

Article

Evaluating Droughts and Trends in Data-Scarce Regions: A Case Study of Palestine Using ERA5, Standardized Precipitation Index, Bias Correction, Classical and Innovative Trend Approaches

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Abstract

The increasing droughts and climate change effects and their frequencies worldwide are a critical threat, especially to regions facing water scarcity and wars. Therefore, comprehensive drought evaluation and trend analysis are crucial for water resources management, climate change, and drought mitigation plans. Classical drought evaluation methods predominantly rely on in situ observations, often limited or unavailable in many regions, particularly in developing countries such as Palestine. This study investigates the temporal and spatial characteristics and trends of drought across Palestine between 1940 and 2025. To the best of our knowledge, for the first time in the literature, bias-corrected ERA5 precipitation data are employed alongside ground-based observations to assess drought using the Standardized Precipitation Index (SPI) at multiple timescales (1-, 6-, and 12-month). Trend detection was performed through conventional statistical approaches, including the Mann–Kendall test, Spearman’s Rho, and Sen’s slope (SS), as well as the Frequency-Innovative Trend Analysis (F-ITA) method. Furthermore, the performance of the original and bias-corrected ERA5 precipitation datasets was evaluated against observational data using statistical metrics. The main findings indicated that the bias correction significantly improves the accuracy of the ERA5 precipitation data. Also, droughts in SPI-1 and SPI-6 ranged from 4 to 5 months, the minimum at which a drought can be classified. In addition, the average drought duration at a 12-month timescale ranged between 14 and 16 months. At short (SPI-1) and medium (SPI-6) timescales, no significant trends were found, whereas at the long timescale (SPI-12) all stations showed a significant decreasing SPI trend, such as -5.611 in Jenin, reflecting intensifying drought conditions. For F-ITA, the frequencies of extreme drought classification increased from 0.4% in the first period to 2.18% in the second period. The findings of this research have important implications for drought management, water policy planning, and climate adaptation in Palestine.

Keywords: drought; climate change; bias correction; reanalysis; linear scaling; standardized precipitation index (SPI); Palestine



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1. Introduction

Drought is among the most destructive natural disasters worldwide [1,2]. It affects all aspects of life, including the industrial and agricultural sectors [2,3]. Numerous studies have demonstrated the economic implications of drought, highlighting its detrimental

effects on food insecurity, wildfires, water resource management, and a decline in hydropower [4,5]. Drought is divided into four primary types [4,6]: meteorological, agricultural, hydrological, and socioeconomic droughts. Meteorological drought pertains to reductions in precipitation that fall below normal or standard values for a specific period. According to the World Meteorological Organization (WMO) [7], the minimum period for conducting drought analysis is 20–30 years. Agricultural drought refers to soil moisture deficiency that affects plant production, while hydrological drought is related to decreased surface and groundwater resources [8]. Given the negative impacts of drought, precise and efficient drought evaluation and assessment are crucial for sustainable water resource management and mitigating drought's negative consequences [9,10].

Various standardized drought indices are employed to evaluate and monitor drought conditions, each focusing on specific hydrometeorological variables related to a particular type of drought [11,12]. For instance, the Standardized Precipitation Evapotranspiration Index (SPEI) [13] and the Standardized Precipitation Index (SPI) [14]. SPI is based on precipitation data and is used to assess meteorological drought. A key benefit of standardization is that it transforms the hydrometeorological variable datasets into a dimensionless drought index form, allowing for comparisons between different time series, locations, and indices [15]. SPI was used in various studies in the literature, such as Hussain et al. [16], Hasan et al. [17], Abu Arra and Şişman [18], Achite et al. [19], Abu Arra et al. [20], Mehta and Yadav [21,22], Kesgin et al. [23], and Hınıs and Geyikli [24].

Drought analysis relies heavily on accurate precipitation data, a key factor in assessing water scarcity and drought severity [25]. Traditionally, drought conditions have been monitored using ground-based precipitation measurements from rain gauges and weather stations, which provide detailed local data [26,27]. However, alternative data sources are critical in regions with limited station coverage or difficult access. Satellite-based products, like NASA's IMERG, offer global precipitation estimates with frequent updates, aiding in real-time drought monitoring. Reanalysis datasets, including ERA5 and ERA5-Land, are widely used to provide long-term precipitation records by combining observational data with climate model outputs. While ERA5 represents the original reanalysis product, ERA5-Land is derived from ERA5 through an interpolation technique designed to offer higher spatial resolution, particularly over land surfaces. These alternative data sources are indispensable for assessing drought conditions in data-scarce areas and improving drought management and mitigation strategies [28]. However, these data sources have been used in the literature without validation regarding drought evaluation, such as Li et al. [29] and Serban and Maftai [30].

Bias correction methods such as Quantile Mapping (QM) and Linear Scaling (LS) are commonly applied to validate and improve the accuracy of satellite-derived and reanalysis precipitation data [31,32]. These methods adjust the model and satellite data to better match observed in situ measurements, enhancing their reliability for hydrological applications [33,34]. Based on the literature, bias correction is widely used in different applications in hydrology. For example, it is used in hydrological modeling in precipitation and temperature data to enhance streamflow and runoff predictions [35–37], in flood prediction [38,39], in climate change studies [40,41], in water resources management [42,43], and in drought [44,45]. However, the effects of bias correction on drought evaluation still need more explanation and validation. Using bias correction in drought studies can be considered a research gap that needs in-depth research.

In addition, drought trend analyses are accepted as an important essential tool that researchers have included in their studies in recent years for detailed regional assessments in many subjects, such as understanding the effects of climate change on droughts [46], ensuring the efficient use of water resources to mitigate drought [47], developing drought

combat policies and measures [48], developing drought early warning systems and ensuring their efficient use [49,50], defining long-term changes, planning the agricultural sector due to drought and managing food security issues [51]. For this purpose, it is understood that certain analysis methods have come to the fore in the literature. Along with these innovative methods, the classical and traditional methods are very important methods for trend analyses, including Mann–Kendall (MK) [52,53], Sen’s Slope (SS) [54], and Spearman’s rank correlation coefficient [55]. Among them is the Innovative Trend Analysis (ITA) method, which was developed by Şen [56] as a valuable tool for detecting trends in indifferent hydrometeorological data, as well as in the drought indices, such as the SPI, which is widely used for assessing drought conditions [57]. Also, ITA methodology can be used at different lengths [58]. Abu Arra et al. [59,60] improved the ITA by adding the frequency and drought classification to enhance its applicability to capture the drought variations, resulting in Frequency ITA (F-ITA). Applying F-ITA to the drought SPI makes it possible to identify precise trends and shifts in drought patterns over time, providing a more detailed understanding of the temporal behavior of droughts across different time scales [60].

Given the importance of bias correction and its wide application in hydrology and water resources management, along with the challenge of data scarcity in developing countries, this research aims to (1) evaluate the performance of ERA5 monthly precipitation data using different statistical metrics, as well as evaluate the performance of ERA5 monthly precipitation data in terms of drought evaluation in regions facing data availability problems, such as Palestine, (2) evaluate the drought conditions and characteristics using the well-known SPI at different time scales (short-1, medium-6, and long-12 months), (3) apply the classical trend analysis methods (MK, Spearman, and SS) and newly proposed F-ITA for the SPI for Palestine with alternative data sources, and compare between them and check their agreement, (4) evaluate the performance of linear scaling (LS) bias correction method in drought analysis using different statistical metrics, and (5) compare between ERA5 and bias-corrected ERA5 data regarding the observational precipitation data. This research establishes a novel framework for drought research by concurrently incorporating ERA5 data, drought analysis, bias correction, both classical and innovative trend evaluation, and the assessment of drought characteristics. The selection of Palestine as a representative application is made due to the importance of its location, its water resources management plans, and considering it as a developing country facing many challenges, including data scarcity issues. Five stations in Palestine are used, with monthly precipitation data between 2005 and 2021, and monthly precipitation data from ERA5 (grid points) between 1940 and 2024. The number of drought studies conducted in Palestine over the past two decades remains very limited. This research will contribute to the academic field and provide authorities with new insights into how to face the effects of climate change and drought.

2. Materials and Methods

2.1. Study Area

Palestine, located in the eastern Mediterranean, experiences a diverse climate influenced by its geographical location and topography. The West Bank has diverse topography, with surface heights ranging from 1022 m above mean sea level at Tall Asur in Al-Khalil (Hebron) in the south to 375 m below mean sea level near Jericho, adjacent to the Dead Sea [61]. The region has a Mediterranean climate, characterized by hot, dry summers and mild, wet winters, with significant variation between coastal, mountainous, and desert areas. Typically, the rainy season lasts from November to March. The precipitation changes from around 600–700 mm annually in the more mountainous northern and central areas to

less than 200 mm in the arid southern regions. Precipitation is concentrated over a specific duration, with over 60% of the yearly precipitation often falling during two months [62].

2.2. Data Collection

2.2.1. In Situ Meteorological Stations

The precipitation data used in this research were collected from the Palestine Meteorological Department for the available monthly precipitation data, which is only available for five stations (Jenin, Nablus, Al-Khalil, Jericho, and Ramallah) between 2005 and 2021 (Figure 1). These are the only meteorological stations with continuous precipitation data, and due to several circumstances, there are no records after 2021, indicating the need for using different alternatives, such as satellite and reanalysis data. Table 1 summarizes the climatic characteristics of annual precipitation at five meteorological stations in the West Bank, Palestine. The average annual precipitation ranges between 135.93 mm in Jericho, the area with the least precipitation, and 638.71 mm in Nablus, the area with the highest precipitation. The data also showed variations in the annual precipitation distribution, with the highest standard deviation values in Nablus (79.04 mm) and Ramallah (76.37 mm), indicating significant interannual variation in precipitation. The lowest value was in Jericho (16.97 mm), reflecting relative stability in precipitation amounts.

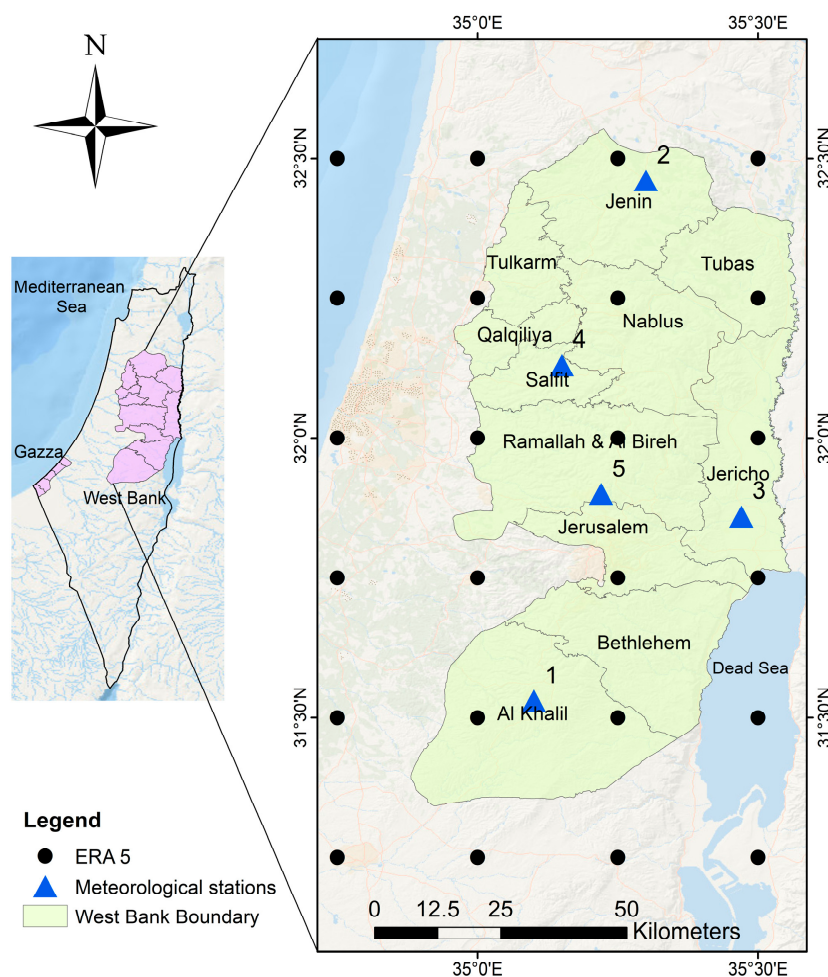


Figure 1. West Bank, Palestine location map with meteorological stations and ERA5 data.

Table 1. Climatic characteristics of the annual total precipitation of the used stations over the West Bank.

#	Station	Lat. (N)	Long. (E)	Elevation (m)	Annual Precipitation (mm)	Standard Deviation (mm)
1	Al-Khalil	31.53	35.1	891	492.64	64.03
2	Jenin	32.46	35.3	145	455.85	56.64
3	Jericho	31.86	35.47	−375	135.93	16.97
4	Nablus	32.13	35.15	73	638.71	79.04
5	Ramallah	31.9	35.22	809	609.34	76.37

2.2.2. ERA5 Data

ERA5, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), is a global atmospheric reanalysis dataset that provides monthly estimates of various climate and weather variables with high spatial and temporal resolution. This research uses ERA5 precipitation data from 1940 to 2025 to analyze long-term meteorological drought and trends. The nearest grid point to each meteorological station was selected to ensure accurate representation, resulting in five selected grid points across the West Bank. Figure 1 above illustrates the meteorological stations and ERA5 grid points over the West Bank, Palestine, highlighting the spatial distribution of the selected data sources.

2.3. Methodology

2.3.1. Standardized Precipitation Index (SPI)

The SPI, developed by McKee et al. [14], assesses drought across various timescales, such as 1-month, 6-month, and 12-month periods, using only monthly precipitation data. The monthly precipitation records are initially fitted to an appropriate probability density function (PDF). Selecting a proper PDF involves evaluating the goodness-of-fit tests, such as the Chi-Square and Kolmogorov–Smirnov tests, on the original precipitation records [57,63]. Once the probabilities are derived from the monthly precipitation data, they are standardized into a standard normal PDF with a mean of zero and a standard deviation of one.

2.3.2. Drought Characteristics

The preliminary stage in drought assessment is calculating the drought index. Consequently, three principal characteristics [4,12,14], duration (D), severity (S), and intensity (I), are calculated from this index. The characteristics of drought are determined using the drought index and are based on the definition of a drought event. McKee et al. [14] characterized the initiation of drought event occurrences using a threshold of -1 rather than 0 . This research primarily focuses on D, which, according to SPI theory, is defined as the total number of months during which the drought index remains below -1 until it reverts to a positive value. The second component represents the cumulative sum of the drought index over the duration. Furthermore, dividing the severity by the duration of the drought yields the intensity of the drought.

2.3.3. Inverse Distance Weighting (IDW) Interpolation Technique

IDW is a prominent interpolation method employed across various fields, including drought spatial assessment, to predict drought indices and attributes at unsampled locations utilizing data from observation stations or grid points as inputs. Philip and Watson [64] assert that points nearer to the target location significantly influence the assessed value more than those at a greater distance. The method's simplicity contributes to its

popularity and extensive application in creating drought maps, facilitating thorough study and display of geographical drought conditions. According to Abu Arra et al. [65], the IDW approach is the most effective interpolation technique for drought study. The IDW method was used as the interpolation technique for this study using the bias-corrected ERA5 grid points.

2.3.4. Bias Correction_Linear Scaling

Linear Scaling is a simpler method that adjusts the Reanalysis data's mean to match the observed data's mean. This method involves calculating a scaling factor based on the ratio of the mean observed precipitation to the mean ERA5 precipitation data. The ERA5 data is then multiplied by this scaling factor to correct for biases in the overall precipitation amounts [66]. Equation (1) shows the formula of the LS factor.

$$\text{LS factor} = \frac{\text{Mean observed precipitation}}{\text{Mean ERA 5 precipitation}} \quad (1)$$

2.3.5. Statistical Metrics

This research evaluates the effectiveness of the ERA5 monthly precipitation data by applying the LS bias correction method. The evaluation and comparison process includes different statistical metrics [67] such as Pearson's Correlation Coefficient (CC), the coefficient of determination (R^2), Root Mean Squared Error (RMSE), Mean Bias Error (MBE), and Percent Bias (PB). These metrics provide a comprehensive assessment of the corrected data's performance, highlighting the reduction in biases and improvements in data accuracy. By employing these metrics, the study ensures a robust analysis of the bias correction methods, facilitating a detailed comparison and validation against observed in situ data. Table 2 summarizes the statistical metrics used with their equations and ideal values.

Table 2. Statistical Metrics with their equations [67].

Statistic Metric	Equation	Value Range	Ideal Value
Correlation Coefficient (CC)	$CC = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$	(−1)–(1)	1
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - X_i)^2}$	(0)–(∞)	0
Mean Bias Error (MBE)	$MBE = \frac{1}{n} \sum_{i=1}^n (Y_i - X_i)$	(−∞)–(∞)	0
Percent Bias (PB)	$PB = \frac{\sum_{i=1}^n (Y_i - X_i)}{\sum_{i=1}^n X_i} \times (100)$	(−∞)–(∞)	0
Coefficient of determination (R^2)	$R^2 = \left[\frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \right]^2$	(0)–(1)	1

Notes: X = Observational monthly precipitation data, Y = ERA5 monthly precipitation data or Bias-corrected ERA 5 monthly precipitation data, n = number of months/samples, $\bar{X}$ = mean Observational monthly precipitation data, $\bar{Y}$ = mean ERA5 monthly precipitation data or Bias-corrected ERA5 monthly precipitation data.

2.3.6. Mann–Kendall (MK) Test

The MK test is a non-parametric statistical method employed to identify trends in time series data within different sectors [59]. Mann [52] initially proposed the test in 1945, and Kendall [53] revised it in 1975. The MK test statistic S is derived from the ranks of the data points. A strong positive S indicates an upward tendency, whereas a substantial negative S signifies a downward trend. It is computed in Equation (2) as [52,53]:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (2)$$

where n is the number of observations, x_i and x_j represent the i th and j th observation data values ($j > i$). The sgn function gives a value of $+1$ when $(x_j - x_i) > 0$, 0 when $(x_j - x_i) = 0$, and -1 when $(x_j - x_i) < 0$. S is obtained by adding the results of the sgn function for all possible (x_i, x_j) data pairs.

The variance of the test statistic S is calculated to assess its statistical significance. When the number of observations is $n \geq 10$, it is computed using Equation (3) [53]:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5)}{18} \quad (3)$$

where n is the number of data points, m is the number of data points with the same value called tied groups, and t_i is the number of groups of size t_i .

The MK Z statistic assesses the significance of the trend observed in a time series of data. The Z statistic is computed using Equation (4) as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}; & S > 0 \\ 0; & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}; & S < 0 \end{cases} \quad (4)$$

2.3.7. Spearman's Rank Correlation Coefficient

Spearman's rank correlation coefficient (ρ) is a widely used non-parametric statistic for detecting monotonic trends in time series data [55]. Unlike parametric correlation measures, it does not assume a normal distribution of the variables, making it particularly suitable for hydrological and climatological datasets that often display skewness and outliers. The method evaluates the relationship between the ranks of two variables, commonly time and the variable of interest, to determine whether a monotonic increasing or decreasing trend exists. The coefficient is computed as in Equation (5) [54]:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (5)$$

where d_i is the difference between the ranks of paired observations and n is the number of data points. The value of ρ ranges from -1 to $+1$, with positive values indicating an increasing monotonic trend, negative values indicating a decreasing monotonic trend, and values near zero reflecting the absence of a monotonic relationship. In trend studies, Spearman's Rho serves as a robust complementary test alongside other methods such as the MK test and SS estimator, enhancing the reliability of statistical inferences.

2.3.8. Sen's Slope Estimator (SS)

SS is a non-parametric method for calculating the slopes of a linear trend [54]. The method does not rely on distributional assumptions. Thus, it is very useful when working with outliers and non-normal data. It was introduced independently by Theil [68] and Sen [54]. For a sample of n pairs, the slope is calculated in Equation (6) as:

$$SS_i = \frac{x_j - x_i}{j - i}, \text{ for all } i < j \quad (6)$$

where x_j and x_i are the data values, the slope is calculated for each data pair ($i = 1, 2, \dots, n$) when $j > i$.

The SS_i values are sorted from the smallest to the largest values, and the median of the values is accepted as SS. The median is calculated in Equation (7) as [54]:

$$SS_{med} = \begin{cases} SS_{[(n+1)/2]}, \\ (SS_{[n/2]} + SS_{[(n+2)/2]})/2 \end{cases} \quad (7)$$

If n is odd, the first part of the equation is used. If there is an even number of n pairs, the mean of the two midmost slopes is calculated as described in the second part of Equation (5).

2.3.9. Frequency—Innovative Trend Analysis (F-ITA)

For decades, trend detection in hydrometeorological data has been a prominent focus in the literature. The Innovative Trend Analysis (ITA) approach, which has recently gained considerable popularity [56], offers notable advantages by clearly visualizing monotonic and nonmonotonic trends. Furthermore, the ITA method does not require any underlying assumptions and can identify five distinct trend types, as illustrated in Figure 2a. Also, Abu Arra et al. [59,60] improved the ITA method to cover the drought classification and frequencies, resulting in F-ITA (Figure 2b).

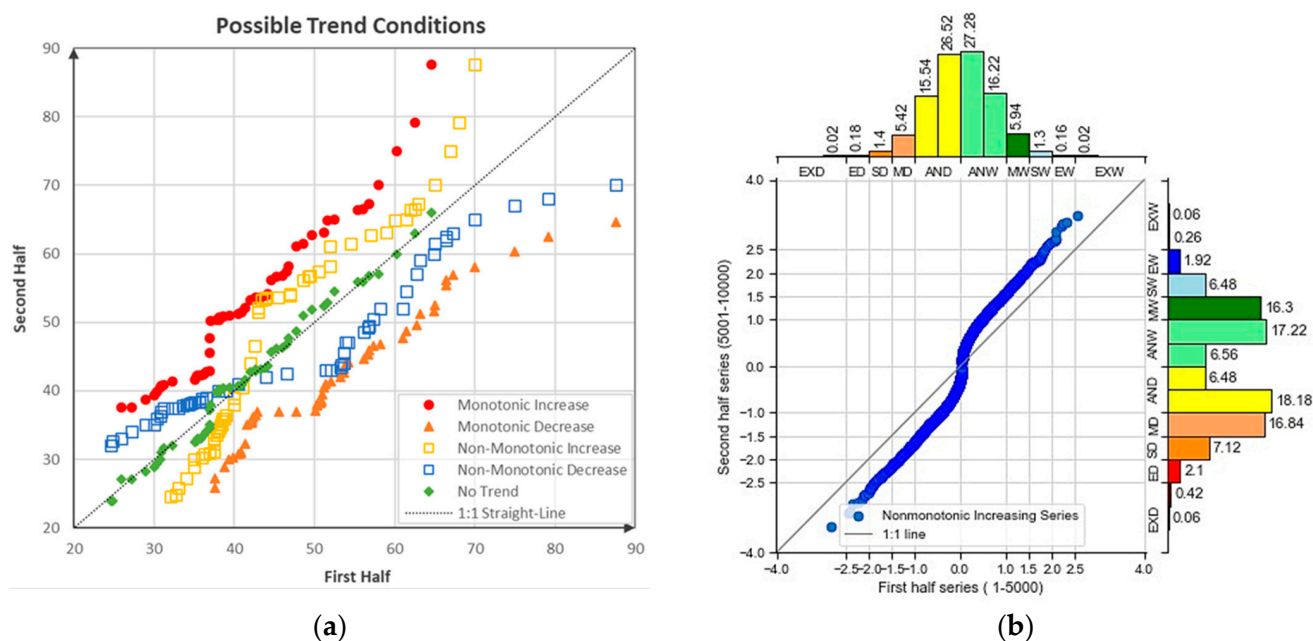


Figure 2. Trend conditions according to: (a) ITA method [69] and (b) F-ITA method [59].

The ITA method involves splitting the time series data into two equal segments: the first half representing the “earlier” period and the second half representing the “later” period. The data from these segments are plotted against each other on a scatter plot. The distribution and alignment of the points on this plot reveal the presence and direction of trends. For example, an increasing trend is indicated when points are positioned above the 1:1 line, while a decreasing trend is suggested when points fall below the 1:1 line. In drought (wet) trend analysis, an increasing trend is shown when points fall below (above) the 1:1 line, and a decreasing trend is indicated when points are above (below) the 1:1 line. Table 3 summarizes the drought classification used in this research.

Table 3. Drought classifications based on McKee et al. [14] and Abu Arra et al. [59].

Drought Index_DI	Classification	Frequency (%)
$2.50 \leq DI$	Exceptional wet (EXW)	0.62%
$2.00 \leq DI < 2.50$	Extreme wet (EW)	1.69%
$1.50 \leq DI < 2.00$	Severe wet (SW)	4.42%
$1.00 \leq DI < 1.50$	Moderate wet (MW)	9.22%
$0.00 \leq DI < 1.00$	Abnormally wet (ANW)	34.05%
$-1.00 \leq DI < 0.00$	Abnormally dry (AND)	34.05%
$-1.50 \leq DI < -1.00$	Moderate drought (MD)	9.22%
$-2.00 \leq DI < -1.50$	Severe drought (SD)	4.42%
$-2.50 \leq DI < -2.00$	Extreme drought (ED)	1.69%
$-2.50 > DI$	Exceptional drought (EXD)	0.62%

3. Results

3.1. Results of Statistical Metrics

Before conducting the drought analysis, the performance of ERA5 precipitation data and the data corrected using bias correction methods (LS) were analyzed against observed monthly precipitation data between 2005 and 2021 for five stations: Al-Khalil, Jenin, Jericho, Nablus, and Ramallah. Several statistical parameters, including the CC, R^2 , RMSE, MBE, and PB (Table 2), were used to evaluate the performance of ERA5 data before and after bias correction. The scatter plots comparing gauge data, ERA5, and bias-corrected ERA5 for the five stations used are presented in Figure S1 of the Supplementary Materials. The scatterplots illustrate that ERA5 generally underestimates monthly precipitation compared to gauge observations across the stations. This underestimation is consistent with the MBE, which shows negative values for all stations except Jericho (Table 4). These findings highlight the systematic bias in ERA5 data prior to bias correction.

Table 4. Results of the statistical metrics for ERA 5, bias-corrected ERA 5, and observation of monthly precipitation data.

	CC	R^2	RMSE (mm)	MBE (mm)	PB
Al-Khalil					
Obs. vs. ERA5	0.87	0.76	57.41	−27.66	−67.4%
Obs. vs. Biassed ERA5	0.87	0.76	32.05	0.0	0.0%
Jenin					
Obs. vs. ERA5	0.91	0.83	29.57	−7.69	−20.2%
Obs. vs. Biassed ERA5	0.91	0.83	24.68	0.0	0.0%
Jericho					
Obs. vs. ERA5	0.86	0.74	9.72	2.78	24.5%
Obs. vs. Biassed ERA5	0.86	0.74	8.73	0.0	0.0%
Nablus					
Obs. vs. ERA5	0.91	0.82	50.84	−19.83	−37.2%
Obs. vs. Biassed ERA5	0.91	0.82	34.70	0.0	0.0%
Ramallah					
Obs. vs. ERA5	0.90	0.81	50.62	−19.68	−38.8%
Obs. vs. Biassed ERA5	0.90	0.81	34.57	0.0	0.0%

At Al-Khalil Station, the original ERA5 data achieved a CC of 0.87 and a R^2 of 0.76, indicating a strong correlation between the ERA5 data and the observed data. However, there was a significant error in the precipitation estimate, with an RMSE of 57.41 mm, a significant negative bias in the MBE of -27.66 mm, and a PB of -67.4% , indicating an underestimation of the precipitation compared to the observed data (Table 4). After applying the bias correction, the CC and R^2 values remained unchanged. Still, a significant improvement was observed in the RMSE, which decreased to 32.05 mm, with the bias completely removed, as the MBE and PB values equaled 0.0. The original ERA5 data for Jenin Station yielded good results, with a CC of 0.91 and an R^2 of 0.83, indicating a relatively high accuracy in estimating the overall precipitation. However, the RMSE was relatively high at 29.57 mm, and the MBE value indicated a negative bias of -7.69 mm, with a PB of -20.2% (Table 4). After applying the LS bias correction, the RMSE improved to 24.68 mm, completely removing the bias. Both MBE and PB were now equal to 0.0 (Table 4), demonstrating that the correction significantly improved the accuracy of the estimates.

The Jericho station (with the least precipitation over the West Bank, Palestine) showed a strong correlation between ERA5 data and observed data, with a CC of 0.86 and an R^2 of 0.74. However, there was a clear positive bias in the estimated precipitation, with the MBE value reaching approximately 2.78 mm, with a positive bias of 24.5%. After applying bias correction, the RMSE improved slightly to 8.73 mm, eliminating the bias, with both the MBE and PB values equal to 0.0 (Table 4). All stations' bias metrics were negative, except for Jericho station, where the ERA5 data showed an overestimation. The ERA5 data for the Nablus station showed a high correlation with observed data, with a CC of 0.91 and an R^2 of 0.82. Despite the strong correlation, there was a significant error in the precipitation estimate, with the RMSE reaching 50.84 mm, a clear negative bias of -19.83 mm, and a bias of -37.2% . After bias correction, the CC and R^2 values remained stable, but the RMSE decreased significantly to 34.70 mm (Table 4). The bias was removed, with the MBE and PB values now equal to 0.0.

For Ramallah Station, ERA5 data also showed a good correlation with observed data, with a CC value of 0.90 and an R^2 of 0.81. However, the RMSE was high at 50.62 mm, indicating a significant error in the precipitation estimation. Furthermore, the estimation had a negative bias, with the MBE value being approximately -19.68 mm, with a bias ratio of -38.8% . After bias correction, the RMSE decreased to 34.57 mm, eliminating the bias (Table 4).

3.2. Temporal Drought Evaluation

Figure 3a,b show the temporal evaluation of SPI-1 and SPI-6 at Al-Khalil station, which are used for meteorological and agricultural drought evaluation. Dry periods were more severe than wet periods, indicating that SPI-6 values exceeded -2 at several points during the study period, reflecting severe and frequent droughts. In contrast, SPI-6 exceeded 2 at only one or two points, indicating that precipitation excesses were less severe and frequent than droughts. Furthermore, droughts in SPI-1 and SPI-6 ranged from 4 to 5 months, the minimum at which a drought can be classified, indicating that the durations for SPI up to 6-month timescales are about 4–5 months. The maximum SPI-6 dry value was -3 in 1973. For SPI-12, Figure 3c shows the temporal evaluation, representing drought on a longer timescale—hydrological drought. Droughts have become longer and more persistent than SPI-6, with the average droughts increasing to approximately 15 months, reflecting the effect of accumulated precipitation deficits over time. This difference demonstrates that prolonged dry events are more pronounced as the timescale increases, showing the cumulative effect of long-term precipitation deficits. The longest

drought event was between 1976 and 1979, spanning 46 months, and it indicated that there was a critical issue regarding hydrological drought.

Figure 3d,e reflect SPI-1 and SPI-6 values, while Figure 3f shows SPI-12 values for the Jenin station. Figure 3g–i show SPI-1, SPI-6, and SPI-12 for the Jericho station. SPI-6 represents agricultural drought, where precipitation deficits over six months affect short-cycle crops and vegetation. At the same time, SPI-12 reflects hydrological drought, which relates to long-term water reserves, such as groundwater levels and runoff from rivers and dams. The SPI-6 graphs (Figure 3e,h) show rapid fluctuations and variable values from 1940 to 2025, with dry periods in red bars and wet values in blue bars. In some years, the negative SPI-6 values reached less than -2.5 , such as in 1989 and 2022, reflecting severe droughts that significantly impacted agricultural production.

In contrast, positive values show some wet periods but did not exceed $+2.0$ in most cases, indicating that the wet periods were not as severe as the dry periods. It is also noteworthy that the dry periods occurred at relatively short intervals, indicating that agricultural droughts have been common and fluctuating over the past decades. The SPI-12 graphs (Figure 3f,i) reflect the effects of drought on larger water resources such as aquifers and rivers, where the longer droughts are more pronounced and persistent compared to SPI-6. For example, Figure 3i shows that the drought period from 1998 to 2001 reached values below -2.5 , indicating a severe water crisis in those years. The period from 1999 to 2002 also witnessed prolonged drought, with negative values remaining below -1.0 for over three years, indicating declining surface and groundwater flows.

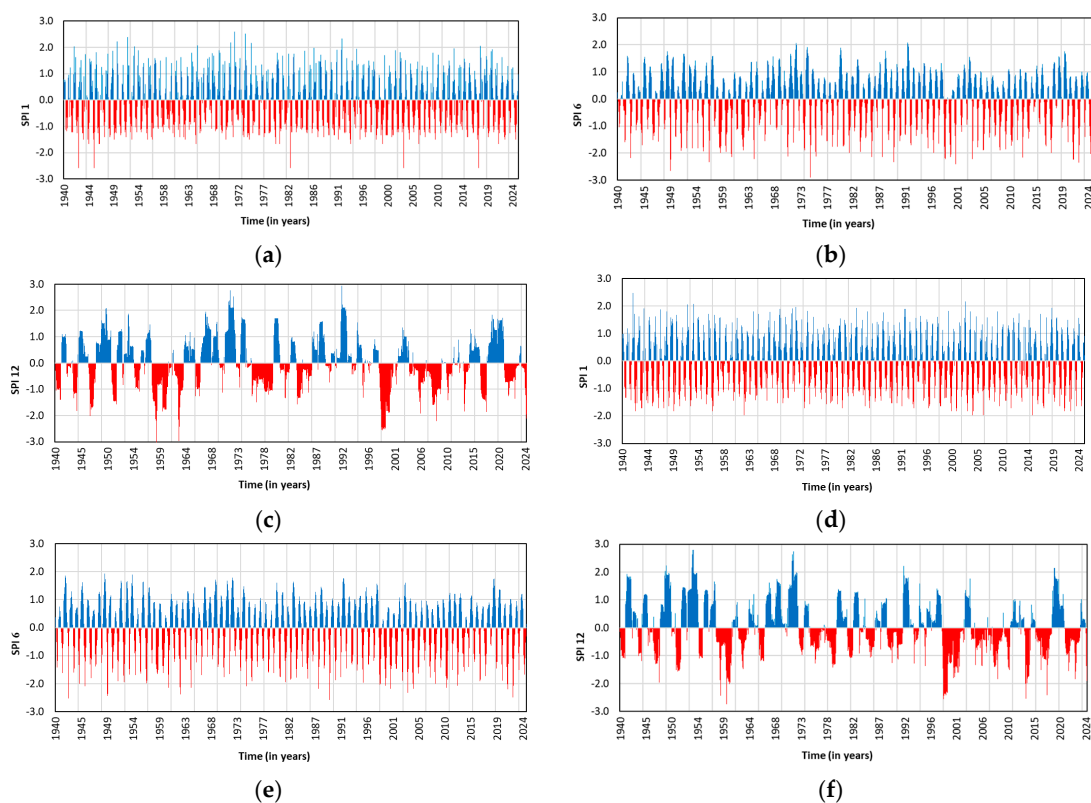


Figure 3. Cont.

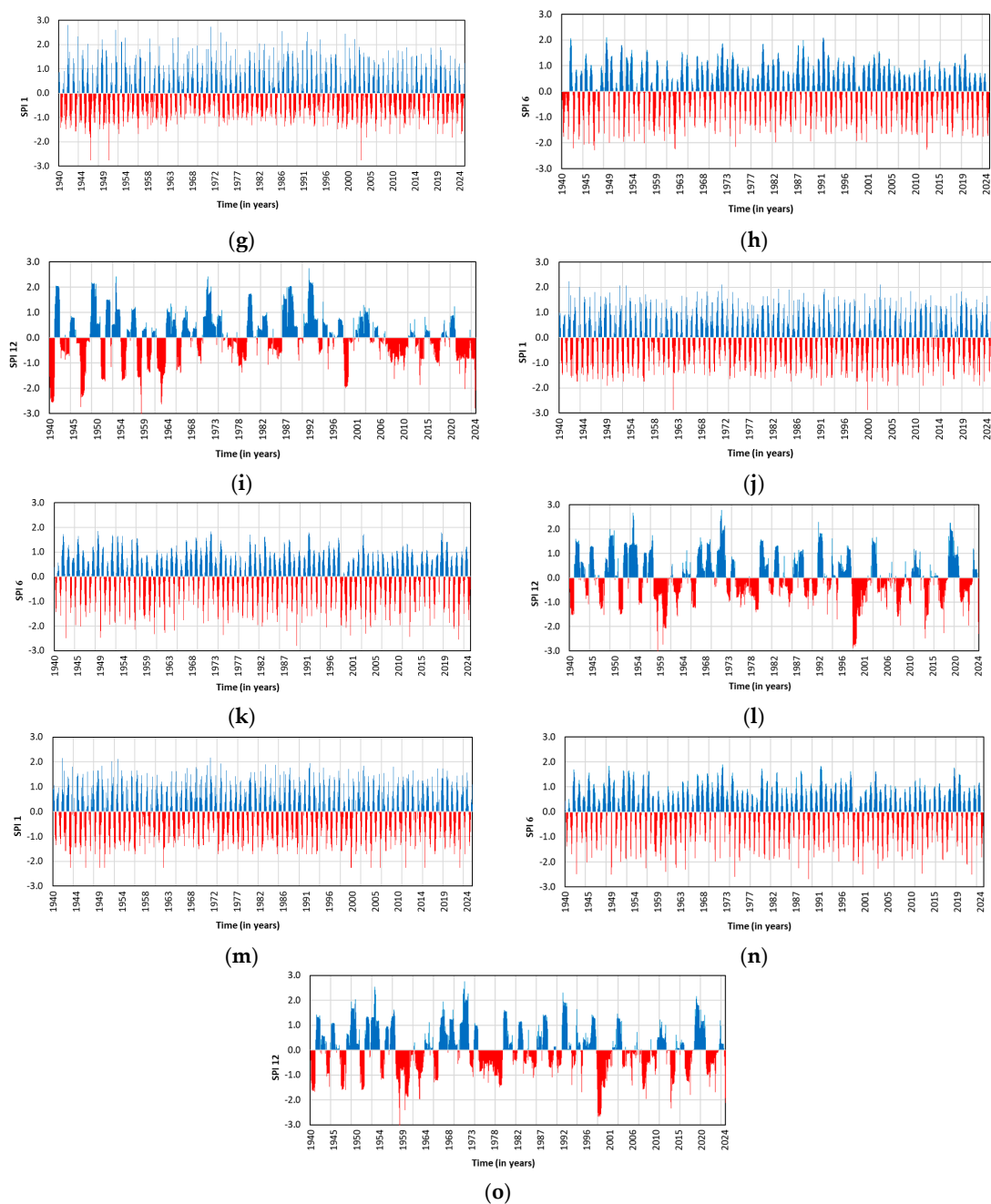


Figure 3. Temporal drought evaluation using SPI at West Bank: (a) SPI-1 at Al-Khalil, (b) SPI-6 at Al-Khalil, (c) SPI-12 at Al-Khalil, (d) SPI-1 at Jenin, (e) SPI-6 at Jenin, (f) SPI-12 at Jenin, (g) SPI-1 at Jericho, (h) SPI-6 at Jericho, (i) SPI-12 at Jericho, (j) SPI-1 at Nablus, (k) SPI-6 at Nablus, (l) SPI-12 at Nablus, (m) SPI-1 at Ramallah, (n) SPI-6 at Ramallah, and (o) SPI-12 at Ramallah.

Figure 3j,k,m,n show SPI-1 and SPI-6 for Nablus and Ramallah stations, respectively, which show rapid oscillations between dry and wet periods, making it a suitable indicator for assessing short-term agricultural drought. Severe droughts are frequent, reaching an average of less than -2.5 , while wet periods are short and unsustainable. In contrast, Figure 3l,o show SPI-12, reflecting long-term water availability changes. Dry periods lasting several years, such as 1998–2002, indicate serious water crises, while wet periods appear to be more common in the middle of the last century than in recent decades, reflecting the increasing frequency of droughts and the impacts of climate change.

Overall, SPI-6 shows rapid impacts on agricultural yields. At the same time, SPI-12 reflects long-term climate trends, indicating the increasing frequency of droughts in recent decades and their potential impact on water and agricultural resources.

3.3. Spatial Evaluation of Drought Characteristics

Figure 4 shows the drought duration and intensity across the West Bank governorates using the SPI for short, medium, and long durations. The three maps in Figure 4a–c show a detailed analysis of the distribution of drought duration. These analyses demonstrate the extent to which regions are affected by drought in the short, medium, and long terms, helping to understand the different impacts on natural resources and economic activities, particularly agriculture and water supplies.

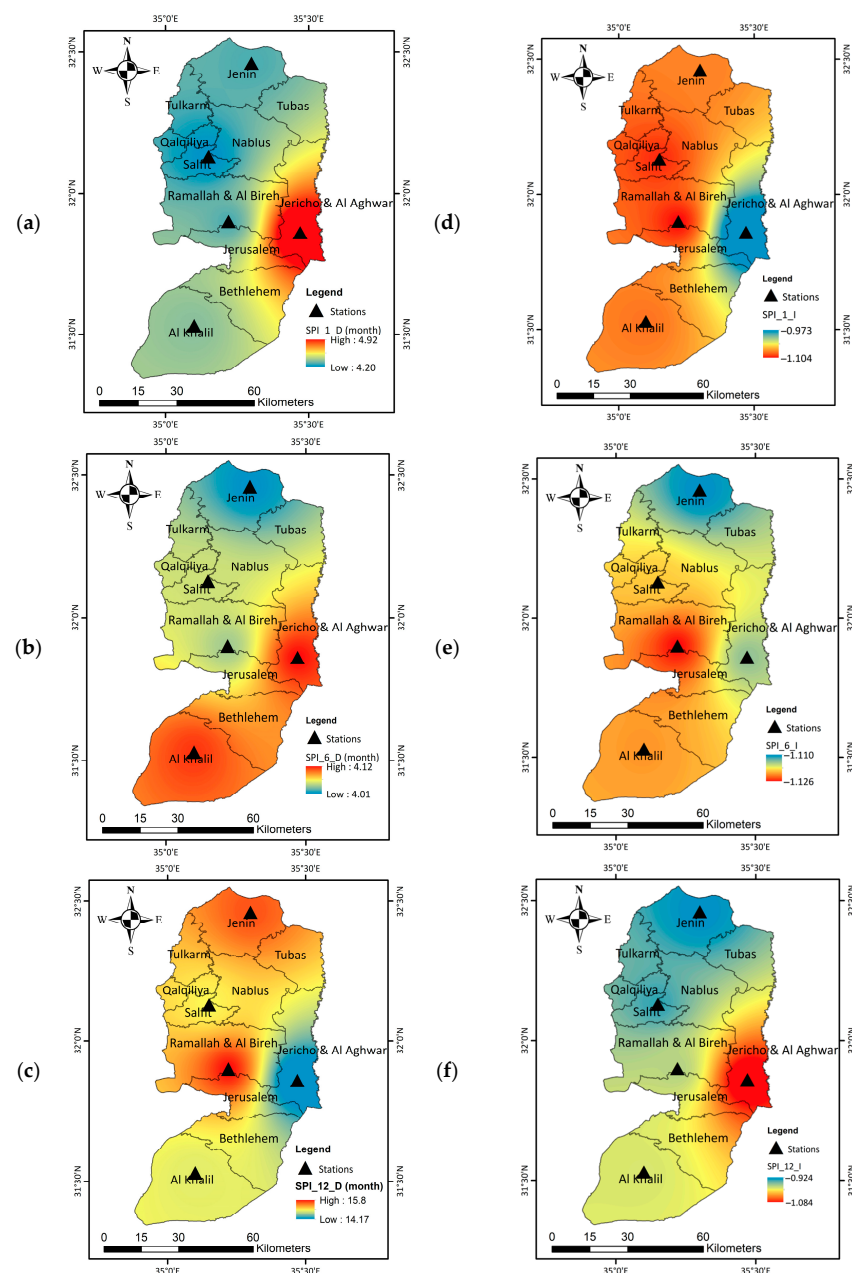


Figure 4. Spatial distribution of the drought duration (D_month) and intensity of SPI-based drought events between 1940 and 2025 for the West Bank: (a) SPI-1_Duration, (b) SPI-6_Duration, (c) SPI-12_Duration, (d) SPI-1_Intensity, (e) SPI-6_Intensity, and (f) SPI-12_Intensity.

The short-term drought map (Figure 4a) showed that the eastern regions of the West Bank, particularly the Jericho Governorate, suffered from longer drought periods than other regions, with the maximum drought duration reaching approximately 4.92 months. In contrast, the northern and western regions, such as Jenin, Tulkarm, Qalqilya, and Nablus, recorded the lowest drought durations, reaching 4.20 months. The color gradient in the map indicates that areas closer to the eastern areas are more susceptible to rapid drought than the more temperate regions in the west. Looking at medium-term drought (Figure 4b), we find that the southern and eastern regions, such as Jericho, Al-Khalil, and part of Bethlehem, exhibited longer drought durations, reaching 4.12 months, compared to the northern and western regions, which recorded the lowest drought duration of 4.01 months, but still very near to each other. The long-term drought map (Figure 4c) indicates that northern regions, such as Jenin, and central regions, such as Ramallah and Jerusalem, experienced long dry periods of up to 15.8 months, while southern regions, such as Al-Khalil, and eastern regions, such as Jericho, experienced shorter dry periods of up to 14.17 months. This pattern demonstrates that long-term drought more severely affects the highlands in the north and center compared to the lowlands in the east. The results of the drought analysis in the West Bank highlight the geographic variation in drought duration across different regions. Eastern regions, such as Jericho, suffer more from short-term drought. In contrast, medium-term drought is more prevalent in the south, while long-term drought severely affects the central and northern regions. These results underscore the need for local strategies for managing water resources and adapting agricultural activities to expected drought patterns, especially in light of potential climate changes over the coming decades.

On the other hand, Figure 4d–f show the spatial distribution of drought intensity in the West Bank from 1940 to 2025. The areas with the highest drought intensity levels over short, medium, and long timescales were highlighted according to the IDW spatial interpolation. Figure 4d indicated that western regions, such as Salfit, and central regions, such as Ramallah and Jerusalem, experienced high drought intensity in the short term, with maximum values reaching approximately -1.10 . This indicates that these regions suffered from short but highly impactful droughts. Jericho had lower drought intensity levels due to its longest duration, resulting in the minimum drought intensity. Looking at Figure 4e, which represents the intensity of medium-term drought, the spatial distribution changed slightly. Central regions, such as Ramallah, showed the highest levels of drought intensity, with values reaching -1.13 , meaning that drought was more severe in these areas than in other regions.

On the contrary, northern regions, such as Jenin and Tubas, showed lower levels of drought intensity, indicating that these areas may receive higher amounts of precipitation over six months, reducing the impact of drought compared to other regions. For the intensity of SPI-12, as shown in Figure 4f, the results indicated that eastern regions, such as Jericho, experienced the most severe levels of long-term drought intensity, with values reaching -1.08 . This prolonged drought impacts surface and groundwater resources, posing a challenge to water management, especially in light of the increasing demand for water due to population growth and needs.

3.4. Mann–Kendall, Spearman Rho, and Sen's Slope Results

The results of the MK test, Spearman Rho, and SS on the SPI from the Palestinian monitoring stations (5 stations) showed a clear variation, such as the temporal trends across the different periods (Table 5).

Table 5. Mann–Kendall, Spearman’s Rho, and Sen’s Slope results.

Station	SPI	MK_Trend	MK_Z	Spearman Rho	Sen’s Slope
Al-Khalil	1	no trend	−0.054	−0.002	0.0000
	6	no trend	−0.611	−0.020	−0.0001
	12	decreasing **	−2.155	−0.071	−0.0003
Jenin	1	no trend	−0.535	−0.016	−0.0001
	6	decreasing ***	−1.718	−0.054	−0.0002
	12	decreasing *	−5.611	−0.176	−0.0006
Jericho	1	no trend	0.770	0.023	0.0001
	6	no trend	−0.445	−0.012	0.0000
	12	decreasing *	−3.725	−0.100	−0.0004
Nablus	1	no trend	−0.136	−0.004	0.0000
	6	no trend	−1.100	−0.035	−0.0001
	12	decreasing *	−3.489	−0.118	−0.0004
Ramallah	1.1	no trend	0.200	0.006	0.0000
	6.1	no trend	−0.574	−0.020	−0.0001
	12.1	decreasing **	−2.005	−0.071	−0.0002

Note: *: 99% confidence level, ** 95% confidence level, and *** 90% confidence level.

The trend of SPI for the Hebron Station showed relative stability over the 1- and 6-month periods. No significant trends were recorded according to the MK test, and Spearman’s rho values were very weak and negative (−0.002 and −0.020), reflecting limited temporal correlation (Table 5). In contrast, over the 12 months, a significant downward trend was observed ($Z = -2.155$) at the 95% confidence level, accompanied by a negative Spearman’s rho value (−0.071) and a slight and negative slope (−0.0003) (Table 5). This indicates that the Hebron Station is heading towards increased drought over the long term, while short-term periods do not reflect a clear change.

Clearly negative trends in the SPI characterized the Jenin Station. At the 1 month, there was no significant trend ($Z = -0.535$), but at the 6 months, there was a significant downward trend ($Z = -1.718$) at a 90% confidence level, accompanied by a negative Spearman’s value (−0.054) and a slope of −0.0002. At the 12 months, the trend was strongly negative ($Z = -5.611$) at a 99% confidence level, with Spearman’s value (−0.176) and a slope of −0.0006 (Table 5). These results confirm that Jenin Station is experiencing a significant increase in the severity and frequency of drought events, especially over the long term.

Jericho Station showed relative stability over short periods, with no significant trends recorded at the 1- and 6-month periods ($Z = 0.770$ and -0.445), and Spearman’s values being weak and close to zero (0.023 and -0.012). At the 12-month period, a strong downward trend emerged ($Z = -3.725$) at the 99% confidence level, with a negative Spearman’s value (−0.100) and slope (−0.0004). This reflects that Jericho, despite its drought nature, shows increasingly clear signs of drought in the long-term analysis (Table 5).

At the Nablus station, short periods (1 and 6 months) showed no significant trend, with low Z values (−0.136 and -1.100) and weak Spearman’s values (−0.004 and -0.035), with a slope close to zero. However, the 12-month period revealed a clear downward trend ($Z = -3.489$) at a 99% confidence level, with a negative Spearman’s (−0.118) and a slope of −0.0004 (Table 5). This suggests that the Nablus station, like other stations, only exhibits strong drought signals over the long term, while short-term fluctuations do not reflect ongoing climate change.

The Ramallah station’s short-term periods (1 and 6 months) showed no significant trends. Z values were erratic (0.200 and -0.574), Spearman’s values were very weak (0.006 and -0.020), and the slope was almost nonexistent. However, over the 12 months, a

significant downward trend was observed ($Z = -2.005$) at the 95% confidence level, with a negative Spearman's value (-0.071) and slope (-0.0002). Thus, drought trends in Ramallah are primarily evident over long-term periods, while their signals are absent over short-term periods.

3.5. Frequency—Innovative Trend Analysis (F-ITA) Results

The F-ITA results for all stations in the West Bank are presented in Figure 5, corresponding to SPI-1, SPI-6, and SPI-12. Figure 5a–c show the F-ITA at Al-Khalil station corresponding to the SPI-1, SPI-6, and SPI-12 timescales, respectively. It illustrated the distribution of SPI values across two periods (1941–1982 and 1983–2024), revealing shifts in drought classifications and frequencies over time. The 1:1 reference line in each plot serves as a benchmark, allowing for a visual comparison of changes in precipitation anomalies. Additionally, the frequency distributions provide insights into the occurrence probabilities of different drought and wetness categories.

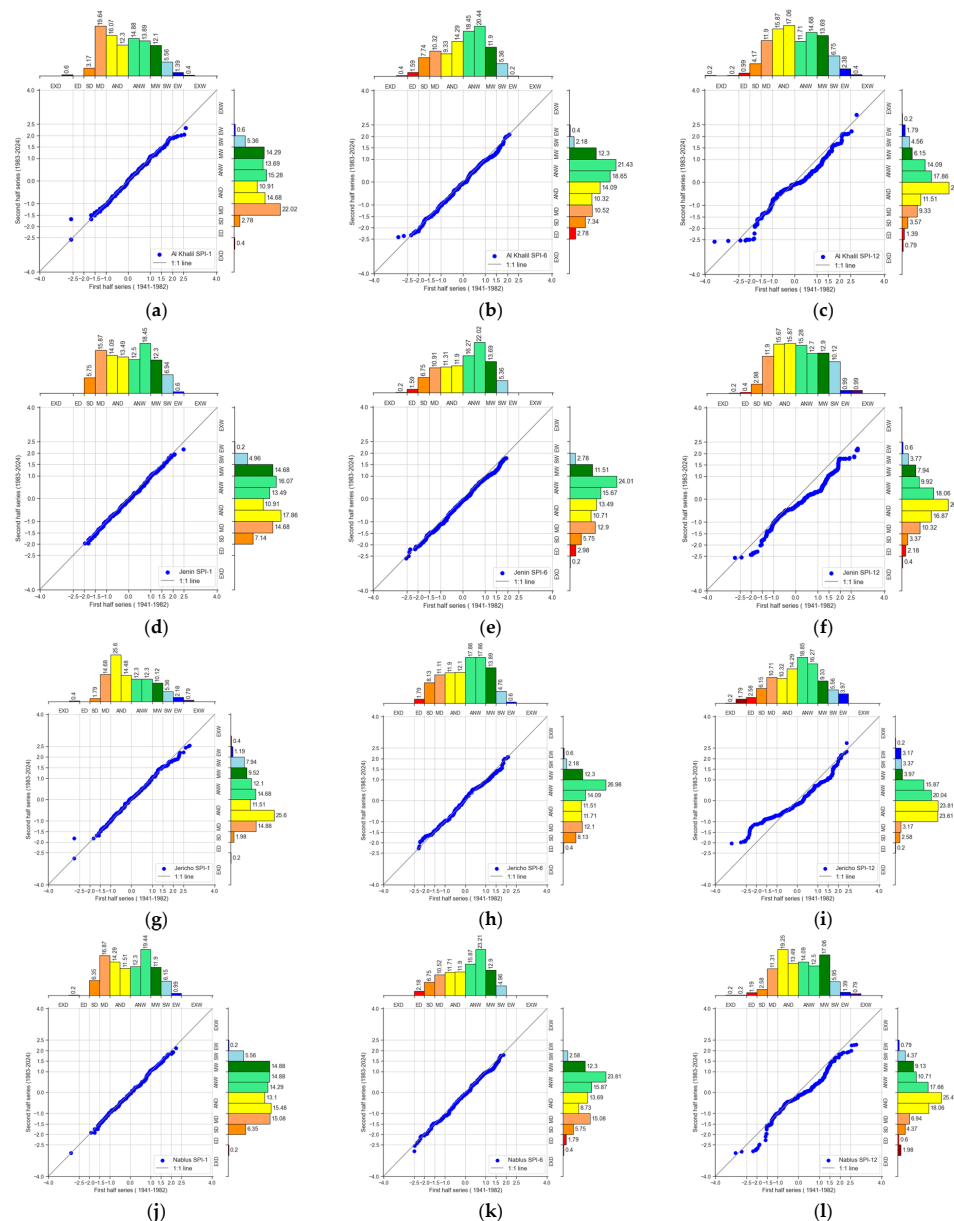


Figure 5. Cont.

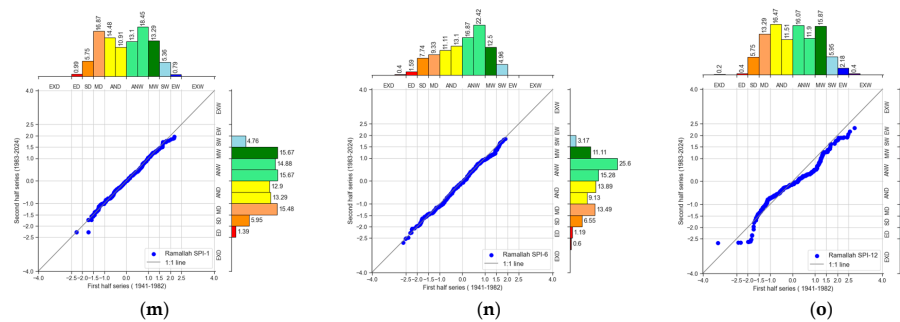


Figure 5. F-ITA for SPI at West Bank: (a) F-ITA_SPI-1 at Al-Khalil, (b) F-ITA_SPI-6 at Al-Khalil, (c) F-ITA_SPI-12 at Al-Khalil, (d) F-ITA_SPI-1 at Jenin, (e) F-ITA_SPI-6 at Jenin, (f) F-ITA_SPI-12 at Jenin, (g) F-ITA_SPI-1 at Jericho, (h) F-ITA_SPI-6 at Jericho, (i) F-ITA_SPI-12 at Jericho, (j) F-ITA_SPI-1 at Nablus, (k) F-ITA_SPI-6 at Nablus, (l) F-ITA_SPI-12 at Nablus, (m) F-ITA_SPI-1 at Ramallah, (n) F-ITA_SPI-6 at Ramallah, and (o) F-ITA_SPI-12 at Ramallah.

For SPI-1 F-ITA (Figure 5a), the results indicated notable fluctuations in extreme wet (EXW) and partially extreme dry (EXD) events. The most dominant category is moderate dry (MD), which increased from 19.64% in the first period to 22.02% in the second period. This suggested a tendency for more frequent moderate drought episodes in the short term, highlighting the vulnerability of Al-Khalil to abrupt shifts in precipitation. The classification also showed that severe drought (SD) events decreased from 3.17% in the first period to 2.78% in the second. In comparison, moderate wet (MW) increased from 12.1% in the first period to 14.29% in the second period. In general, for SPI-1 at Al-Khalil station, there is no trend. The classification frequencies exhibit a different pattern for SPI-6 F-ITA (Figure 5b). The EXD frequency decreased from 0.4% in the first period to 0% in the second. Also, the frequencies increased from 1.59% to 2.78% for ED classification, indicating a quite increasing trend. However, there is generally no trend over the Al-Khalil station on a medium time scale. For SPI-12 F-ITA (Figure 5c), the most prominent feature is the increased frequency of EXD and ED conditions, which increased from 0.4% and 0.99% in the first period to 0.79% and 1.39% in the second period. And SD and MD classification decreased from 4.17% and 11.9% to 3.57% and 9.33%. There was a decreasing trend for wet events in almost all wet classifications.

For SPI-1 F-ITA at Jenin station (Figure 5d), the frequency classification highlighted no trend in almost all drought classifications. For example, the frequency of EXD and ED classifications was 0% in the first and second periods at Jenin station. In general, the SPI-1 values were at a 1:1 trendless line. The SPI-6 F-ITA results for Jenin station (Figure 5e) presented the same results obtained in SPI-1, with quite a difference in ED classification, which increased from 1.59% to 2.98%, and the frequency of MD increased from 10.91% to 12.9%, indicating a specific increasing trend in these drought categories. However, for wet conditions, the frequency of EXW and EW was 0% in both periods. The SPI-12 F-ITA (Figure 5f) for the Jenin station showed an increasing trend in drought events and a decreasing trend in wet events. For example, the frequencies of EXD, ED, SD, and AND classifications increased from 0.2%, 0.4%, 2.98%, and 31.54% in the first period to 0.4%, 2.18%, 3.37%, and 43.46% in the second period, respectively, indicating the effect of climate change on the annual changes in Jenin station. For EXW, the frequency decreased from 0.99% to 0% in the second period.

For the Jericho station, the least precipitation station over the West Bank, the SPI-1 and SPI-6 F-ITA graphs (Figure 5g,h) showed the same trend performance, showing no trend over almost all drought classifications. However, for SPI-12 F-ITA, the trend was decreasing for all dry and wet classifications. For example, the frequencies of EXD, ED, SD, and MD decreased from 1.99%, 2.58%, 6.15%, and 10.71% in the first half (1941–1982) to 0%, 0.2%,

2.58%, and 3.17% in the second half (1983–2024), respectively. For Nablus station, there was the same trend at short and medium timescales (Figure 5j,k). However, the drought showed an increasing trend for SPI-12 F-ITA (Figure 5l). For example, the frequencies of EXD, SD, and AND increased from 0.4%, 2.58%, and 19.25% + 13.49% = 32.74% in the first half to 1.98%, 4.37%, and 18.06% + 25.4% = 43.46% in the second half, respectively. In contrast, the wet events decreased in almost all wet classifications. For the last station over the West Bank, the Ramallah station showed the same trend performance over all timescales (Figure 5m–o). There was no trend in short and medium timescales. And for SPI-12 F-ITA (Figure 5o), the frequencies for dry events increased EXD and ED classifications from 0.2% and 0.4% in the first half (1941–1982) to 1.79% and 0.6% in the second half (1983–2024).

4. Discussion

Drought analysis in data-scarce regions such as Palestine presents significant challenges due to limited observational records and uncertainties in climate data. This study aimed to evaluate drought characteristics in Palestine using bias-corrected ERA5 monthly precipitation data and trend analysis of SPI. By implementing bias correction, the reliability of the precipitation dataset was improved, thereby enhancing its applicability in drought assessment. This study provides insights into droughts' temporal and spatial variability, which is crucial for effective drought management and water resource planning. This discussion interprets the results, compares them with previous studies, and highlights their implications for policymaking and sustainable water resource management.

4.1. Importance of Bias Correction in Drought Analysis

ERA5 reanalysis data are widely used for climate and hydrological studies [70–73]; however, their direct application in drought analysis can be limited due to biases inherent in modeled precipitation estimates. In this research, bias correction was applied to improve the accuracy of ERA5 precipitation data before using it for drought evaluation. The ERA5 data before correction showed a strong correlation with observed data at all stations, with CC values ranging between 0.86 and 0.91 (Table 3), demonstrating ERA5's ability to represent the overall behavior in monthly precipitation well. However, there was a clear bias at all stations, with the bias being negative at most stations (except for Jericho, which showed a positive bias). This suggests that ERA5 tends to underestimate precipitation in most cases, which may affect its use in hydrological studies that require high accuracy in precipitation amounts. However, the RMSE decreased significantly at all stations, reflecting an improvement in the accuracy of precipitation estimates. Furthermore, the bias was completely removed, with the MBE and PB values now equal to 0.0 (Table 4), demonstrating the success of bias correction techniques in improving the quality of ERA5 data and making them more consistent with observed data.

4.2. Spatial Analysis of Drought Characteristics

For conducting spatial analysis, the number and distribution of stations or grid points are critical to ensure accurate representation of drought characteristics. However, in Palestine, a data-scarce region with limited observational records and challenges in conducting field research, this study performs spatial analysis using ERA5 reanalysis data, which have been evaluated and validated against the available in situ data from five stations. In terms of drought characteristics, comparing SPI-6 and SPI-12 (Figure 4), SPI-6 reflects short-term fluctuations, making it more sensitive to seasonal changes in precipitation. At the same time, SPI-12 shows long-term trends in drought and precipitation, making it a more suitable indicator for assessing water security and hydrological risks. Overall, drought durations and intensities demonstrate that drought has been a recurring phenomenon over the past

decades, with prolonged dry periods becoming more severe since the 1990s, indicating potential climate changes affecting the water cycle and precipitation in the West Bank, Palestine. Medium-term drought (SPI-6) (Figure 4) is an important indicator of agricultural drought, affecting the soil's ability to retain moisture for extended growing periods. The greatest impact is seen in the southern and eastern West Bank, meaning farmers in Al-Khalil and Jericho will face increasing challenges in growing rain-fed crops. Long-term drought is more closely linked to hydrological drought, affecting groundwater, the main water source in the West Bank. The results indicate that the central and northern regions will be most affected over the years, necessitating strategies for groundwater management and reducing reliance on seasonal precipitation.

4.3. Classical and Innovative Trend Analysis

The results indicate that most of the studied stations in Palestine exhibit a long-term downward trend in the SPI, particularly over extended timescales (12 months), reflecting a marked increase in the severity and frequency of droughts over the past two decades. These results are consistent with regional trends in the Eastern Mediterranean, where previous studies have indicated that the region is experiencing increasing climate stresses leading to declining rainfall and rising temperatures, thus exacerbating drought conditions.

High confidence levels (95–99%) demonstrate that the detected trends are not merely transient natural fluctuations, but rather statistically significant indicators reflecting a real change in the local climate system. The consistency of the results across multiple stations strengthens the conclusion that drought is increasing on a widespread scale, rather than a geographically confined phenomenon.

On the other hand, the absence of significant trends over shorter time scales (1 and 6 months) highlights the importance of using longer time series in the analysis. While short periods may show insignificant seasonal or interannual fluctuations, long periods reveal structural changes in climate. This makes long-term SPI more useful for monitoring future climate trends and planning water resource management.

These results are largely consistent with the F-ITA methodology, as both methods showed that long-term trends provide clearer and more reliable indicators of climate change than short-term analyses. This confirms that the integration of statistical methods (MK and SS) with the F-ITA method enhances the robustness of the findings and is an effective tool for interpreting drought dynamics in Palestine.

4.4. Previous Studies

Due to several challenges, including data scarcity and political issues in Palestine, the number of studies addressing drought conditions in the region remains limited. One such study by Shadeed [74] investigated meteorological drought in the Faria catchment in the northeastern West Bank. Using the SPI, the study analyzed spatial and temporal drought vulnerability based on the frequency and severity of drought events at a 1-year time step. Given the lack of detailed climate data, Shadeed [74] relied on annual precipitation records from 1960 to 2003, restricting the ability to assess drought conditions at finer temporal scales. The findings revealed that drought occurred in 21 out of 43 years, with an estimated maximum drought duration of 3.3 years across the catchment.

In comparison to the research conducted by Shadeed [74], the first key difference in our study is the use of finer timescales, including 1, 6, and 12 months, allowing for a more detailed analysis of meteorological, agricultural, and hydrological droughts. While Shadeed [74] focused solely on annual precipitation data for the Faria catchment, our research provides a comprehensive drought assessment across the entire West Bank, capturing spatial and temporal variations in drought characteristics. For example, at a 12-month

timescale, the average drought duration across all drought events, based on the SPI, ranged between 14 and 16 months across the West Bank. This broader and more refined analysis offers valuable insights into drought evaluation; however, a critical need remains for more accurate drought evaluation to further enhance the region's drought monitoring and water resource planning.

4.5. Limitations

This study has several limitations, primarily stemming from data availability and methodological constraints beyond the authors' control. First, ERA5 data were used instead of ERA5-Land, which may offer higher spatial accuracy; however, accessibility and data continuity considerations constrained this choice. Second, the analysis relied on only five observation stations, as these were the only long-term records available in this data-scarce region. The limited number of stations was further influenced by institutional and infrastructural constraints in Palestine, including difficulties in movement, conducting field visits, and accessing research sites. Despite this limitation, using these five stations provides a reasonable and robust approach under the given constraints and offers valuable and reliable ground-based references, as precipitation data remain the most direct and trustworthy validation source compared to alternative datasets (e.g., ecosystem or agricultural data), which are subject to greater uncertainties.

Third, drought assessment was conducted exclusively using the SPI, while the inclusion of additional drought indices in future research could provide a more comprehensive evaluation. Finally, the LS bias correction method was applied in this study, but future investigations could explore and compare multiple correction techniques to enhance analytical robustness. It is also noteworthy that, in the wider literature, ERA5 and other reanalysis datasets are frequently applied in drought and climate studies without field-based validation due to similar data scarcity challenges, particularly in conflict-affected or developing regions. By incorporating the available ground-based observations, even if limited in number, this study strengthens the credibility of the ERA5 bias-correction and trend analysis and represents a practical methodological contribution for advancing drought research in Palestine.

4.6. Implications for Drought Management and Water Resource Planning

The findings of this research have significant implications for drought management and water resource planning in Palestine. Given the increasing frequency and severity of droughts and the limited water resources in Palestine, there is an urgent and detailed need for drought management for effective and adaptive water management strategies. These strategies include improved water storage, early warning systems and monitoring, sustainable agricultural practices, and climate change adaptation strategies. For example, Shadeed and Alawna [75] investigated the optimal sizing of rooftop rainwater harvesting tanks in the West Bank, Palestine, to enhance water storage capacity and support domestic water use during dry months. Also, this research underscores the importance of developing and implementing drought early warning systems. Continuous monitoring of precipitation and drought indicators using improved datasets, such as bias-corrected ERA5, can enhance preparedness and response efforts [49]. The agricultural sector is one of the most affected sectors during droughts. Adopting drought-resistant crops, efficient irrigation techniques, and soil moisture conservation practices can help mitigate agricultural losses and ensure food security. Also, Abu Arra et al. [76] discussed the critical drought using different time periods. Using the same concept, joining the time period and different data sources can improve the critical drought concept.

In conclusion, the findings highlight the urgent need for integrated water management approaches and strengthened resilience to drought in the most vulnerable regions. Priority should be given to advancing water harvesting methods and encouraging sustainable irrigation practices, particularly in the southern and central areas most affected by severe drought. Furthermore, water-use efficiency can be enhanced through developing groundwater infrastructure, greater utilization of desalination technologies, and the reuse of treated wastewater in regions experiencing prolonged drought conditions.

5. Conclusions

This study evaluated drought characteristics and trends in Palestine, a data-scarce region, using bias-corrected ERA5 precipitation data, the SPI, classical trend methods (MK, Spearman, and SS), and F-ITA. The findings highlighted significant temporal and spatial variability in drought occurrences, emphasizing the region's susceptibility to prolonged dry periods. The main key findings can be summarized as follows:

- By applying bias correction, the reliability and accuracy of ERA5 monthly precipitation data were improved, enhancing its applicability for drought evaluation and assessment, particularly in data-scarce regions. RMSE decreased in all stations and timescales.
- One of the key insights from this research is the increasing duration and intensity of droughts across the West Bank, Palestine, particularly over the past few decades. The multi-timescale SPI analysis (1-month, 6-month, and 12-month) provided a comprehensive understanding of short-term and long-term drought impacts, covering meteorological, agricultural, and hydrological droughts.
- The droughts in SPI-1 and SPI-6 ranged from 4 to 5 months, the minimum at which a drought can be classified, indicating that the durations for SPI up to 6-month timescales are about 4–5 months.
- The results indicated that the average drought duration at a 12-month timescale ranged between 14 and 16 months, underscoring the need for sustainable water resource management strategies to mitigate drought risks.
- Considering the trend analysis over the study period spanning about 84 years using MK, Spearman Rho, SS, and F-ITA methodologies, there was no trend in the short (SPI-1) timescale. However, the results indicated a decreasing trend in SPI values, particularly at longer time scales (SPI-12), which reflects an increasing trend in drought conditions. For example, the SPI-12 F-ITA for the Jenin station showed an increasing trend in drought events, and the frequencies of EXD, ED, SD, and AND classifications increased from 0.2%, 0.4%, 2.98%, and 31.54% in the first period (1941–1982) to 0.4%, 2.18%, 3.37%, and 43.46% in the second period (1982–2024), respectively.
- For SPI-12, MK-Z values were -2.155 (Al-Khalil), -5.611 (Jenin), -2.676 (Jericho), -3.489 (Nablus), and -2.005 (Ramallah), all significant at the 95–99% confidence levels, indicating a decreasing SPI trend and hence intensifying drought. Corresponding SS values (-0.0003 to -0.0006) confirm a gradual long-term drought intensification.
- Despite the advancements in data processing and bias correction, data scarcity remains a major challenge, and further research is needed to refine drought assessment methods using additional climate variables and higher-resolution datasets.
- The findings of this study have important implications for drought management, water policy planning, and climate adaptation in Palestine.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w17182780/s1>, Figure S1: Scatter plot between gauge data, ERA5, and biased-ERA5: (a) gauge data and ERA5 at Al-Khalil station, (b) gauge data and bias-corrected ERA5 at Al-Khalil station, (c) gauge data and ERA5 at Jenin station, (d) gauge data and bias-corrected ERA5 at Jenin station, (e) gauge data and ERA5 at Jericho station, (f) gauge data and bias-corrected ERA5 at Jericho station, (g) gauge data and ERA5 at Nablus station, (h) gauge data and bias-corrected ERA5 at Nablus station, (i) gauge data and ERA5 at Ramallah station, and (j) gauge data and bias-corrected ERA5 at Ramallah station.

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

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