al. (2007) [3] developed RDI to analyze drought depending on total precipitation, minimum and maximum temperatures received at a site for a number of n months. RDI is computed on monthly basis for n months, where n : 1, 3, 6, 9, 12, or 24 months based on the collected precipitation and temperature data during the time period of interest. The drought indices—for example, RDI-3—can be used as an indicator for the short-term meteorological drought, RDI-6 or RDI-9 can be used as indicators for mid-term meteorological drought, and RDI-12 or RDI-24 can be used for detecting the long-term meteorological drought. Tsakiris and Vangelis (2005) [37] established a classification to define the intensity of drought on RDI and SPI values, as shown in Table 1.

Table 1. Classification of time periods by RDI/SPI.

RDI/SPI Value	Classification
≥ 2	Extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	Moderately wet
0.99 to -0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	very dry
≤ -2	Extremely dry

To calculate RDI using DrinC, there are different methods to compute its values including the initial value (a_k), normalized value (RDI_n) and standardized value (RDI_{st}). Equations (7)–(9) show how these three values can be calculated.

The initial value a_k can be computed monthly, seasonally, annually using a monthly time step. The calculation is based on a time basis of k (months) using the following equation [3]:

$$a_k^{(i)} = \frac{\sum_{j=1}^k P_{ij}}{\sum_{j=1}^k PET_{ij}}, \quad i = 1 \text{ to } N \text{ and } j = 1 \text{ to } k \quad (7)$$

where

P_{ij} and PET_{ij} are the precipitation and the potential evapotranspiration of j -th month of i -th year.

N is the total number of years of the available data.

The normalized form of RDI (RDI_n) is calculated using the following equation [2]:

$$RDI_{n(k)}^{(i)} = \frac{a_k^{(i)}}{\bar{a}_k} - 1 \quad (8)$$

where

$\bar{a}_k$ is the arithmetic mean of a_k values.

The mathematical version of the standardized RDI (RDI_{st}) assumed that a_k values follow lognormal distribution. Therefore:

$$RDI_{st(k)}^{(i)} = \frac{y_k^{(i)} - \bar{y}_k}{\sigma_{yk}} \quad (9)$$

where

y_k is $\ln a_k^{(i)}$;
 $\bar{y}_k$ is arithmetic mean of y_k ;
 σ_{y_k} is its standard deviation.

Standardized Precipitation Index (SPI)

SPI depends only on precipitation and has been applied by various researchers to monitor drought events in numerous areas of the world due to its simplicity. In the current study, the monthly precipitation data for 157 years from 1864 to 2021 were used for calculating SPI at different time scales: 3, 6 and 12 months for droughts analysis and comparison with RDI in the Lisbon region. SPI is calculated based on the long-term rainfall data that are fitted to a probability distribution and then converted to normal distribution (McKee et al. 1993; Edwards and McKee 1997) [43,44]. When SPI is normalized, wetter and drier conditions can be characterized. Thom (1958) [45] presented the gamma distribution to model rainfall time series. The frequency density function of the gamma distribution can be expressed as follows:

$$g_x = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \text{ for } x > 0 \quad (10)$$

where

α and β are the shape and the scale parameters.

x is the volume of precipitation and Γ is gamma function.

Maximum probability for α and β can be estimated as following:

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right), \quad \beta = \frac{\bar{x}}{\alpha}, \quad \text{where} \quad A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad (11)$$

where n is the number of observations.

The cumulative probability of rainfall event is subsequently calculated using acquired parameters. Therefore, since the gamma function remains unspecified and the precipitation distribution may contain zeros, the cumulative probability is determined as follows:

$$H(x) = q + (1 - q)G(x) \quad (12)$$

where

q is the likelihood of no precipitation.

$G(x)$ is the cumulative probability of the incomplete gamma function.

The formula (m/n) can be utilized to obtain q , where m represents the total count of zeros in a precipitation time series. Subsequently, the cumulative probability $H(x)$ is transformed into the standard normal random variable z , which has a mean of zero and a variance of one [46], to find out the SPI value. A drought event, as characterized by the SPI value, occurs when the index consistently attains an intensity of -1.0 or lower. Consequently, the initiation and conclusion of each drought event delineate its duration.

The SPI drought value for each month during the drought episode is calculated as the positive summation [47]. As illustrated in Table 1, there are seven categories of drought [48–50].

It is widely recognized that RDI outperforms SPI as it incorporates both precipitation and temperature data, along with evapotranspiration. In contrast, SPI remains the most commonly utilized drought index globally.

2.4. Statistical Analysis of Climate Data at Lisbon for the Period (1864–2021)

In this study, the statistical analysis of climate data (precipitation and temperature) is done to detect the trends in the time series for 157 years from 1864 to 2021 using two types of statistics as follows:

1. Descriptive Statistics: presents the minimum, maximum, mean, median, standard deviation, and coefficient of variation to understand average rainfall patterns, monthly, seasonal variability, and the degree of inconsistency in the data.
2. Trend Detection: Non-parametric tests, Mann–Kendall (MK) test and Sen's slope are used to identify trends in precipitation and temperature.

The data series is divided into three periods of length 56, 50 and 50 years (1865 to 1920, 1921 to 1970 and 1971 to 2020) explaining that the selected time windows were intended to capture distinct climatic phases and data characteristics. For the three periods, a statistical set of climatic variable parameters was conducted by the Pettitt statistical test at a significance level of 0.05 [51]. These periods were chosen to facilitate a more effective comparison among them.

The resulting annual precipitation series, Tav , $Tmin$ and $Tmax$ were subsequently subjected to statistical trend analysis using Mann–Kendall test. This non-parametric test was originally introduced by Mann (1945); Kendal (1975) later transformed it to the modified Mann–Kendal test by Hamed & Rao 1998 [52–54]. The modified Mann–Kendall test is used to assess the presence of a monotonic increasing or decreasing trend in a time series. Instead of altering the data, the variance is adjusted using an effective sample size.

First, compute the ranks R_i of observations and estimate autocorrelations of the ranked series.

$$\rho_k = \text{autocorrelation at lag } k \quad (13)$$

The variance inflation factor is:

$$\frac{n}{n^*} = 1 + \frac{2}{n(n-1)(n-2)} \sum_{k=1}^{n-1} (n-k)(n-k-1)(n-k-2)\rho_k \quad (14)$$

where n^* is the effective sample size.

Then

$$Var^*(S) = Var(S) \left(\frac{n}{n^*} \right) \quad (15)$$

And

$$Z^* = \frac{S}{\sqrt{Var^*(S)}}$$

Then $|Z^*| > Z\alpha/2$ indicates that the null hypothesis has been rejected with α being the significance level of the test. For this study, a significance level of 0.05 was utilized [52–54].

The Mann–Kendall (MK) test and Sen's slope are widely used together in time series analysis especially in hydrology and climatology to detect trends without assuming a normal distribution. Using the two tests together can help in the analysis of time series data and trend detection as MK test tells if a trend exists and SS tells how strong the trend is and both of them together provide a complete trend analysis including direction, significance and magnitude. MK is used to identify whether a monotonic trend (increasing or decreasing) exists in a dataset over the time using standardized test statistic (Z) ($Z > 0 \rightarrow$ increasing trend, $Z < 0 \rightarrow$ decreasing trend, $Z = 0 \rightarrow$ No trend), p -value determines whether the trend is statistically significant (for example: $p < 0.05 \rightarrow$ significant trend at significant statistical level $\alpha = 0.05$, $p \geq 0.05 \rightarrow$ no significant trend at significant statistical level $\alpha = 0.05$). Sen's slope is used to estimate the true slope (Q) of a trend in the data ($Q > 0 \rightarrow$ increasing trend, $Q < 0 \rightarrow$ decreasing trend) and the number represents the magnitude. However, B is the constant/intercept.

3. Results

3.1. Analysis of Climate Data Trends at Lisbon for the Period (1864–2021)

3.1.1. Precipitation

The annual average precipitation for the entire observation period from 1864 to 2021 is shown in Figures 3 and 4 presents the average monthly precipitation at Lisbon from 1864 to 2021. The minimum average annual rainfall during this period was 260.9 mm, while the maximum was 1497.0 mm. The linear trend line indicates a slight increase in precipitation over time. The years 1944–1945 and 2004–2005 correspond to periods of low precipitation, whereas 1876–1877 and 2009–2010 are characterized by high precipitation activity.

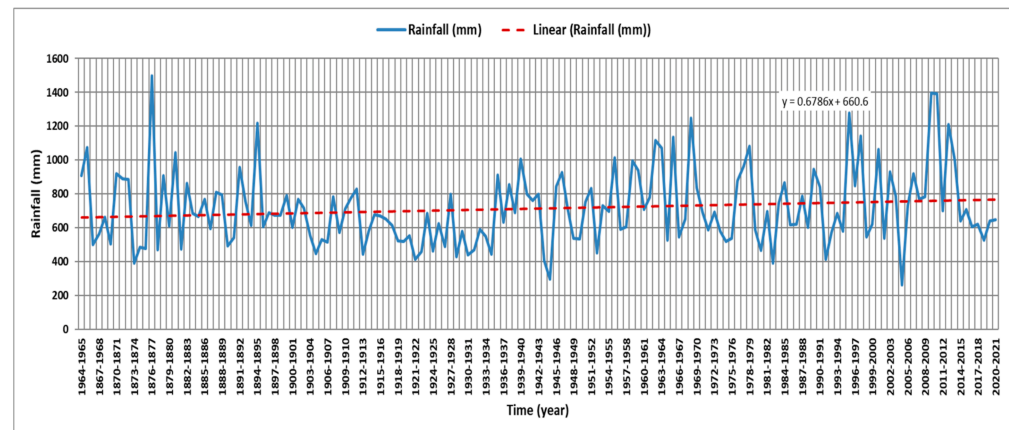


Figure 3. The annual average precipitation trend in Lisbon from 1864 to 2021.

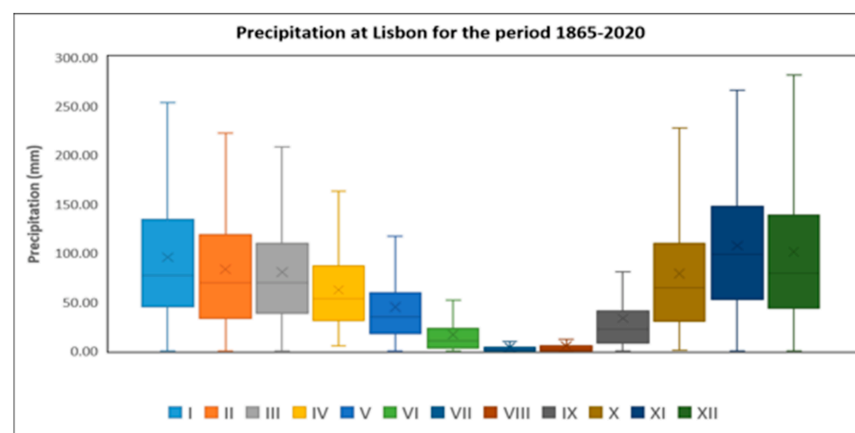


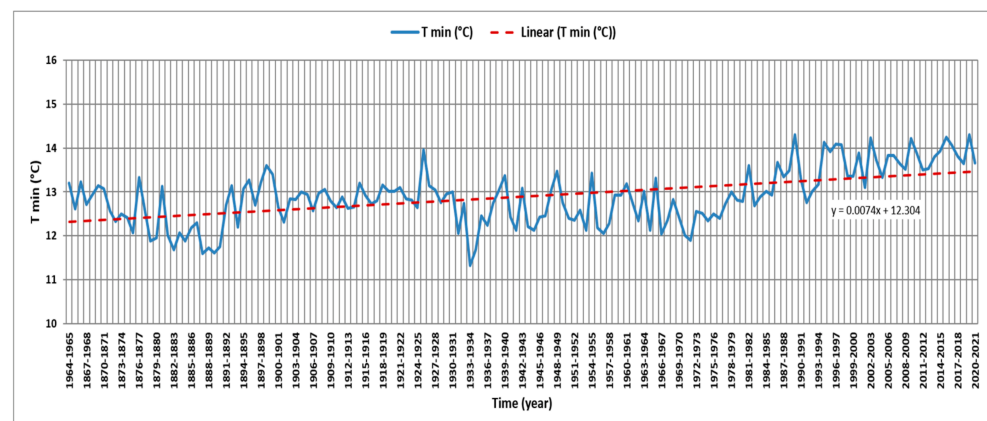
Figure 4. The average monthly precipitation in Lisbon from 1864 to 2021.

3.1.2. Temperature

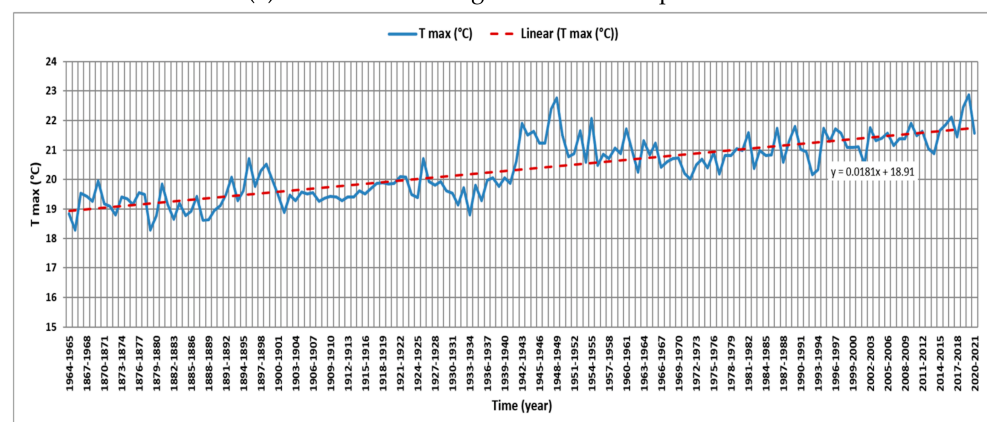
The annual temperature for the entire observation period from 1864 to 2021 is shown in Figure 5. From Figure 5a–c, the temperature tendency can be seen, i.e., the average, minimum and maximum temperature. Figure 6 presents the average monthly temperature at Lisbon from 1864 to 2021. In all three cases, a slight temperature increase is graphically and mathematically recorded. The smallest value of $T_{\min}$ for the entire 157 year period is 11.32 °C (in year 1933–1934) and the highest value is 14.3 °C (in year 1989–1990), while the average temperature of $T_{\min}$ is 12.89 °C. The smallest value of $T_{\max}$ for the entire 157 year period is 18.28 °C (in year 1865–1866) and the highest value is 22.86 °C (in year 2019–2020), while the average temperature of $T_{\max}$ is 20.34 °C. The T_{av} over the 157-year period ranges from 15.06 °C to 18.58 °C, with an average of 16.61 °C. The linear trend line for the three values of temperature (min, max, av) indicates an increasing tendency over time. This

could give an indication of the increasing drought possibilities in the area studied in the future.

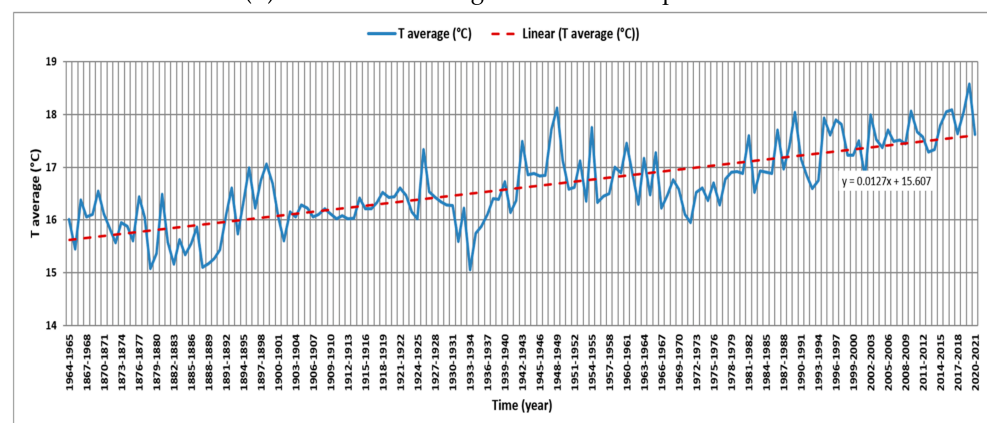
The distribution of total precipitation and monthly temperature for individual months over 157 years are shown in Figure 7. The most precipitation for the entire 157-year precipitation period was in the month of November, while the least precipitation occurred in the month of July. The warmest months for the entire 157-year period were June, July, August and September. It is possible to read from Figure 7 that the period with a small amount of precipitation occurs mainly in the summer (July and August); these months are when the highest air temperatures are also recorded, which essentially affects evaporation from the water surface as well as evapotranspiration from the soil. This increases the need for soil moisture regulation during the growing season.



(a) The annual average minimum temperature.

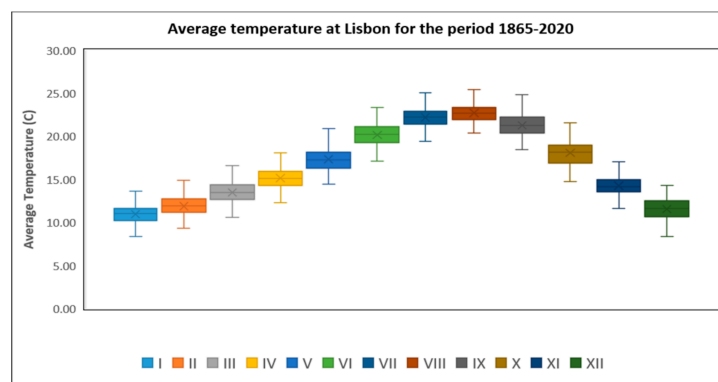


(b) The annual average maximum temperature.

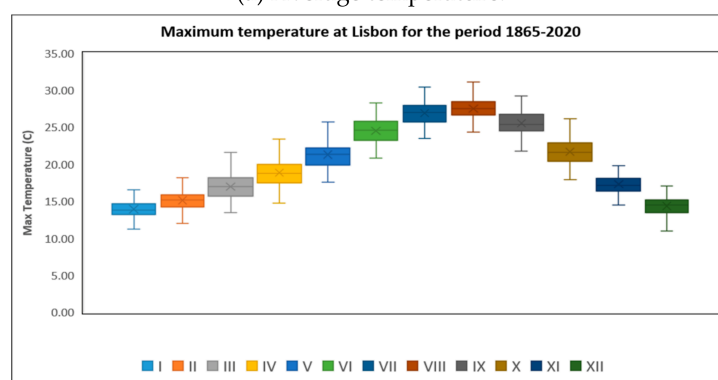


(c) The annual average temperature.

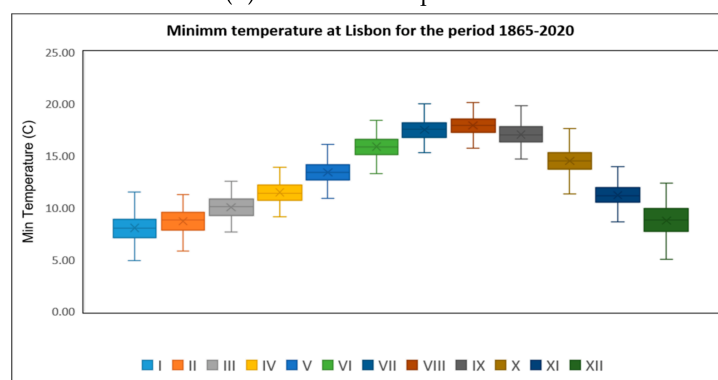
Figure 5. The annual average temperature trend in Lisbon from 1864 to 2021.



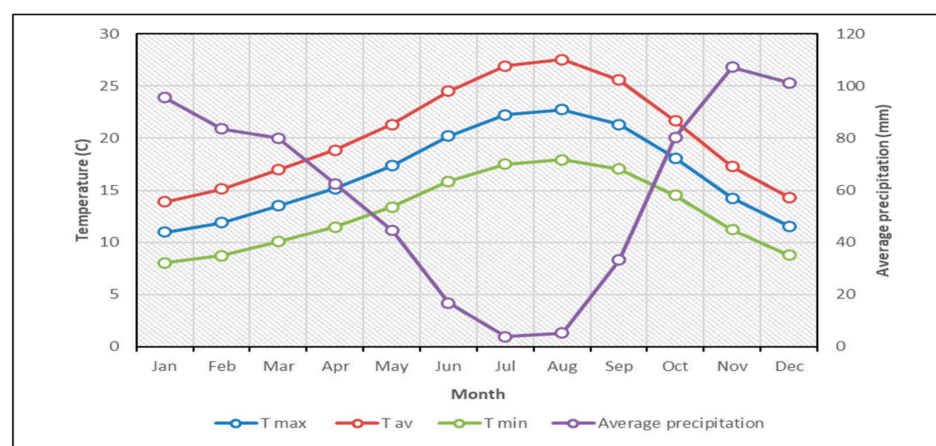
(a) Average temperature.



(b) Maximum temperature.



(c) Minimum temperature.

Figure 6. The average monthly temperature in Lisbon from 1864 to 2021.**Figure 7.** Distribution of total precipitation and monthly temperature, Tav, Tmax, Tmin in Lisbon from 1864 to 2021.

3.1.3. Results of Statistical Analysis of Climate Data in Lisbon for the Period (1865–2020)

The results of descriptive statistics are presented in Tables 2–5 and the results of trend detection using Mann–Kendall (MK) test are presented in Tables 6–9.

Table 2. Descriptive statistics for the precipitation in Lisbon for the period 1865–2020.

		I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.
1865–1920	Min	5	1	1	7	2	0	0	0	0	3	0	5
	Max	275	257	190	216	140	74	40	47	199	222	252	395
	Mean	85	82	79	63	46	16	3	5	34	74	103	95
	Median	60	79	69	52	36	11	1	0	22	65	98	86
	Standard deviation	61	61	47	46	33	16	7	10	40	52	64	65
	Coefficient of variation	72	75	59	72	72	95	188	182	117	70	62	68
1921–1970	Min	1	5	0	5	2	0	0	0	0	2	7	0
	Max	329	318	219	178	149	98	27	36	149	283	243	336
	Mean	101	81	96	55	38	16	3	3	34	68	100	96
	Median	78	62	85	52	30	11	0	1	25	52	88	75
	Standard deviation	75	66	56	34	33	18	6	6	36	56	59	70
	Coefficient of variation	74	81	58	62	88	111	179	170	107	82	59	73
1971–2020	Min	0	0	1	5	0	0	0	0	0	0	2	14
	Max	353	282	239	163	156	69	42	58	129	257	376	383
	Mean	101	87	65	68	49	16	4	6	30	94	119	111
	Median	79	75	46	64	45	7	1	2	22	81	104	77
	Standard deviation	69	68	55	40	42	19	7	11	32	71	91	93
	Coefficient of variation	68	78	85	58	84	123	182	182	104	75	76	83
1865–2020	Min	0	0	0	5	0	0	0	0	0	1	0	0
	Max	354	319	240	216	156	98	43	59	199	283	376	396
	Mean	96	83	80	63	45	17	4	5	33	79	108	101
	Median	77	70	70	53	35	10	1	1	22	64	98	79
	Standard deviation	68	65	54	40	36	18	7	9	37	61	73	77
	Coefficient of variation	72	78	68	65	82	108	184	183	110	77	67	76

Table 3. Descriptive statistics for the average temperature (Tav) in Lisbon for the period 1865–2020.

		I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.
1865–1920	Min	8	8	10	12	14	17	18	19	18	14	11	8
	Max	12	13	15	17	18	22	24	24	23	20	16	13
	Mean	10	11	12	14	16	19	21	22	20	17	13	11
	Median	10	11	12	14	16	19	21	22	20	17	13	10
	Standard deviation	0	1	1	1	1	1	1	0	1	1	0	1
	Coefficient of variation	9	8	8	8	6	6	5	4	5	6	6	11
1921–1970	Min	8	7	11	12	14	17	20	20	19	16	11	8
	Max	14	14	16	18	20	22	24	25	24	20	17	13
	Mean	11	11	13	15	17	20	22	22	21	18	14	11
	Median	11	11	13	15	17	20	22	22	21	18	14	11
	Standard deviation	1	1	1	1	1	1	0	1	1	1	1	1
	Coefficient of variation	10	10	8	8	8	5	4	4	5	5	8	11
1971–2020	Min	9	10	12	12	14	17	20	21	19	15	12	9
	Max	13	14	18	19	21	23	25	25	24	21	17	14
	Mean	11	12	14	15	17	20	22	23	22	18	14	12
	Median	11	12	14	15	17	20	22	23	22	18	14	12
	Standard deviation	0	1	1	1	1	1	1	1	1	1	0	1
	Coefficient of variation	8	8	8	8	8	6	4	4	5	7	6	8
1865–2020	Min	8	8	11	12	14	17	18	19	18	14	11	8
	Max	14	14	18	19	21	23	25	25	25	22	17	14
	Mean	11	12	14	15	17	20	22	23	21	18	14	12
	Median	11	12	14	15	17	20	22	23	21	18	14	12
	Standard deviation	1	1	1	1	1	1	1	1	1	1	1	1
	Coefficient of variation	10	10	10	9	8	7	5	5	6	8	8	11

Results of Descriptive Statistics

Table 2 shows descriptive statistics for precipitation (minimum, maximum, mean, median, standard deviation, and coefficient of variation) for each month. Similarly, Tables 3–5 show descriptive statistics for temperature (min, max, av).

Table 4. Descriptive statistics for the maximum temperature (Tmax) in Lisbon for the period 1865–2020.

		I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.
1865–1920	Min	11	11	13	14	17	20	22	23	21	17	14	11
	Max	14	16	18	22	22	27	29	29	27	22	18	15
	Mean	13	14	15	17	20	23	25	26	24	20	16	13
	Median	13	14	15	17	20	23	25	26	24	20	16	13
	Standard deviation	0	1	1	1	1	1	1	1	1	1	0	1
	Coefficient of variation	6	7	8	8	6	6	5	4	5	5	5	7
1921–1970	Min	0	1	1	1	1	1	1	1	1	1	0	1
	Max	16	18	21	23	25	27	30	31	29	25	21	17
	Mean	14	14	16	18	20	24	26	26	24	21	16	13
	Median	13	15	16	19	21	24	27	27	25	22	17	14
	Standard deviation	2	2	2	3	3	4	4	5	4	3	3	2
	Coefficient of variation	16	17	17	18	18	17	18	18	18	18	18	16
1971–2020	Min	13	14	15	16	18	21	24	25	22	19	15	12
	Max	17	18	23	23	26	28	31	30	30	26	21	16
	Mean	14	15	17	19	21	24	27	27	25	22	17	15
	Median	14	15	17	19	21	25	27	28	26	22	17	15
	Standard deviation	0	2	2	2	3	3	3	3	3	3	2	2
	Coefficient of variation	5	13	14	14	14	13	13	13	13	13	12	13
1865–2020	Min	11	11	13	14	18	21	22	24	22	18	14	11
	Max	17	19	24	24	26	28	32	31	30	26	22	17
	Mean	14	15	17	19	21	25	27	28	26	22	17	14
	Median	14	15	17	19	21	25	27	27	25	22	17	14
	Standard deviation	1	1	2	2	2	2	2	1	2	2	1	1
	Coefficient of variation	8	9	11	10	9	7	6	5	7	8	8	9

Table 5. Descriptive statistics for the minimum temperature (Tmin) in Lisbon for the period 1865–2020.

		I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.
1865–1920	Min	4	4	7	9	11	13	15	15	14	11	8	5
	Max	10	11	11	12	14	18	19	19	18	17	13	12
	Mean	7	8	9	11	13	15	17	17	16	14	10	8
	Median	7	8	9	11	13	15	17	17	16	13	11	8
	Standard deviation	1	1	0	1	0	0	0	0	0	1	0	1
	Coefficient of variation	15	15	10	9	7	6	5	4	5	8	9	19
1921–1970	Min	5	3	7	9	10	13	15	15	14	12	7	5
	Max	11	11	12	13	15	16	19	20	20	16	13	11
	Mean	8	8	10	11	13	15	17	17	16	14	11	8
	Median	7	8	10	11	13	15	16	17	16	14	10	8
	Standard deviation	1	1	0	0	1	0	0	0	0	0	1	1
	Coefficient of variation	17	17	9	7	7	4	4	5	5	6	11	17
1971–2020	Min	5	6	8	9	11	12	15	16	15	11	9	6
	Max	10	11	13	15	16	18	20	20	19	17	13	12
	Mean	8	9	10	11	13	16	18	18	17	15	11	9
	Median	8	9	10	11	13	16	18	18	17	14	11	9
	Standard deviation	1	1	1	1	1	1	0	0	1	1	1	1
	Coefficient of variation	14	11	10	10	9	7	5	5	5	8	9	13
1865–2020	Min	5	4	8	9	11	13	15	16	15	11	8	5
	Max	12	11	13	15	18	19	20	21	20	18	14	12
	Mean	8	9	10	11	13	16	18	18	17	14	11	9
	Median	8	9	10	11	13	16	18	18	17	15	11	9
	Standard deviation	1	1	1	1	1	1	1	1	1	1	1	2
	Coefficient of variation	16	15	11	9	9	7	5	5	6	8	10	18

From the descriptive statistics results in Tables 2–5 it can be observed that the values of the coefficient of variation (CV) are relatively small for all the data used which indicates that the data points are close to the mean (less variability). Moreover, small standard deviation values are close to the mean which indicates (less variability).

Table 6. Non-parametric tests (MK and SS) for the precipitation in Lisbon for the period 1865–2020.

Period	M	MK		SS		Trend Direction	Significance
		Z	P	Q	B		
1865–1920	I	−0.99		−0.346		Decreasing	Not significant
	II	−0.23		−0.128		Decreasing	Not significant
	III	−1.29		−0.553		Decreasing	Not significant
	IV	−1.28		−0.342		Decreasing	Not significant
	V	−1.60		−0.42		Decreasing	Not significant
	VI	0.39		0.035		Increasing	Not significant
	VII	−1.16		−0.005		Decreasing	Not significant
	VIII	−1.12		−0.008		Decreasing	Not significant
	IX	−0.42		−0.054		Decreasing	Not significant
	X	−0.25		−0.095		Decreasing	Not significant
	XI	0.28		0.216		Increasing	Not significant
	XII	−0.63		−0.298		Decreasing	Not significant
1921–1970	I	2.81	*	1.735		Increasing	Significant
	II	2.24	*	1.281		Increasing	Significant
	III	1.77	*	0.946		Increasing	Significant
	IV	−0.30		−0.119		Decreasing	Not significant
	V	1.74	*	0.462		Increasing	Significant
	VI	0.87		0.095		Increasing	Not significant
	VII	−1.92	*	−0.017		Decreasing	Significant
	VIII	1.00		0.011		Increasing	Not significant
	IX	3.44		0.026		Increasing	Not significant
	X	0.28		0.12		Increasing	Not significant
	XI	1.14		0.74		Increasing	Not significant
	XII	0.67		0.423		Increasing	Not significant
1971–2020	I	0.05		0.067		Increasing	Not significant
	II	−1.15		−0.583		Decreasing	Not significant
	III	0.79		0.292		Increasing	Not significant
	IV	2.21	*	0.819		Increasing	Significant
	V	0.28		0.11		Increasing	Not significant
	VI	−0.38		−0.037		Decreasing	Not significant
	VII	−1.30		−0.028		Decreasing	Not significant
	VIII	0.47		0.000		Increasing	Not significant
	IX	1.25		0.210		Increasing	Not significant
	X	2.02	*	1.226		Increasing	Significant
	XI	2.14	*	1.674		Increasing	Significant
	XII	−0.05		−0.038		Decreasing	Not significant
1865–2020	I	1.59		0.162		Increasing	Not significant
	II	0.25		0.025		Increasing	Not significant
	III	−1.46		−0.130		Decreasing	Not significant
	IV	0.9		0.067		Increasing	Not significant
	V	−0.22		−0.013		Decreasing	Not significant
	VI	−1.06		−0.017		Decreasing	Not significant
	VII	0.07		0.000		Increasing	Not significant
	VIII	0.31		0.000		Increasing	Not significant
	IX	−0.24		−0.007		Decreasing	Not significant
	X	0.99		0.098		Increasing	Not significant
	XI	1.06		0.142		Increasing	Not significant
	XII	−0.19		−0.018		Decreasing	Not significant

Table 7. Non-parametric tests (MK and SS) for the average temperature (Tav) in Lisbon for the period 1865–2020.

Period	M	MK		SS		Trend Direction	Significance
		Z	P	Q	B		
1865–1920	I	0.05		0.001		Increasing	Not significant
	II	0.87		0.007		Increasing	Not significant
	III	0.22		0.002		Increasing	Not significant
	IV	−0.26		−0.003		Decreasing	Not significant
	V	1.70	*	0.017		Increasing	Significant
	VI	0.65		0.008		Increasing	Not significant
	VII	1.02		0.011		Increasing	Not significant
	VIII	1.60		0.014		Increasing	Not significant
	IX	2.17	*	0.019		Increasing	Significant
	X	1.05		0.009		Increasing	Not significant
	XI	0.54		0.004		Increasing	Not significant
	XII	3.40	*	0.039		Increasing	Significant
1921–1970	I	1.36		0.015		Increasing	Not significant
	II	1.10		0.017		Increasing	Not significant
	III	1.00		0.012		Increasing	Not significant
	IV	1.68	*	0.021		Increasing	Significant
	V	1.46		0.028		Increasing	Significant
	VI	0.22		0.003		Increasing	Not significant
	VII	0.90		0.009		Increasing	Not significant
	VIII	−0.36		−0.005		Decreasing	Not significant
	IX	1.72	*	0.019		Increasing	Not significant
	X	1.18		0.011		Increasing	Not significant
	XI	0.08		0.001		Increasing	Not significant
	XII	0.32		0.005		Increasing	Not significant
1971–2020	I	2.23	*	0.021		Increasing	Significant
	II	0.67		0.008		Increasing	Not significant
	III	1.19		0.013		Increasing	Not significant
	IV	2.76	*	0.037		Increasing	Significant
	V	2.09	*	0.031		Increasing	Significant
	VI	3.59	*	0.048		Increasing	Significant
	VII	1.79	*	0.020		Increasing	Significant
	VIII	3.51	*	0.036		Increasing	Significant
	IX	1.32		0.018		Increasing	Not significant
	X	2.83	*	0.040		Increasing	Significant
	XI	1.31		0.013		Increasing	Not significant
	XII	1.39		0.015		Increasing	Not significant
1865–2020	I	5.69	*	0.011		Increasing	Significant
	II	3.71	*	0.007		Increasing	Significant
	III	4.28	*	0.010		Increasing	Significant
	IV	3.82	*	0.009		Increasing	Significant
	V	3.21	*	0.008		Increasing	Significant
	VI	4.02	*	0.010		Increasing	Significant
	VII	4.53	*	0.009		Increasing	Significant
	VIII	4.15	*	0.007		Increasing	Significant
	IX	4.81	*	0.010		Increasing	Significant
	X	4.23	*	0.010		Increasing	Significant
	XI	3.97	*	0.007		Increasing	Significant
	XII	5.72	*	0.013		Increasing	Significant

Table 8. Non-parametric tests (MK and SS) for the maximum temperature (Tmax) in Lisbon for the period 1865–2020.

Period	M	MK		SS		Trend Direction	Significance
		Z	P	Q	B		
1865–1920	I	−0.09		−0.001		Decreasing	Not significant
	II	0.24		0.003		Increasing	Not significant
	III	0.00		0.000		None	Not significant
	IV	0.11		0.002		Increasing	Not significant
	V	1.99	*	0.026		Increasing	Significant
	VI	0.81		0.012		Increasing	Not significant
	VII	1.41		0.017		Increasing	Not significant
	VIII	2.13	*	0.022		Increasing	Significant
	IX	2.31	*	0.026		Increasing	Significant
	X	1.36		0.012		Increasing	Not significant
	XI	−0.02		−0.001		Decreasing	Not significant
	XII	3.33	*	0.033		Increasing	Significant
1921–1970	I	2.02	*	0.020		Increasing	Significant
	II	2.19	*	0.030		Increasing	Significant
	III	2.01	*	0.034		Increasing	Significant
	IV	2.58	*	0.044		Increasing	Significant
	V	1.91	*	0.039		Increasing	Significant
	VI	0.55		0.007		Increasing	Not significant
	VII	2.12	*	0.026		Increasing	Significant
	VIII	0.74		0.009		Increasing	Not significant
	IX	2.02	*	0.030		Increasing	Significant
	X	0.58		0.012		Increasing	Not significant
	XI	0.50		0.006		Increasing	Not significant
	XII	1.81	*	0.020		Increasing	Significant
1971–2020	I	−2.16	*	−0.023		Increasing	Significant
	II	−1.72	*	−0.028		Increasing	Significant
	III	−2.11	*	−0.042		Increasing	Significant
	IV	−1.52		−0.037		Increasing	Not significant
	V	−2.21	*	−0.045		Increasing	Significant
	VI	−2.00	*	−0.045		Increasing	Significant
	VII	−1.84	*	−0.040		Increasing	Significant
	VIII	−1.93	*	−0.037		Increasing	Significant
	IX	−2.08	*	−0.043		Increasing	Significant
	X	−1.68	*	−0.038		Increasing	Significant
	XI	−1.62		−0.023		Increasing	Not significant
	XII	0.79		0.009		Increasing	Not significant
1865–2020	I	4.85	*	0.999		Increasing	Significant
	II	4.14	*	0.999		Increasing	Significant
	III	4.59	*	0.999		Increasing	Significant
	IV	4.34	*	0.999		Increasing	Significant
	V	3.77	*	0.999		Increasing	Significant
	VI	4.23	*	0.999		Increasing	Significant
	VII	4.50	*	0.999		Increasing	Significant
	VIII	4.53	*	0.999		Increasing	Significant
	IX	4.62	*	0.999		Increasing	Significant
	X	4.25	*	0.999		Increasing	Significant
	XI	3.91	*	0.999		Increasing	Significant
	XII	5.41	*	1		Increasing	Significant

Table 9. Non-parametric tests (MK and SS) for the minimum temperature (Tmin) in Lisbon for the period 1865–2020.

Period	M	MK		SS		Trend Direction	Significance
		Z	P	Q	B		
1865–1920	I	0.32		0.004		Increasing	Not significant
	II	0.70		0.006		Increasing	Not significant
	III	0.62		0.005		Increasing	Not significant
	IV	−0.42		−0.003		Decreasing	Not significant
	V	1.10		0.009		Increasing	Not significant
	VI	0.53		0.005		Increasing	Not significant
	VII	0.25		0.002		Increasing	Not significant
	VIII	0.55		0.004		Increasing	Not significant
	IX	1.56		0.011		Increasing	Not significant
	X	0.74		0.006		Increasing	Not significant
	XI	0.31		0.002		Increasing	Not significant
	XII	3.19	*	0.046		Increasing	Significant
1921–1970	I	0.08		0.001		Increasing	Not significant
	II	−0.13		−0.002		Decreasing	Not significant
	III	−0.52		−0.005		Decreasing	Not significant
	IV	−0.53		−0.006		Decreasing	Not significant
	V	1.00		0.010		Increasing	Not significant
	VI	−0.67		−0.006		Decreasing	Not significant
	VII	−1.42		−0.009		Decreasing	Not significant
	VIII	−2.36	*	−0.020		Decreasing	Significant
	IX	−1.24		−0.009		Decreasing	Not significant
	X	−1.07		−0.010		Decreasing	Not significant
	XI	−0.64		−0.008		Decreasing	Not significant
	XII	−0.52		−0.008		Decreasing	Not significant
1971–2020	I	1.76	*	0.023		Increasing	Significant
	II	0.42		0.005		Increasing	Not significant
	III	1.34		0.010		Increasing	Significant
	IV	3.91	*	0.041		Increasing	Significant
	V	1.99	*	0.028		Increasing	Significant
	VI	1.52		0.021		Increasing	Significant
	VII	2.91	*	0.027		Increasing	Significant
	VIII	1.82	*	0.016		Increasing	Significant
	IX	1.61		0.017		Increasing	Significant
	X	4.07	*	0.047		Increasing	Significant
	XI	1.63		0.019		Increasing	Significant
	XII	1.23		0.017		Increasing	Not significant
1865–2020	I	2.77	*	0.007		Increasing	Significant
	II	2.18	*	0.005		Increasing	Significant
	III	3.5	*	0.006		Increasing	Significant
	IV	2.03	*	0.004		Increasing	Significant
	V	1.88	*	0.004		Increasing	Significant
	VI	2.73	*	0.006		Increasing	Significant
	VII	2.79	*	0.005		Increasing	Significant
	VIII	2.10	*	0.004		Increasing	Significant
	IX	3.27	*	0.006		Increasing	Significant
	X	3.01	*	0.007		Increasing	Significant
	XI	3.59	*	0.006		Increasing	Significant
	XII	2.77	*	0.010		Increasing	Significant

Explanations: * the existence of trend at $\alpha = 0.05$ level of significance.

A statistical set of climatic variable parameters were subjected to the Pettitt statistical test at a significance level of 0.05. The Pettitt test was applied to sets of variables arranged into three time periods (first period: 1865–1920, second period: 1921–1970 and third period: 1971–2020). The periods were selected for better comparison between them. Pettitt test detected homogeneity of statistical data in the mathematical software MATLAB 2023 [51]. The precipitation data in the three time intervals are homogeneous. The average monthly temperature data are also homogeneous in the three analyzed periods. The monthly maximum temperature data are also homogeneous except for the second period. The monthly minimum temperature data are also homogeneous except for the third period. Homogeneous statistical sets may have autocorrelation and are therefore further subjected to the statistical modified Mann–Kendall test.

Results of Non-Parametric Tests

The results of Non-parametric tests, MK (Z and p) and (Q and B) are presented in Tables 6–9 for precipitation and temperature (min, max, av).

From the results of Mann–Kendall (MK) test and Sen’s slope (SS) for climate data in Lisbon for the period 1865–2020 presented in Tables 6–9, we can conclude:

1. For precipitation, small increasing trends were observed in the years 1921–1970 that is Non-Significant in most of the months.
2. For Temperature (Tav, Tmax, Tmin), increasing trends were observed in the years 1921–1970 that is significant in most of the months especially the summer season.

The results revealed that temperature trends are increasing significantly in the period (1971–2020) which gives an indication of increasing the drought at this period that may continue in the future with the continuous increase in greenhouse gasses emissions and global warming. The results match also with the linear trends of precipitation and temperature (Tav, Tmax, Tmin) presented in Figures 3 and 5a–c.

The result of statistical significance do not have limited hydrological relevance in many cases, but in two cases—for Tmax in period 1921–1970 and for Tmin in period 1971–2020—the statistical data are heterogeneous. The results of the statistical test become distorted and lose their informative value; furthermore, the hydrological relevance of several trends are statistically significant according to the modified Mann–Kendall test with a significance level of 0.05.

3.2. Analysis of Potential Evapotranspiration (PET) Using Different Methods

This study focuses on the west of Portugal on the Mediterranean coasts where the climate is changing from season to season. Drought occurrence is assessed using RDI and SPI using climate data over 157 years. RDI and SPI are computed for the Lisbon station with different time scales using DrinC. The results of DrinC were validated by comparing the results of PET method to estimate RDI and current drought conditions.

Figure 8 shows the PET using the three methods. In Figure 8, it can be seen that Blaney–Criddle equation gives higher values of potential evapotranspiration, while Thornthwaite or Hargreaves equation gives lower values. Significant difference with Hargreaves is around up to 63% for a Blaney–Criddle in mean value; for Thornthwaite it is less than 17% from the mean value. Potential evapotranspiration PET using the Blaney–Criddle method demonstrates variation from 66.66 to 172.06 mm/month with a mean value of 113.41 mm/month. The PET using the Hargreaves method demonstrates variation from 24.20 to 180.91 mm/month with a mean value of 81.78 mm/month; the Thornthwaite method demonstrates variation from 13.77 to 154.98 mm/month with a mean value of 67.47 mm/month. The results reveal that the Hargreaves method has balanced variation and a mean value of PET compared to Thornthwaite and Blaney–Criddle methods.

Therefore, this method can be recommended to calculate PET for the current case study, particularly when data is not sufficient to use the FAO-Penman Monteith method. Hargreaves and Allen 2003) [55] recommended using Hargreaves method to estimate PET with a high accuracy especially when it is not possible to use the FAO-Penman Monteith due to data availability.

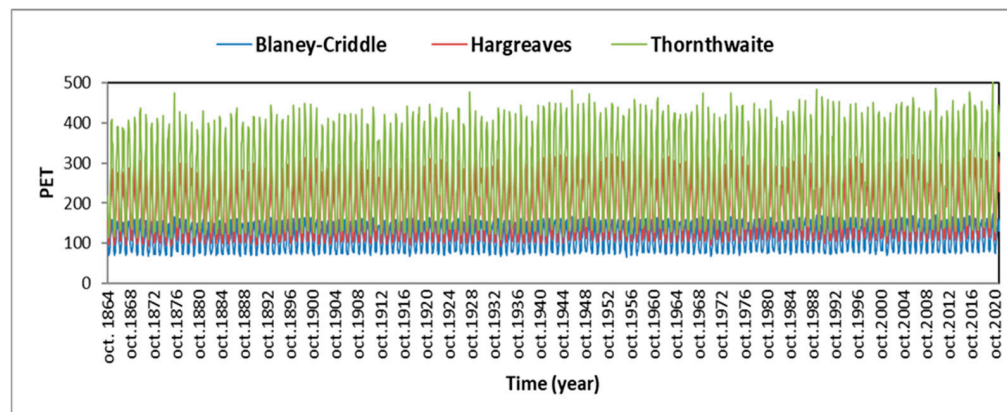


Figure 8. The potential evapotranspiration PET for various method.

In this study, the software DrinC allowed three widely used empirical temperature-based PET formulations to be used (Blaney–Criddle, Hargreaves, and Thornthwaite). These were compared in order to choose one of them for the current case study. This comparison was necessitated by the long-term historical record available at the Lisbon station, which lacks the complete suite of radiation, humidity, and wind observations required to apply the FAO-56 Penman–Monteith reference method consistently over the 1864–2021 period. The standardized RDI series derived from these three PET methods showed negligible differences, indicating that the drought episode identification at this site is only weakly sensitive to the specific empirical PET formulation; this is consistent with the previous literature reporting that RDI is robust to the choice of PET method. On this basis and following the recommendations of Hargreaves and Allen (2003) [55] for data-scarce conditions, the Hargreaves equation was selected as a representative empirical PET method for the subsequent SPI–RDI comparison, without claiming its absolute accuracy for the Lisbon site rather than its acceptable accuracy compared to other methods available in the software DrinC.

3.3. Analysis of Drought Using Different Methods

After comparison of using different methods to calculate the PET and selecting Hargreaves method for the current case study. Drought analysis using RDI was done for a 12 months' time scale using different methods at the chosen station based on the three methods for calculating PET. The results of RDI-12 are shown in Figures 9–11 for the three methods. Figures 9–11 show the values of RDI using the initial value (a_k), normalized RDI (RDI_n) and standardized RDI (RDI_{st}). The figure presents the results of the hydrological year starting from October to September for the period 1864 to 2021.

3.3.1. The Initial Value (a_k)

In the initial values a_k (see in Figure 9) there is some significant influence from the PET method. The values of a_k are less for the Hargreaves method compared to the a_k values with the Blaney–Criddle and Thornthwaite methods.

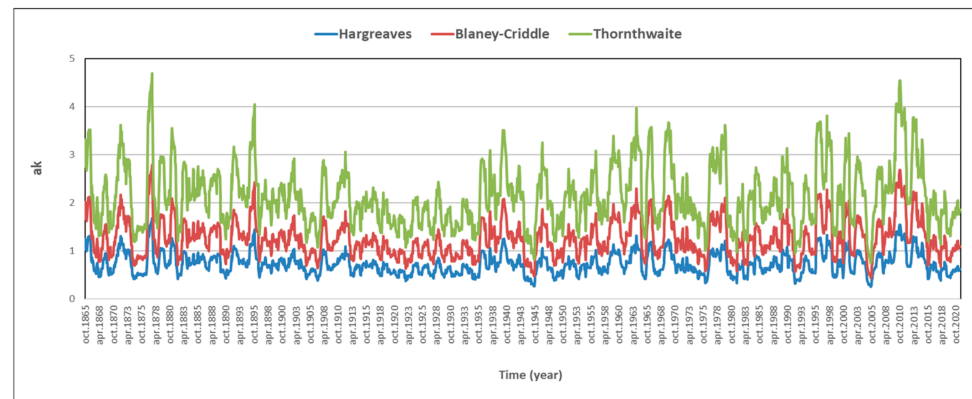


Figure 9. Initial values of a_k for various PET methods.

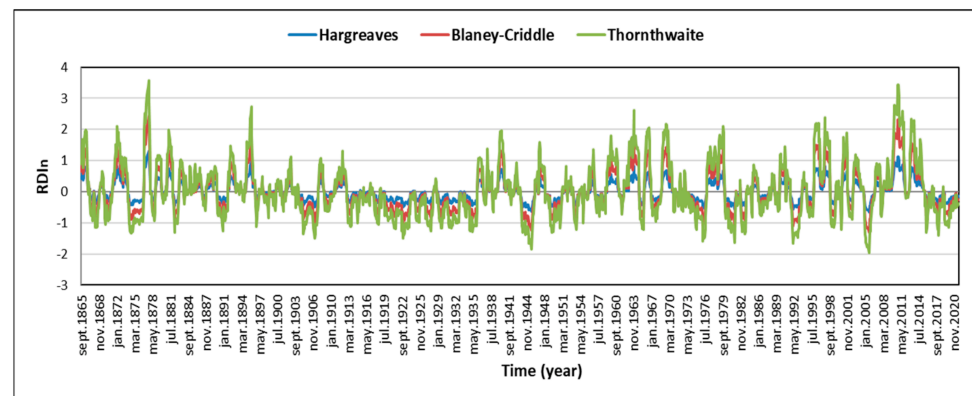


Figure 10. The normalized RDI_n values for various PET methods.

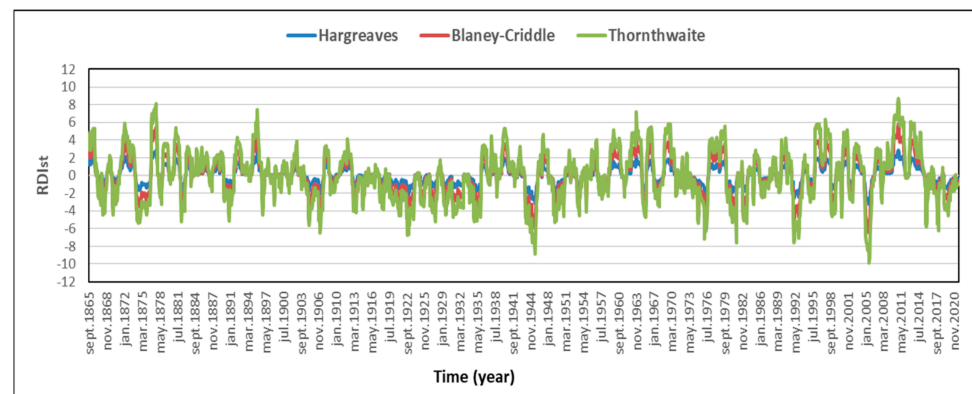


Figure 11. The standardized RDI_{st} values for various PET methods.

3.3.2. The Normalized RDI (RDI_n)

The average percentage difference in values of RDI_n from the Hargreaves method for the Blaney-Criddle is -23% and for the Thornthwaite method it is -8% . Normalized drought index RDI_n estimated by Blaney-Criddle method had a variation from -0.64 to 1.18 with a mean of -0.04 . Normalized drought index RDI_n obtained by the Hargreaves method had a variation from -0.66 to 1.32 with a median -0.04 . Normalized drought index RDI_n calculated with the Thornthwaite method had a variation from -0.66 to 1.15 with a median -0.04 . Normalized RDI_n values are seen in Figure 10.

3.3.3. The Standardized RDI (RDI_{st})

The average percentage difference in values of RDI_{st} from the Hargreaves method for the Blaney-Criddle is -9% and for the Thornthwaite method is 110% . Standardized

drought index RDI_{st} estimated with the Hargreaves method had a variation from -3.27 to 2.83 with a median 0.00 . Standardized drought index RDI_{st} estimated with the Hargreaves method had a variation from -2.82 to 3.22 with a median -0.04 . Standardized drought index RDI_{st} estimated with Blaney-Criddle method had a variation from -3.25 to 2.96 with a median -0.02 . Standardized drought index RDI_{st} obtained with the Thornthwaite method had a variation from -3.36 to 2.92 with a median 0.00 . It can be observed that the index, in its standardized form, shows negligible differences across individual PET methods. Therefore, it can be said that the index can be calculated from this territory by anyone using the PET method and the result in the identification of dry periods will be the same.

The results in Figures 9–11 reveal that using initial or normalized forms of RDI gave more significant variations in recorded drought episodes. However, the RDI_{st} values did not show significant differences across different PET methods and therefore this index is mostly used in a standardized form for a better comparison of natural droughts. The results match well with Zarei et al. (2017) who concluded that RDI_{st} is a resilient drought index, unaffected by the method used for PET calculation [56].

Historical drought analysis using RDI_{st} for 12 months' time for the western part of Portugal from 1864 to 2021 is estimated and presented in Figure 11. It can be seen from the figure that extreme droughts often occurred during the period (1864–2021). The results show that the driest years were recorded in 1907, 1922–1923, 1944–1945, 1976, 1981, 1992–1993 and 2018. However, the average inter-arrival time of extreme drought in the period from 1864 to 2021 is estimated to be 7.92 years.

3.4. Assessment of Drought Risks in Lisbon Region Using RDI and SPI

For the assessment of historical drought events, drought events were analyzed using drought indices (SPI and RDI) across three time intervals: a short-term (three-month) drought interval (as shown in Figure 12), a mid-term (six-month) drought interval (as shown in Figure 13), and long-term (twelve-month) drought interval (as shown in Figure 14). In each mentioned type of drought, it is reached extreme dry conditions when drought indices (RDI or SPI) are smaller than -2 .

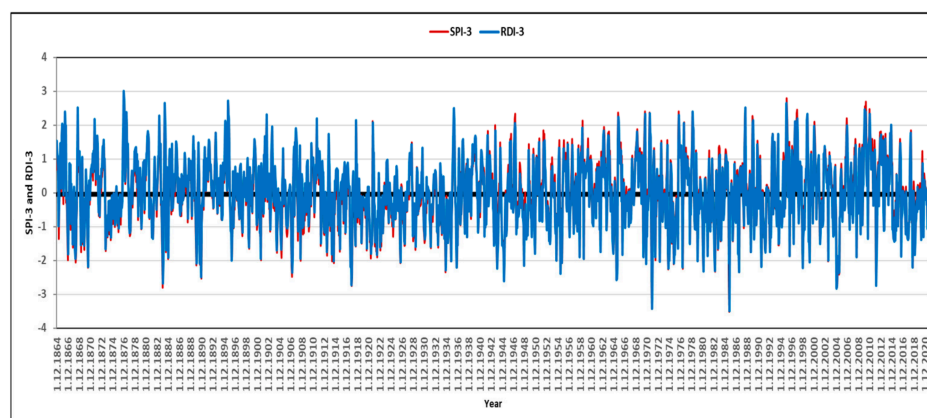


Figure 12. SPI-3 and RDI-3 in Lisbon region for the period 1864–2021.

3.4.1. Short-Term Drought (3 Months' Time Scale)

Figure 12 shows the RDI and SPI values over three-month scales to identify short-term meteorological drought. In what concerns the short-term meteorological drought by RDI-3 and SPI-3, the results show that 40 extreme events occurred during the period (1864–2021). Total duration of extreme events with RDI-3 is 52 months but it is one month longer with

SPI-3. The most intense extreme short-term meteorological drought identified using both indices occurred in 1970 and 1985.

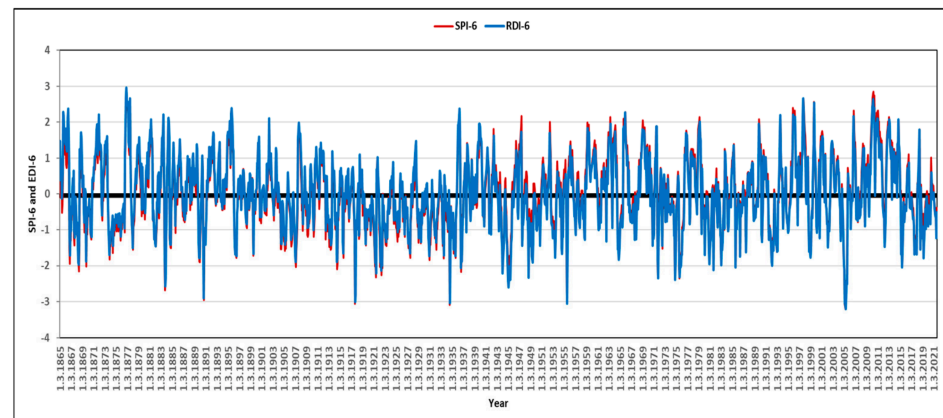


Figure 13. SPI-6 and RDI-6 in Lisbon region for the period 1864–2021.

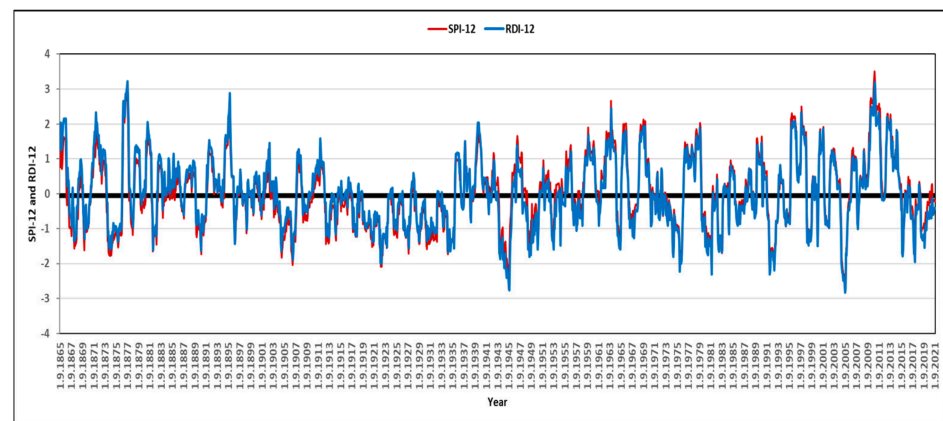


Figure 14. SPI-12 and RDI-12 in Lisbon region for the period 1864–2021.

3.4.2. Mid-Term Indices (6 Months' Time Scale)

Figure 13 displays six-month RDI and SPI values used to identify mid-term meteorological drought. In the Lisbon region, 19 extreme events were recorded by RDI-6 and 25 by SPI-6. Total duration of these extreme events is 31 months for RDI-6 and 33 months for SPI-6. The six months extreme mid-term meteorological drought was identified by both indices in 2005.

3.4.3. Long-Term Drought (12 Months' Time Scale)

Figure 14 displays twelve-month RDI and SPI values used to identify extreme long-term meteorological drought. In the Lisbon region 15 extreme events were estimated by RDI-12 while by SPI-12 were estimated 5 events less. Total duration of these extreme events is 37 months for RDI-6 and 22 months for SPI-12. The most intensive extreme long-term meteorological droughts were recorded in 1945 and 2005.

Tables 10 and 11 present the duration, severity, average inter-arrival time and average return time of drought events at Lisbon using SPI and RDI. With increasing time intervals or time steps of drought the number of events decreases, and the average return time of the drought increases. The average return time of short-term meteorological drought with RDI-3 is 3.79 while with SPI-3 it is 3.86. The average return time of mid-term meteorological drought with RDI-6 is 7.31 while with SPI-6 it is 5.69. The average return time of long-term meteorological drought with RDI-12 is 7.92 while with SPI-12 it is 10.88. The findings of this

study reveal that RDI and SPI indices are accepted and quite similar with some differences in the average return time. However, RDI is a more useful tool to assess the severity of drought especially using the standatized index RDI_{st} that is not affected by the method of PET calculation [56].

Table 10. Drought identification using RDI in Lisbon region for the period (1864–2021).

Index	Number of Events	Duration	Severity	Average Inter-Arrival Time (Month)	Average Return Time (Year)	Years
RDI-3	40	52	−119.77	45.59	3.79	1870, 1883, 1884, 1890, 1896, 1907, 1914, 1917, 1926, 1934, 1935, 1936, 1944, 1945, 1948, 1954, 1955, 1965, 1970, 1971, 1973, 1974, 1975, 1977, 1980, 1981, 1983, 1985, 1987, 1991, 1998, 2000, 2003, 2005, 2012, 2010
RDI-6	19	31	−76.79	87.72	7.31	1883, 1884, 1890, 1917, 1921, 1922, 1934, 1936, 1944, 1945, 1948, 1955, 1971, 1974, 1975, 1981, 1985, 2005, 2015
RDI-12	15	37	−90.49	95.07	7.92	1907, 1922, 1923, 1944, 1945, 1976, 1981, 1992, 1993, 2005, 2018

Table 11. Drought identification using SPI in Lisbon region for the period (1864–2021).

Index	Number of Events	Duration	Severity	Average Inter-Arrival Time (Month)	Average Return Time (Year)	Years
SPI-3	40	53	−121.96	46.28	3.86	1868, 1870, 1883, 1884, 1890, 1907, 1908, 1914, 1917, 1926, 1934, 1935, 1936, 1944, 1945, 1948, 1954, 1955, 1965, 1970, 1971, 1973, 1974, 1975, 1977, 1981, 1983, 1985, 1987, 1991, 1998, 2003, 2005, 2012, 2018
SPI-6	25	34	−82.42	68.33	5.69	1868, 1869, 1883, 1884, 1890, 1907, 1914, 1917, 1921, 1922, 1934, 1936, 1944, 1945, 1948, 1955, 1971, 1974, 1975, 1981, 1985, 2005
SPI-12	10	22	−49.33	130.67	10.88	1907, 1922, 1923, 1945, 1976, 1981, 1992, 1993, 2005

4. Discussion

The current study presented a long-term assessment of meteorological drought at Lisbon using SPI and RDI for 157 years over the period 1864–2021. Different drought indices have been calculated using SPI and RDI for different time scales (e.g., short-, mid-, and long-term). The study focused on the Lisbon area and climate data for 157 years were examined and analyzed and trends for temperature and precipitation were presented and discussed for Lisbon. According to the literature and previous studies listed below, the results of the current study for Lisbon are in line with their findings where climate change predictions show rising temperatures, changed precipitation patterns, and more frequent droughts across the Iberian Peninsula and Mediterranean basin countries, including Portugal. This indicates the necessity of drought monitoring and assessment [1].

The study by Paulo et al., (2012) [5] concluded that drought is one of the most destructive climate-related threats faced by Mediterranean countries, including Portugal. Portugal's vulnerability is heightened by its Mediterranean climate, which is marked by significant seasonal rainfall fluctuations, extended dry summer months, and rising temperature trends. Climate change projections indicate rising temperatures, altered precipitation patterns, and more frequent extreme droughts across the Iberian Peninsula. Several warming trends were observed at Portuguese meteorological stations and identified declining precipitation. These changes may intensify drought severity because higher temperatures increase evapotranspiration demand [5]. Moreover, Trigo et al., 2004 [57] concluded that Portugal represents one of the most drought-prone countries in southern Europe due to its

geographical location within the western Mediterranean climatic transition zone. Portugal exhibits climatic heterogeneity, with humid Atlantic conditions dominating northern regions and semi-arid Mediterranean characteristics. This spatial variability significantly influences drought occurrence, intensity, and impacts [57]. Moreover, climate change is projected to intensify hydroclimatic extremes across the Iberian Peninsula through increased temperatures, reduced precipitation, altered atmospheric circulation patterns, and enhanced evapotranspiration (IPCC, 2023) [1]. The Mediterranean regions, precipitation variability and seasonal water scarcity are dominant climatic characteristics, drought constitutes a recurrent and increasingly severe threat to water security, agricultural productivity, ecosystem functioning, and energy generation. The Mediterranean setting of Portugal increases sensitivity to hydroclimatic shifts. Southern Portugal tends to experience more frequent and intense drought conditions than northern regions due to lower annual precipitation and higher evaporative demand. Consequently, drought monitoring frameworks in Portugal increasingly emphasize regionalized approaches and climate sensitive drought indices. Vicente-Serrano et al., (2010) [58] compared the results of drought indices SPEI and self-calibrated Palmer drought severity index (sc-PDSI) for different time with different climate characteristics in different parts of the world. The results showed that under the global warming conditions, sc-PDSI and SPEI identified an increase in drought severity associated with higher water demand as a result of evapotranspiration in different regions of the world and specifically the Mediterranean regions [58].

Based on the mentioned above, the selected case study area is vulnerable to drought events and monitoring of drought has become a crucial issue in Lisbon and other parts of Portugal. The current study presented the analysis of climate data trends in Lisbon for the period (1864–2021). For precipitation, the results reveal that the years 1944–1945 and 2004–2005 presents periods of low precipitation, whereas 1876–1877 and 2009–2010 are characterized by high precipitation activity. For temperature, an increasing trend is recorded. For the entire 157 years, the smallest and highest values of T_{min} 11.32 °C and 14.3 °C, for T_{max} 18.28 °C and 22.86 °C, for T_{av} 15.06 °C and 18.58°. The linear trend line for the three values of temperature (min, max, av) indicates an increase over time which could give an indication of increasing the drought possibilities in the area in the future which is on line with as results of the previous studies [5,57,58].

Statistical analysis including descriptive and non-parametric tests for the climate data in Lisbon for the period (1864–2021) were performed. The findings of the descriptive statistics indicate that the values of coefficient of variation (CV) are relatively small for all the data used which indicates that the data points are close to the mean (less variability). Moreover, small standard deviation values are close to the mean which indicates less variability. For non-parametric tests (Mann-Kendell test and Sen's slope) the results indicate that small increasing trends in precipitation were observed in the years 1921–1970 which are non-Significant in most of the months and increasing trends were observed in temperature in the years 1921–1970 which are significant in most of the months, especially the summer season. The temperature trends are increasing significantly in the period (1971–2020) which gives an indication of the increasing drought in this period which may continue in the future—this matches with the published results [5,57,58].

Before the analysis of drought, three methods of computing Potential evapotranspiration PET (Blaney-Criddle, Hargreaves and Thornthwaite) were used to indicate the appropriate method for the current case study. The variation in PET by Hargreaves ranged from 24.20 to 180.91 mm/month with mean 81.78 mm/month which gave the lowest variation compared to the other methods which matches with the previous studies that recommended Hargreaves method when it is not possible to use the FAO-Penman Monteith (e.g., Hargreaves and Allen 2003) [55]. Then, the drought risks were analyzed in

Lisbon for the period 1864 to 2021 using two different indices (SPI and RDI). The drought analysis in Lisbon from 1864 to 2021 using RDI and SPI for different time scale presented in Figures 12–14 reveal that the area is exposed to repeated extreme drought events which matches with Paulo et al. (2012) [5], who reported an overall warming trend at several weather stations, along with specific changes in precipitation, declining rainfall in March, and increasing rainfall in October at certain locations in Portugal [5].

The results of the current study match with the previous studies for Lisbon (e.g., Parente et al., 2019) [36] who concluded in his study that Portugal has experienced several severe drought episodes over recent decades, notably during 1980–1983, 1991–1995, 2004–2005, 2011–2012, and 2017–2019. Among these, the 2004–2005 drought has frequently been classified as one of the most extreme in Portuguese climatological records, affecting over 90% of national territory [36]. Also, Pérez and Grazia (2023) [59] conducted climate change research in the Iberian Peninsula by analyzing weather types and temperature. They used an extensive database covering 74 years to determine weather types and their temperature fields in the Iberian Peninsula. They created objective weather-type classifications combined with meteorological variables as a foundation for more detailed regional climate impact studies in Portugal [59]. The results reveal that the temperature increased by 0.5 °C in this period. The longest short-term meteorological droughts were recorded in the years 1965, 1971, 2025, lasting three months. The longest mild-term meteorological drought was obtained in 2005, lasting seven months. The longest long-term meteorological droughts were recorded in 1945 and 2005, with the duration of these droughts varying throughout the years. In 1945, the duration was 5 months with SPI-12 index and 9 months with RDI-12 index, and in 2005, the duration lasted 8 months for SPI-12 and 10 months for the RDI-12.

Although SPI and RDI identify broadly similar sequences of extreme drought events at the Lisbon station, their behavior diverges more clearly at the 6- and 12-month scales, where RDI indicates shorter return times and longer cumulative durations of severe drought. This reflects the fact that SPI responds only to precipitation deficits, whereas RDI incorporates potential evapotranspiration and is therefore sensitive to the combined effect of reduced rainfall and enhanced atmospheric water demand. In Lisbon's Mediterranean climate, most annual rainfall occurs in the cool season while summers are both dry and, according to our trend analysis and previous studies, increasingly warm, particularly in recent decades. When multi-season precipitation deficits coincide with warmer conditions, RDI amplifies drought severity relative to SPI, which helps explain why years such as 1944–1945 and 2004–2005 are highlighted as particularly intense long-term droughts. From a management perspective, this suggests that relying solely on precipitation-based indices like SPI may underestimate the stress on surface water resources and urban supply systems during compound dry-and-warm episodes, whereas RDI provides a more integrative signal that is better aligned with the growing evaporative demand expected under ongoing warming at Lisbon.

Finally, we would like to clarify that the current study has some limitations that we recommend to be addressed in future work. These limitations include applying other softwares and more data that we hope to manage in the future. The current study focuses on temporal variation at one station but we recommend using different stations for spacial distribution in Portugal for future work. Also, we recommend using other drought indices such as SPEI that depend on both P and PET and compare with RDI. In addition, comparing the PET results with benchmarks such as FAO-56 Penman–Monteith is highly recommended for future work. The future climate change scenario that integrates CMIP6 projections and emission scenarios to strengthen long-term climate impact assessments are also strongly recommended for future work. Moreover, we recommend the integration of socioeconomic

and environmental vulnerability indicators in future research for more comprehensive drought risk assessment. Future work could extend this atmospheric drought analysis by incorporating root-zone soil moisture and actual evapotranspiration, which would help link precipitation deficits and evaporative demand more directly to plant water stress and ecosystem functioning. More broadly, this would reflect the growing view of drought as an ecosystem water limitation rather than solely a lack of rainfall, while preserving SPI and RDI as useful reference metrics for atmospheric drought conditions.

5. Conclusions

Continuous climate change could expand the likelihood of drought in Mediterranean coastal climate regions such as Lisbon, Portugal which significantly impacts the entire water resource system. A comprehensive understanding of the temporal patterns of short-term, mid-term as well as long-term meteorological drought is crucial for management with water resources during these episodes. This study presents a long-term assessment of meteorological drought at Lisbon climatological station using SPI and RDI indices based on monthly precipitation and temperature data collected for 157 years in the period (1864–2021). The impact of PET on the identification of drought is studied in addition to the occurrence of drought over short-term scales (SPI-3 and RDI-3), mid-term scales (SPI-6 and RDI-6), and long-term scales (SPI-12 and RDI-12). The study evaluates three methods for calculating PET (Hargreaves, Thornthwaite, and Blaney-Criddle) that are available in the DrinC software which is used for calculating RDI. Hargreaves method is chosen as a practical and comparatively suitable option within the scope of this study due to the absence of data to apply FAO-56 Penman–Monteith for this station, and Hargreaves formulation is retained as a representative empirical PET for subsequent SPI and RDI comparison. Drought analysis was done using RDI and SPI for the period from 1864 to 2021. The results observed significant historical drought events in Lisbon. As a result, terrible drought was recorded in the years 1907, 1922–1923, 1944–1945, 1976, 1981, 1992–1993, 2005 and 2018. The estimated average return times by RDI for (1) short-term meteorological droughts are 3.79 years, (2) mid-term meteorological droughts are 7.31 years, and (3) long-term meteorological droughts are 7.92 years. For SPI, they are 3.86 years, 5.69 years, and 10.88 years, respectively. Drought estimation of average return time could help decision makers to manage water resources and minimize the negative effects on fauna, flora, the environment, and humans in the Lisbon region. Short-term meteorological drought mainly affects soil moisture and thus agricultural activity at the time of its occurrence, in a given area, this phenomenon can be expected every 3.79 (3.86) years. A mid-term meteorological drought affects soil moisture, as well as surface water resources. Long-term meteorological drought affects soil moisture, surface and underground water resources. Finally, the findings indicate that the drought index can be computed using any of the specified PET methods, with a preference for the Hargreaves methods in the specified region. Furthermore, the RDI showed better results compared to the SPI, underscoring the significance of incorporating PET in drought evaluations. However, RDI is a very useful tool to assess the severity of drought, and it is important to indicate that RDI_{st} is a resilient drought index, unaffected by the method used for PET calculation. The characteristics of drought are analyzed in relation to long-term warming trends and recorded rainfall variability in Lisbon. The results offer a single-station reference for historical drought patterns, which can aid local water resource management and serve as a foundation for future studies involving multiple stations and climate projections in Portugal.

Author Contributions: Conceptualization, H.F.A.-E., T.S. and M.Z.; methodology, T.S. and H.F.A.-E.; software, T.S., H.F.A.-E. and M.Z.; validation, M.M.P. and L.A.E. and H.F.A.-E.; formal analysis, M.Z., T.S., J.B. and K.B.; investigation, M.Z.; resources, M.Z. and M.M.P.; data curation, T.S. and L.A.E.; writing—original draft preparation, T.S. and H.F.A.-E.; writing—review and editing, H.F.A.-E., M.M.P., L.A.E., J.B. and K.B.; visualization, M.Z.; supervision, M.Z. and M.M.P.; project administration, M.Z., J.B. and K.B.; funding acquisition, J.B. All authors have read and agreed to the published version of the manuscript.

Funding: The research was supported by (PRO-CLIMATE, 101137967, <https://pro-climate.eu>, accessed on 1 January 2026) and Erasmus+/KA220-HED—Cooperation partnerships in higher education “CERMA: Center of Excellence for Environmental Risk Management”, Project N°: 2024-1-SK01-KA220-HED-000243758.

Data Availability Statement: The core meteorological data and the derived drought indices used in this study are publicly available in the figshare repository at Espinosa, Luis Angel; Portela, Maria Manuela (2026) [38]. Long-term Meteorological Time Series and Drought Indices (SPI, SPEI) for the Lisbon Geophysical Station Lisboa/Geofísico (535) (1864–2021). figshare. Dataset. <https://doi.org/10.6084/m9.figshare.32813015>. The raw meteorological data are also accessible via the Instituto Português do Mar e da Atmosfera (IPMA) website (<https://www.ipma.pt/en/index.html>, accessed on 15 January 2026).

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

Abbreviations

The following abbreviations are used in this manuscript:

PET	Potential Evapotranspiration
RDI	Reconnaissance Drought Index
eRDI	Effective Reconnaissance Drought Index
RDIst	Standardized Reconnaissance Drought Index
SPI	Standardized Precipitation Index
PDSI	Palmer Drought Severity Index
scPDSI	Self-Calibrating Palmer Drought Severity Index
SPEI	Standardized Precipitation Evapotranspiration Index
DrinC	Drought Indices Calculator
Tav	Average temperature
Tmax	Maximum temperature
Tmin	Minimum temperature
NAO	North Atlantic Oscillation
CDPMS	Copula-Based Continuous Drought Probability Monitoring System

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