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Innovative Drought Classification Matrix and Acceptable Time Period for Temporal Drought Evaluation

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Abstract
Evaluating drought is paramount in water resources management and drought mitigation plans. Drought indices are essential tools in this evaluation, which mainly depends on the time period of the original datasets. Investigating the effects of time periods is critical for a comprehensive understanding and evaluation of drought. Also, It holds particular significance for regions facing data availability challenges. The existing literature reveals a gap in drought assessment and comparison analysis using conventional methods based on drought indices only. This research proposes an innovative drought classification matrix to compare drought indices and spatial and temporal scenarios; the proposed matrix depends on any drought classification for comparison procedure. Furthermore, it aims to investigate the differences between several time period scenarios based on the proposed matrix and several statistical metrics (R^2, CC, RMSE, HH, and RB) and determine the acceptable/minimum time period. The application of the proposed matrix and selection of an acceptable/minimum time period is presented to three different climates: Durham station in the United Kingdom, Florya station in Türkiye, and Karapinar station in Türkiye. The results show that the time period scenarios are able to catch the reference time period (RTP) scenario reasonably, with strong correlation and negative relative bias. The 10-year time period is sufficient as an acceptable/minimum time period for short timescales, such as meteorological drought. Conversely, for longer timescales, such as hydrological drought, a 20-year time period is the acceptable/minimum time period. The proposed matrix demonstrates a robust and powerful framework for comparison, making it applicable to various drought assessment scenarios globally.

Keywords Drought Evaluation · SPI · Acceptable Time Period (ATP) · Drought Classification · Drought Assessment

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1 Introduction

Natural disasters such as droughts are more frequent, with increasing records observed in recent years (Dabanli et al. 2021; Hussain et al. 2023; Tiwari et al. 2022). Climate change and drought are two of the main driving factors for worldwide natural disasters (Visser et al. 2014; IPCC 2021; Shadeed 2013). Drought is related to a considerable decrease in rainfall, a main input for the hydrological cycle, under a typical level (Şen 2020; Danandeh Mehr and Vaheddoost 2020). Rainfall is an essential metric in assessing the effect of climate change and drought (Kharyutkina et al. 2022; Şen et al. 2020). Drought impacts water availability due to reduced rainfall, affecting supply and demand. Additionally, drought affects various sectors, such as the economy, industry, and agriculture (Du et al. 2022; Nouri 2023). Moreover, droughts are among the most severe natural disasters, causing widespread damage on both global and regional scales (Tsakiris et al. 2016; Khorrami et al. 2023).

Considering this, several drought indices have been developed and applied for drought evaluation and assessment. Examples include the Palmer Drought Severity Index (PDSI) (Palmer 1965), the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010), the Reconnaissance Drought Index (RDI) (Tsakiris et al. 2007), and the most commonly used Standardized Precipitation Index (SPI) (McKee et al. 1993). Whilst defining a global index for drought evaluation and assessment presents a challenge (Tsakiris and Vangelis 2004), the SPI is considered one of the most accepted and widely used methods within scientific communities worldwide (WMO 2012). Its wide acceptance is attributed to its advantage of sole dependency on rainfall data, making the implementation simpler compared to other indices. SPI has a particular strength and priority regarding data availability and data-scarce countries. Furthermore, the standardization concept within these drought indices offers the advantage of transforming the drought index into a unitless measure, allowing for comparative analysis across diverse precipitation time series datasets (Abu Arra and Şişman 2023).

Standardized drought index methods, such as SPI, transform the fitted cumulative probabilities of observed data into a drought index (McKee et al. 1993). Subsequently, the period of original data directly affects the drought index values. One of the weaknesses of the standardized drought index methods is that the drought index values change as the period of original data changes (WMO 2008). The World Meteorological Organization recommends quality-assured minimum records spanning 30 years of monthly values for SPI calculation (WMO 2008). This minimum period is generalized for most drought index methods (WMO 2012). Various studies calculated the standardized drought indices using different time periods, ranging from 30 to 150 years, without investigating and checking the effect of the used time period on the drought index values (Mahmoudi et al. 2019; Kesgin et al. 2024; Elhoussaoui et al. 2021). After a thorough evaluation of the literature, no research have been studied and considered the effects of the selected time period on the drought indices results, which is a significant gap that must be filled.

On the other hand, in various countries worldwide, there are limitations arising from various factors in maintaining continuous meteorological data records, especially in developing countries. Consequently, continuous meteorological records often fall short of the recommended period (30 years) (WMO 2008). This limitation in data availability poses a significant challenge in conducting comprehensive drought analyses. Furthermore, using satellite-derived and reanalysis data presents diverse concerns and challenges in conducting drought analyses. One of the main issues is the need for inclusive validation based on in-situ meteorological data to ensure the accuracy and reliability of the data (Mishra and Singh 2010; Mishra and Singh 2011). In addition, some of these data sources, such as Integrated Multi-satellitE Retrievals for GPM (IMERG) (https://power.larc.nasa. gov/data-access-viewer/) (Huffman et al. 2015), commenced after June 2000, leading their available data to cover a time period of less than 30 years. This temporal limitation poses a challenge, especially when adhering to the recommended minimum duration for reliable meteorological data records recommended by (WMO 2008). The selected drought index with the minimum variables is preferred regarding the data availability challenges.

The existing literature reveals a significant gap in drought assessment methodologies, where conventional evaluations often overlook critical factors. Specifically, researchers commonly neglect the importance of drought classification across distinct periods, utilizing various drought indices and accounting for diverse geographical locations (Ullah and Akbar 2021; Tigkas 2008). The conventional methods depend heavily on drought indices without acknowledging the significance of their classification or considering the time period. Additionally, the duration of the time period, often accepted as an initial condition, is inadequately discussed in terms of its effects and importance in shaping drought assessments. To address this notable gap, our research endeavors to comprehensively understand and assess drought by incorporating a holistic framework that integrates drought indices, statistical metrics, and a newly proposed innovative drought classification matrix. By doing so, we aim to provide a more nuanced perspective, considering the temporal aspect and facilitating the identification of minimum/acceptable time periods for robust drought assessment. This approach fills a crucial void in the existing literature, contributing to advancing drought evaluation methodologies.

The main objectives of this research are to: 1) Develop an innovative drought classification matrix to compare different drought indices, different time periods, and different spatial stations in drought and climate change studies, 2) investigate the effect of time period on standardized drought indices using (SPI) based on drought index values, statistical metrics, and innovative drought classification matrix, 3) determine the acceptable/minimum time period (ATP) for drought evaluation in regions challenging data availability problems, and 4) determine the optimal time period (OTP) and calculate the accuracy of different time periods using statistical metrics and newly proposed innovative drought classification matrix. This research is pivotal because it explores the significance of the time period in drought evaluations and assessments. This research will provide a foundation for studying and evaluating drought in regions with data availability challenges. Also, it suggests and considers the importance of drought classification in water resources management, drought assessment, and comparison processes. By shedding light on this often underestimated aspect, this research contributes significantly to the drought assessment and enhances our understanding of the temporal analysis of drought.

2 Materials and Methods

2.1 Study Area and Data Collection

The application of the newly proposed matrix, statistical metrics, and time period analyses for determining the research objectives were chosen across diverse areas characterized by distinct and different climates. The selection of these stations was specifically tailored to implement the newly proposed matrix and find the acceptable and optimal time period, aiming to showcase its versatility and effectiveness in different climatic contexts. The first one is Karapinar station in Konya city, located in central Türkiye, the largest city in land area. Konya city has a semi-arid climate. The average annual precipitation is 297.5 mm. Hydrological and environmental issues arise because of low rainfall and high temperatures in the summer months, making it one of the most dry cities in Türkiye. The monthly precipitation (P) records are between 1964 and 2022 (58 years) as provided by the Turkish State Meteorological Service (MGM). Secondly, Durham city, which is located in the northeast of the UK. It has a hybrid temperate maritime climate with normal summers and cool winters from a global perspective. The average annual precipitation is 655.62 mm. The monthly precipitation (P) data are between 1872 and 2021 (150 years), as provided by the Durham University meteorological station. The climate data from the Durham station stands as the UK's third lengthiest continuous weather dataset.

The third application is Florya station in Istanbul city, Türkiye. The climate of Istanbul is mild; the summer is humid and hot with little rain, and the winter is rainy, wet, cold, and with some snow. The average annual precipitation is 641.3 mm. The monthly precipitation (P) data are between 1941 and 2020 (80 years), as provided by the Turkish State Meteorological Service (MGM). Table 1 summarizes the station name, latitude, longitude, annual precipitation, standard deviation, time period, and the reference period for all used stations. All obtained rainfall data are processed and controlled for consistency and continuity.

2.2 Standardized Precipitation Index (SPI)

Generally, the drought indices are the main variables in evaluating and assessing the drought. The SPI is depending on the probability of rainfall at any time scale, such as 1-month, 3-month, 9-month, and 12-month. The first step in SPI calculation is selecting a suitable probability distribution function for the original data (precipitation). The Gamma PDF is the most proper PDF for SPI calculations in most studies (Wang et al. 2019). Choosing an appropriate Probability Density Function (PDF) involves evaluating the goodness-of-fit tests for the original datasets (such as rainfall for SPI) using Chi-Square and Kolmogorov–Smirnov tests (Stephens 1970). The probabilities derived from the monthly rainfall data are probabilistically standardized into normal function with a mean of zero and a standard deviation of one. The Gamma distribution's probability density function is defined as:

$$g(x) = \frac{1}{\beta^{\alpha} T(\alpha)} X^{\alpha-1} e^{\frac{-x}{\beta}},\ for\ x > 0 \tag{1}$$

Table 1 Climatic characteristics of the annual total precipitation of the used stations in this study

Station	Latitude	Longitude	Annual Precipitation (mm)	Standard deviation (mm)	Time period	Reference Time Period (RTP) (y)
Florya station	40.97 (N)	28.78 (E)	641.3	43.35	1941–2020	80
Durham station	54.77 (N)	1.59 (W)	655.62	34.85	1872–2021	150
Karapinar station	37.71 (N)	33.52 (E)	297.52	21.57	1964–2022	59

where α and β are the shape and scale parameters, respectively, x is the precipitation. T(α) is the Gamma function. The shape and scale parameters can be calculated using the approximation of Thom:

$$\alpha = \frac{1}{4A}(1 + \sqrt{1 + \frac{4A}{3}}) \tag{2}$$

And

$$\beta = \frac{\overline{X}}{\alpha} \tag{3}$$

With

$$A = \ln\left(\overline{X}\right) - \frac{\sum \ln(X)}{n} \tag{4}$$

where $\overline{X}$ is the average precipitation; n is the number of data; X is the precipitation at a current period. In the next step, the theoretically fitted precipitation data is probability standardized using Matlab as mentioned in (Şen and Şişman, 2023).

McKee et al. 1993, classified the drought into seven classifications based on the standard deviation and probability function, as shown in Table 2. More details and literature regarding SPI can be found in (McKee et al. 1993).

2.3 Time Period Scenarios

The time period directly affects the SPI calculations and the obtained results, and changing the time periods changes the results. This can be attributed to the fact that original data is fitted and transformed into a normal scale. This study divides the time period into several smaller intervals, each shorter than the overall long-term time period, which is referred to as the reference time period (RTP). The RTP is defined as the longest available time period for each station, is supposed to be the most accurate, and is utilized as a benchmark for all calculations and comparisons. Table 3 summarizes the time period scenarios and the RTP for each station.

Table 2 Drought classifications based on SPI theory (McKee et al. 1993)

Drought index DI (SPI)	Drought classification	Probability (%)
2.00 ≤ DI	Extreme wet (EW)	2.31%
1.50 ≤ DI < 2.00	Severe wet (SW)	4.42%
1.00 ≤ DI < 1.50	Moderate wet (MW)	9.22%
-1.00 ≤ DI < 1.00	Normal (N)	68.1%
-1.50 ≤ DI < 1.00	Moderate drought (MD)	9.22%
-2.50 ≤ DI < 1.50	Severe drought (MD)	4.42%
-2.00 ≤ DI	Extreme drought (ED)	2.31%

Table 3 Time period scenarios

Station	Reference Time Period (RTP) (years)	Time period scenarios (years)
Karapınar station	59	59, 30, 20, 10
Durham station	150	150, 120, 90, 60, 30, 20, 10
Florya station	80	80, 60, 30, 20, 10

2.4 Time Period Scenarios Comparison Scheme

The performance of each time period scenario was evaluated based on the continuous statistic metrics with the help of the newly proposed innovative drought classification matrix. These metrics utilized to determine the accuracy of each time period scenario are correlation coefficient (CC), root mean square error (RMSE), and relative bias (RB), as summarized with their formulas in Table 4. The CC value ranges between -1 and 1 and is used to measure the strength and direction between two variables. A value nearing 1 signifies a robust positive relation, -1 indicates a strong negative relation, and 0 implies no correlation. The average absolute error of any time period scenario to the RTP scenario is measured by RMSE; the lower value of RMSE indicates a better time period scenario performance. RMSE measures the average difference between the RTP model and any time period scenario. The time period scenario typical bias is calculated using RB, where 0 indicates no bias, whilst a positive value indicates an overestimate of the time period scenario, and a negative value indicates an underestimate of the time period scenario. One of the limitations of RMSE is that the application of RMSE as the main function in inverse models may not find the global optimal metrics of the model, and to overcome this problem, the Hanna and Heinold metric (HH) is also used (Hanna and Heinold 1985; Mehdinejadiani et al. 2022). The coefficient of determination (R^2) values close to 1 indicate a strong positive relation. Figure 1 shows the research

Table 4 Continuous statistical metrics for SPI values from different time period scenarios

Statistic metric	Equation	Value range	Ideal value
Correlation Coefficient (CC)	$CC = \frac{\sum_{i=1}^{n}\left(R_i-\overline{R}\right)\left(T_i-\overline{T}\right)}{\sqrt{\sum_{i=1}^{n}\left(R_i-\overline{R}\right)^2}\sqrt{\sum_{i=1}^{n}\left(T_i-\overline{T}\right)^2}}$	(-1) – (1)	1
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(T_i - R_i\right)^2}$	(0) – (∞)	0
Hanna and Heinold (HH)	$HH = \sqrt{\frac{\sum_{i=1}^{n}(T_i-R_i)^2}{\sum_{i=1}^{n}T_i.R_i}}$	(0) – (∞)	0
Relative Bias (RB)	$RB = \frac{\sum_{i=1}^{n}(T_i-R_i)}{\sum_{i=1}^{n}R_i}x(100)$	(-∞) – (∞)	0
Coefficient of determination (R^2)	$R^2 = \left[\frac{\sum_{i=1}^{n}\left(R_i-\overline{R}\right)\left(T_i-\overline{T}\right)}{\sqrt{\sum_{i=1}^{n}\left(R_i-\overline{R}\right)^2}\sqrt{\sum_{i=1}^{n}\left(T_i-\overline{T}\right)^2}}\right]^2$	(0) – (1)	1

R = SPI value for RTP, T = SPI value for any time period, n = number of months/samples, $\overline{R}$= mean SPI value for RTP, $\overline{T}$= mean SPI value for any time period

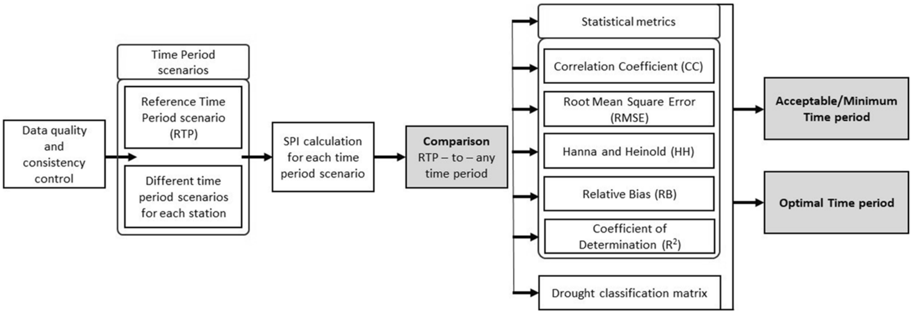

Fig. 1 Research flow chart for comparing and selecting the acceptable/minimum and optimal time period based on statistical metrics and IDCM

methodology flow chart for comparison between the RTP and time period scenarios and selecting the acceptable/minimum and optimal time period scenario.

2.5 Innovative Drought Classification Matrix

McKee et al. (1993) developed the classification shown in Table 2 to define and classify the drought resulting from the SPI values. Regarding the literature, it is the most commonly used drought classification. Drought classification makes the comparison processes, water resources management, and climate change mitigation and adaptation plan easier and more precise because of using one drought classification that is accepted worldwide. Also, because of using the standardization concept, wet and dry climates are represented in the same approach (symmetric); therefore, the wet climates can be evaluated and monitored using the standardized drought indices.

This research proposes a new innovative drought classification matrix (IDCM) to compare and investigate the differences and similarities between the RTP and any time period scenario based on the drought classification and between different drought indices and scenarios. For example, IDCM can be used to find the differences and similarities between several drought indices, such as SPI and SPEI. As shown in Table 5, the first column is the drought classification for the RTP scenario. The first row is the drought classification for

Table 5 Innovative drought classification matrix

DI	Drought classification for Any time period scenario							Sum
Drought classification for RTP scenario	EW	SW	MW	N	MD	SD	ED	
EW								
SW						Underestimation		
MW								
N								
MD		Overestimation						
SD								
ED								
Sum								

any time period scenario. The drought classifications are (from wet to drought) extreme wet (EW), severe wet (SW), moderate wet (MW), normal (N), moderate drought (MD), severe drought (SD), and extreme drought (ED). IDCM can be used based on any drought classification. The proposed IDCM depends on monthly SPI/DI values; each value for each month from both the RTP scenario and any time period scenario is compared based on drought classification. For example, if the SPI value for i month is -0.59 and the SPI value for the same i month for a specific time period scenario is -0.75, then the cell N–N will take 1. This process is conducted for all months. The numbers in the innovative matrix represent the whole time period. The grey-shaded cells represent the months falling within the same drought classification (same classification). Also, the last row and column are the summation of the months within a specific drought classification. The IDCM can include 0 values, meaning no months are within this classification. For example, based on the RTP scenario, the drought classification is EW, and the drought classification based on any time period scenario is ED. In this situation, the zero value is expected. Finally, the DI can be any drought index. The blue-shaded cell is the most important result in the innovative drought classification matrix. It shows the number of months with its percentage for the same drought classifications. Values over the grey-shaded cells (diagonal) indicate that this time period scenario underestimates the drought index values based on the RTP. On the contrary, values below the grey-shaded cells (diagonal) indicate an overestimation of the RTP scenario. The drought classification is based on Table 2. The Newly proposed matrix has no limitations. It can be used for different drought indices, different time periods, and different locations.

3 Results

3.1 Statistical Metrics

The SPI has been calculated at 3 and 12-month timescales corresponding to short and long-period timescales for each station and time period scenario identified in Table 3. The SPI was calculated firstly for each station's RTP, which is 80 years for Florya station, 150 years for Durham station, and 58 years for Karapinar station. These RTPs are regarded as the most accurate and reliable data sets to investigate the differences and select the acceptable/minimum and optimal time period scenario.

The first part of the results was the statistical metrics for each station and time period scenario. Table 6 summarizes the CC, RMSE, HH, R^2, and the percentage of the months falling within the same drought classification using the newly proposed IDCM for Florya station. All time period scenarios correlated strongly with the RTP scenario in estimating SPI values. Only the 10-year time period scenario gave a relatively low value regarding other periods (0.926). In terms of RMSE, the difference between RMSE and HH is negligible for all stations and time scales, so the RMSE is considered in the results and discussion sections. All time periods reported errors of 0.071 to 0.388 and of 0.054 to 0.247 for SPI 3 and SPI 12 values, respectively. For a short timescale (3 months), the RMSE reported a considerable error of 0.388, implying more significant errors and less accurate forecasts. Regarding RB, all time period scenarios for both SPI 3 and 12 underestimated the SPI values with the same quantity, approximately -100%. Giving approximately the same RB indicated no difference between any time period scenario.

Table 6 Summary of the statistical metrics and innovative drought classification matrix for SPI 3 and 12 for all time period scenarios for Florya station

	SPI 3				SPI 12			
	60 Years	30 Years	20 Years	10 Years	60 Years	30 Years	20 Years	10 Years
CC	0.998	0.988	0.988	0.926	0.999	0.999	0.998	0.991
RMSE	0.071	0.163	0.162	0.388	0.054	0.176	0.235	0.247
HH	0.072	0.162	0.161	0.414	0.054	0.163	0.213	0.249
RB	-100.3%	-100.1%	-100.4%	-92.2%	-99.0%	-100.2%	-100.8%	-99.9%
R^2	0.996	0.976	0.977	0.857	0.999	0.998	0.997	0.983
Drought Classification	94.3%	88.8%	91.6%	79.7%	96.2%	82.2%	82.1%	77.1%

Furthermore, the R^2 values were more than 0.85, showing that the SPI values of the time period scenarios fitted the regression model (the goodness of fit) and were explained by the regression line. Figure 2 (a-h) showed the R^2 values and the regression models for each time period scenario and RTP scenario. The red line represented the regression line. Finally, based on the IDCM, the percentage of the months within the same drought classification was more than 82% for time periods above 20 years. However, the percentages were 79.7% and 77.1% for SPI 3 and SPI 9, respectively.

Table 7 summarizes the main statistical metrics: CC, RMSE, R^2, and the percentage of the months falling within the same drought classification using IDCM for Durham station. All time period scenarios (120 – 10 years) correlated very strongly with the RTP scenario in calculating SPI values. Same the Florya station, the minimum CC was at a 10-year time period scenario, giving a relatively low value compared with other time periods (0.96). Regarding RMSE, which calculates the errors between RTP and any time period, all periods addressed errors of 0.059 to 0.399 and 0.019 to 0.669 for SPI 3 and SPI 12 values, respectively. The RMSE addressed a noticeable error of 0.399 for short timescales and 0.669 for long timescales at 10 years, indicating more significant errors and less accurate forecasts for this time period. In terms of RB, all time period scenarios except the 120-year time period for SPI 3 gave the same RB (-100%). The underestimation with approximately the same RB implied no considerable difference between any time period scenario. They all underestimated the SPI values with the same percentage compared to the RTP scenario.

Additionally, the R^2 values were more than 0.926. The SPI values for the time period scenarios demonstrated a fitting alignment with the regression model, indicating a satisfactory goodness of fit. These values were effectively elucidated by the regression line within the model. Figure 3 (a-f) and Fig. 4 (a-f) showed the R^2 and the regression models for each time period scenario and RTP scenario. The red line represented the regression line. Based on these figures, it can be noted that Fig. 4. f had the minimum R^2, and the distance between the points and regression line can be noticed. Lastly, depending on the newly proposed innovative drought classification matrix (Table 5), the percentage of the months within the same drought classification ranged between 70 to 94% and 54% to 97.8% for SPI 3 and 12, respectively. The minimum percentage (54%) was at SPI 12, a 10-year period, addressing a significant difference based on the drought classification matrix. More details regarding this matrix were explained in the discussion section. Generally, values above 70% can be considered acceptable for drought classification. However, the 54% value

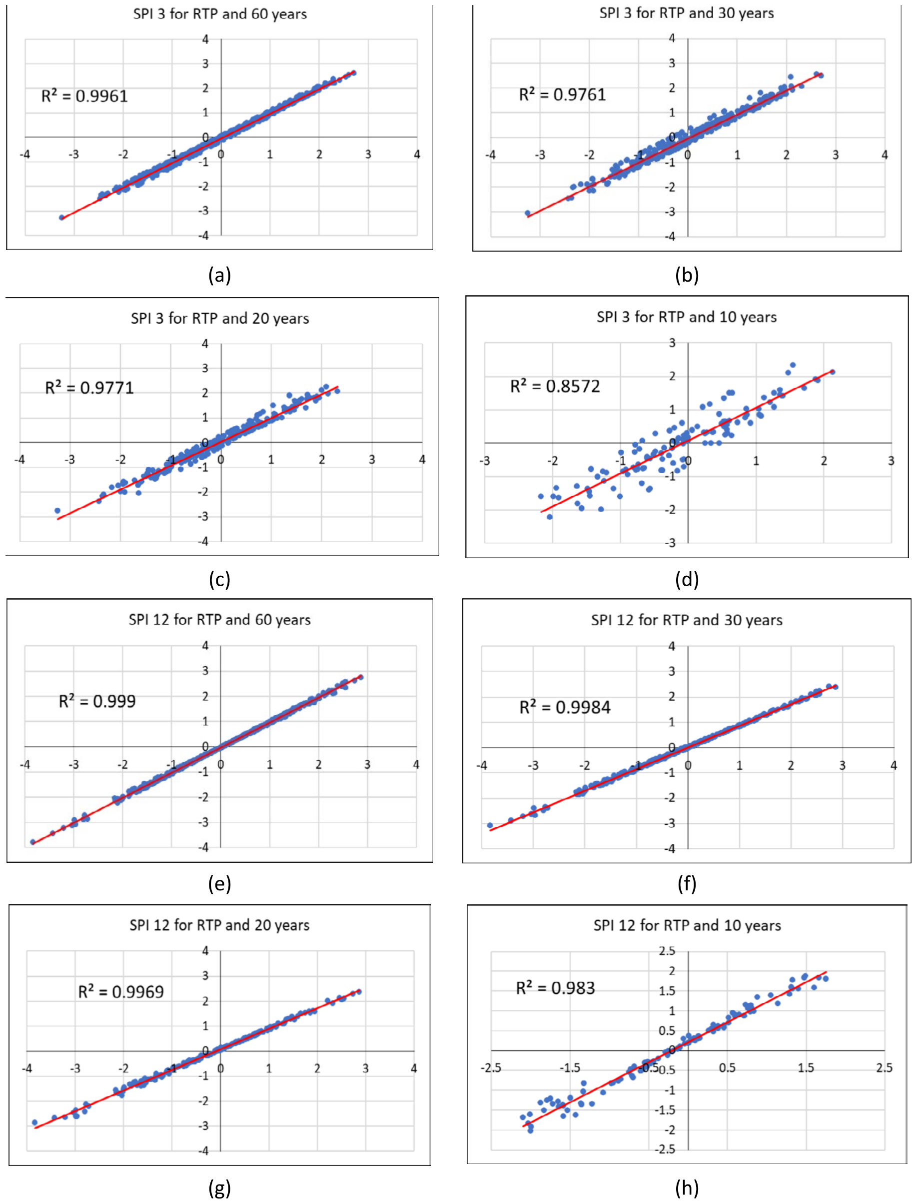

Fig. 2 R^2 between time period scenarios and RTP scenario for SPI 3 and 12 for Florya station

raises significant concerns about managing water resources, particularly in the context of long-term hydrological droughts.

For Karapinar station in Konya city, which is a semi-arid climate area, the results were very similar to the results of Durham station. Table 8 summarizes the main statistical metrics in order to investigate the difference between time period scenarios: CC, RMSE, R^2, and the percentage of the months falling within the same drought

Table 7 Summary of the statistical metrics and innovative drought classification matrix for SPI 3 and 12 for all time period scenarios for Durham station

	SPI 3					
	120 years	90 years	60 years	30 years	20 years	10 years
CC	0.998	0.995	0.992	0.989	0.982	0.977
RMSE	0.059	0.106	0.142	0.209	0.251	0.399
HH	0.059	0.105	0.141	0.208	0.253	0.405
RB	-80.9%	-98.6%	-99.9%	-100.2%	-100.3%	-100.1%
R^2	0.997	0.991	0.983	0.977	0.964	0.954
Drought Classification	94.22%	89.51%	86.91%	80.72%	78.57%	70.34%
	SPI 12					
	120 years	90 years	60 years	30 years	20 years	10 years
CC	1.000	0.999	0.998	0.988	0.991	0.963
RMSE	0.019	0.079	0.123	0.341	0.376	0.669
HH	0.020	0.079	0.122	0.348	0.381	0.661
RB	-99.0%	-100.0%	-100.2%	-100.1%	-100.1%	-100.0%
R^2	0.999	0.998	0.995	0.975	0.981	0.927
Drought Classification	97.83%	92.98%	89.84%	74.21%	68.56%	54.13%

classification using IDCM for Karapinar station. The time period scenarios were 30, 20, and 10 years. They all correlated very strongly with the RTP scenario (59 years) in SPI calculation. The minimum CC was at the minimum time period scenario, giving a comparatively low value (0.926).

The RMSE values for semi-arid regions were acceptable compared to the other areas. The RMSE ranged between 0.2 and 0.431. For SPI 3 and 12, the maximum error was at the same time period scenario. The 30-year time period scenario showed the greatest agreement with the RTP scenario for SPI 12. In comparison with Florya and Durham stations, the RB values were different, ranging from -99.8% to -137.5%. RB values were negative, indicating an underestimation from the 59-year (RTP) scenario. The 20-year time period scenario had the most unfavorable estimation, nearly underestimating by -137.5%. This underestimation differed by about 38% from other time period scenarios.

For Karapinar station, the R^2 values were acceptable and more than 0.85. The SPI values for all time period scenarios exhibited a suitable alignment with the regression model, signifying an adequate goodness of fit. Figure 5 (a-f) showed the R^2 and the regression models for each time period scenario and RTP scenario. The red line represented the regression line. The minimum R^2 was for a short time scale and at the minimum time period scenario. (Fig. 5. f). Using the newly proposed innovative drought classification matrix (Table 5), the percentage of the months within the same drought classification was over approximately 70%, except for the long timescale at the 10-year time period (49.54%). The 10-year time period scenario was the changing year for long timescale analyses. In the worst case, the 10-year time period scenarios can be accepted as the acceptable/minimum time period scenario. More details regarding the drought classification matrix and acceptable scenarios were explained in the discussion section.

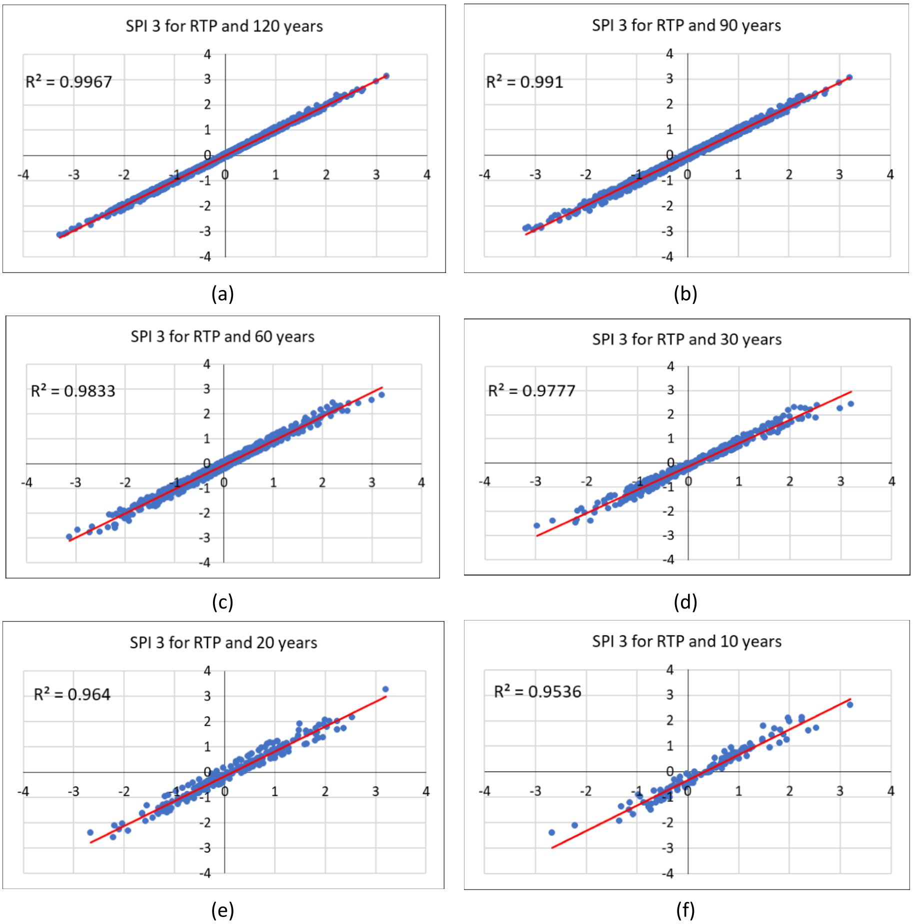

Fig. 3 Coefficient of determination (R^2) between time period scenarios and RTP scenario for SPI 3 for Durham station

3.2 Innovative Drought Classification Matrix

3.2.1 Innovative Drought Classification Matrix for Florya Station

The newly proposed IDCM aimed to understand and investigate comprehensively the differences and similarities between any two sets based on the drought classification. This research used the matrix to compare the RTP scenario with other time period scenarios. For Florya station, the 60-year time period scenario for both short and long timescales gave very similar results compared to the RTP scenario. 94%0.3% and 96.2% of the months were within the same drought classification, and the remaining months were within one different drought classification (Fig. 6. a and c). Also, the drought classification for these scenarios was underestimated according to RTP. For example, 11 months were moderate wet (MW) based on RTP and were normal (N) based on a 60-year time period scenario for SPI 12 (Fig. 6. c). The summation of drought months was more than drought months for

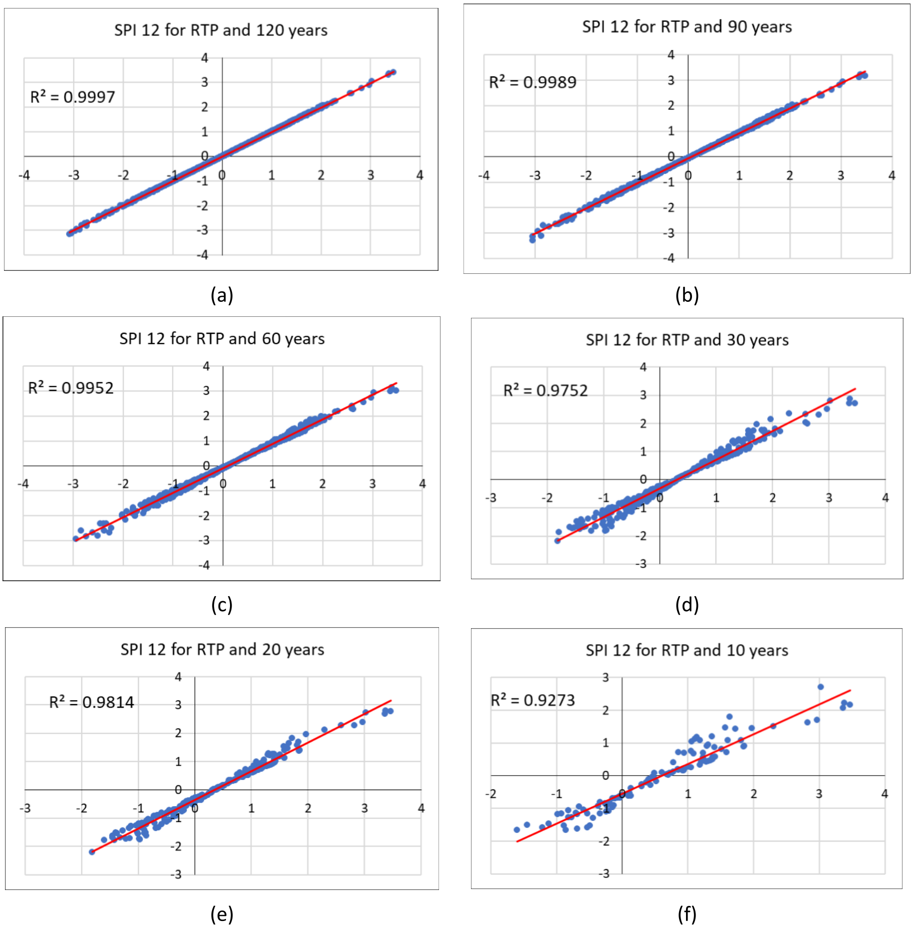

Fig. 4 Coefficient of determination (R^2) between time period scenarios and RTP scenario for SPI 12 for Durham station

Table 8 Summary of the statistical metrics and innovative drought classification matrix for SPI 3 and 12 for all time period scenarios for Karapinar station

	SPI 3			SPI 12		
	30 years	20 years	10 years	30 years	20 years	10 years
CC	0.982	0.971	0.923	0.999	0.996	0.996
RMSE	0.203	0.264	0.431	0.096	0.237	0.415
HH	0.199	0.256	0.420	0.092	0.214	0.370
RB	-114.81%	-108.31%	-100.3%	-104.8%	-137.5%	-99.8%
R^2	0.965	0.944	0.859	0.997	0.992	0.991
Drought Classification	84.36%	78.99%	71.19%	91.40%	66.81%	49.54%

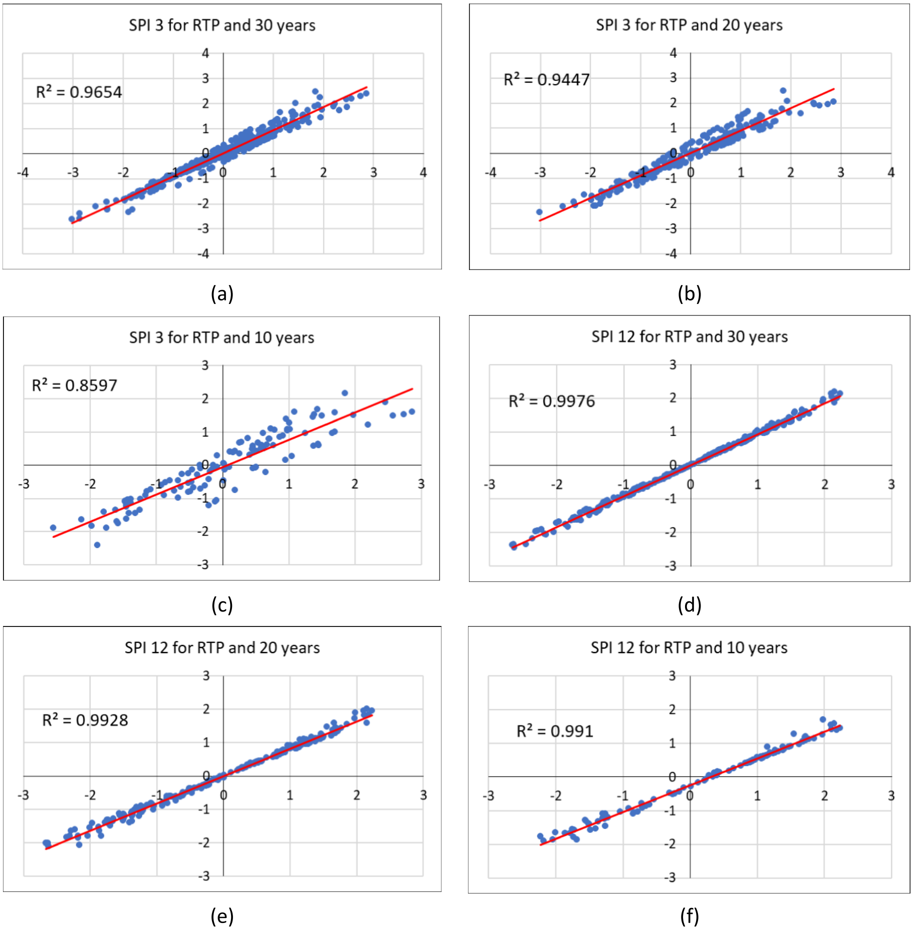

Fig. 5 Coefficient of determination (R^2) between time period scenarios and RTP scenario for SPI 3 and SPI 12 for Karapinar station

RTP. Generally, the summation of each drought classification was approximately the same for the 60-year time period scenarios for both SPI3 and SPI12. However, the results of the 10-year time period scenario were inconsistent with RTP; the percentage was acceptable (about 77%). No months were addressed as extremely wet (EW) for SPI12 at the 10-year time period (Fig. 6. d). The maximum number of months was within the normal (N) classification due to its wide range (from -1 to 1).

3.2.2 Innovative Drought Classification Matrix for Durham Station

This research and the new matrix were applied to Durham station as one of the most continuously recorded data and with a rainy climate. The newly proposed innovative drought classification matrix was used to determine the number of months within each drought classification. The 120-year time period scenario was very similar to the RTP scenario, with a more than 90% percentage (Figure 7. a and c). For SPI 3, the 120-year time period

SPI 3	60 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	15	1	0	0	0	0	0	16
	SW	2	32	3	0	0	0	0	37
	MW	0	2	60	6	0	0	0	68
	N	0	0	2	482	9	0	0	493
	MD	0	0	0	2	47	8	0	57
	SD	0	0	0	0	2	28	4	34
	ED	0	0	0	0	0	0	13	13
	Sum	17	35	65	490	58	36	17	677_94.3%

a

SPI 3	10 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	1	0	0	0	0	0	0	1
	SW	1	3	0	0	0	0	0	4
	MW	1	2	7	2	0	0	0	12
	N	0	2	4	73	3	1	0	83
	MD	0	0	0	3	5	2	0	10
	SD	0	0	0	0	2	4	0	6
	ED	0	0	0	0	0	1	1	2
	Sum	3	7	11	78	10	8	1	94_79.7%

b

SPI 12	60 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	19	1	0	0	0	0	0	20
	SW	0	25	2	0	0	0	0	27
	MW	0	1	60	11	0	0	0	72
	N	0	0	0	485	5	0	0	490
	MD	0	0	0	0	52	4	0	56
	SD	0	0	0	0	1	25	2	28
	ED	0	0	0	0	0	0	16	16
	Sum	19	27	62	496	58	29	18	682_96.2%

c

SPI 12	10 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	0	0	0	0	0	0	0	0
	SW	0	3	0	0	0	0	0	3
	MW	0	6	3	0	0	0	0	9
	N	0	0	5	67	0	0	0	72
	MD	0	0	0	1	7	1	0	9
	SD	0	0	0	0	8	4	1	13
	ED	0	0	0	0	0	3	0	3
	Sum	0	9	8	68	15	8	1	84_77.06%

d

Fig. 6 Innovative drought classification matrix for Florya station for 60 and 10-year time period scenarios at SPI3 and SPI12

SPI 3	120 years							
RTP Scenario	EW	SW	MW	N	MD	SD	ED	Sum
EW	31	2	0	0	0	0	0	33
SW	0	59	9	0	0	0	0	68
MW	0	4	114	15	0	0	0	133
N	0	0	14	945	11	0	0	970
MD	0	0	0	8	116	3	0	127
SD	0	0	0	0	11	56	2	69
ED	0	0	0	0	0	4	34	38
Sum	31	65	137	968	138	63	36	1355_94 %

a

SPI 3	10 years							
RTP Scenario	EW	SW	MW	N	MD	SD	ED	Sum
EW	3	3	0	0	0	0	0	6
SW	1	2	4	1	0	0	0	8
MW	0	1	3	9	0	0	0	13
N	0	0	0	70	14	0	0	84
MD	0	0	0	0	3	2	0	5
SD	0	0	0	0	0	0	0	0
ED	0	0	0	0	0	0	2	2
Sum	4	6	7	80	17	2	2	83_70%

b

SPI 12	120 years							
RTP Scenario	EW	SW	MW	N	MD	SD	ED	Sum
EW	22	3	0	0	0	0	0	25
SW	1	62	3	0	0	0	0	66
MW	0	2	164	4	0	0	0	170
N	0	0	0	948	4	0	0	952
MD	0	0	0	4	121	3	0	128
SD	0	0	0	0	2	53	2	57
ED	0	0	0	0	0	3	28	31
Sum	23	67	167	956	127	59	30	1398_97.8%

c

SPI 12	10 years							
RTP Scenario	EW	SW	MW	N	MD	SD	ED	Sum
EW	4	3	0	0	0	0	0	7
SW	0	1	5	4	0	0	0	10
MW	0	0	5	19	0	0	0	24
N	0	0	0	46	13	5	0	64
MD	0	0	0	0	2	1	0	3
SD	0	0	0	0	0	1	0	1
ED	0	0	0	0	0	0	0	0
Sum	4	4	10	69	15	7	0	59_54%

d

Fig. 7 Innovative drought classification matrix for Durham station for 60 and 10-year time period scenarios at SPI3 and SPI12 expected the drought classification like the RTP with a rate of 94%, and the remaining months were within only one drought classification, indicating a very strong relation between these scenarios (Figure 7. a). Nevertheless, the 10-year time period reported only 70% of the months within the same drought classification, and the remaining months were underestimated regarding RTP. For SPI 12 (long timescales), the results for the 120-year time period were better. The percentage of the months within the same drought classification was about 98% (more than the percentage for SPI 3) (Figure 7. c). Also, the remaining months were within one different drought classification in the underestimation region based on the innovative drought classification matrix (Table 5).

For SPI 12, the 10-year time period scenario gave inconsistent results compared to other scenarios. For example, the percentage of the same months was 54% (Figure 7. d). It can be noted that approximately 50% of the months are within the same drought classification, and the remaining 50% were underestimated regarding RTP. There were no values under the diagonal grey-shaded cells (overestimation region). Also, the number of dry months was 4 and 22, based on the RTP scenario and 10-year time period scenario, respectively.

3.2.3 Innovative Drought Classification Matrix for Karapinar Station

Karapinar station as a semi-arid climate was applied in this research. The number of months and summation within each drought classification have been determined based on the newly proposed innovative drought classification matrix. The 30-year time period scenario was similar to the RTP scenario (59 years), with 84,35% and 91.4% for SPI 3 and SPI 12, respectively (Fig. 8. a and c). For SPI 3, the 60-year time period forecasted the drought classification the same as the RTP with an acceptable rate, and the remaining months were overestimated compared to other time period scenarios for Karapinar station. The summation of dry months were 68 and 61 for the RTP scenario and 30-year time period scenario, respectively. For the 10-year time period scenario at SPI 3, the total dry months were equal (24 months) (Fig. 8. b).

The 10-year time period at SPI 12 reported only 49.54% of the months within the same drought classification, and the remaining months were underestimated regarding RTP (Fig. 8. d). For example, 26 months were moderately wet based on the RTP scenario and normal (N) based on the 10-year time period scenario. Also, 4 months were extremely dry (ED) depending on the RTP scenario, while the same months were severely dry (SD) depending on the 10-year scenario for SPI 12. More details are shown in Fig. 8. a-d.

4 Discussion

Time period scenarios were able to reasonably catch the RTP scenario over different stations and climates, with strong CC and R^2. Generally, all time period scenarios showed the same negative RB across each station, indicating that short time periods can be utilized for regions facing data availability challenges. At the same time, the differences and similarities between these time period scenarios and RTP scenarios were investigated based on statistical metrics and the newly proposed IDCM. This matrix has the advantage of being used in different applications in drought and climate change studies. For example, to find the differences between any two drought indices, two spatially different stations, and two different temporally scenarios.

SPI 3	30 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	4	4	0	0	0	0	0	8
	SW	2	6	8	0	0	0	0	16
	MW	1	7	22	8	0	0	0	38
	N	0	0	6	219	3	0	0	228
	MD	0	0	0	10	30	1	0	41
	SD	0	0	0	0	2	15	2	19
	ED	0	0	0	0	0	2	6	8
	Sum	7	17	36	237	35	18	8	302_84.35%

a

SPI 3	10 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	0	3	2	0	0	0	0	5
	SW	1	2	2	1	0	0	0	6
	MW	0	3	3	5	0	0	0	11
	N	0	0	5	64	3	0	0	72
	MD	0	0	0	3	11	1	0	15
	SD	0	0	0	0	2	4	1	7
	ED	0	0	0	0	0	2	0	2
	Sum	1	8	12	73	16	7	1	84_71.18%

b

SPI 12	30 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	5	1	0	0	0	0	0	6
	SW	0	15	5	0	0	0	0	20
	MW	0	0	36	6	0	0	0	42
	N	0	0	0	214	0	0	0	214
	MD	0	0	0	7	28	0	0	35
	SD	0	0	0	0	6	13	0	19
	ED	0	0	0	0	0	5	8	13
	Sum	5	16	41	227	34	18	8	319_91.4%

c

SPI 12	10 years								
RTP Scenario		EW	SW	MW	N	MD	SD	ED	Sum
	EW	0	2	3	0	0	0	0	5
	SW	0	1	10	2	0	0	0	13
	MW	0	0	0	26	0	0	0	26
	N	0	0	0	37	3	0	0	40
	MD	0	0	0	0	10	2	0	12
	SD	0	0	0	0	3	6	0	9
	ED	0	0	0	0	0	4	0	4
	Sum	0	3	13	65	16	12	0	54_49.54%

d

Fig. 8 Innovative drought classification matrix for Karapinar station for 60 and 10-year time period scenarios at SPI3 and SPI12

Based on (WMO 2008), it was recommended that 30 years is the ideal time period, and the drought evaluation and assessment could not occur for a time period less than 30 years. Also, IPCC (2018, 2021, 2023) reported that data availability is one of the most challenging problems for conducting drought and climate change studies in developing countries. Based on the results of this research, the acceptable/minimum time period for monthly records in some cases can be 10 years instead of 30 years. As one of the most significant contributions of this research, the acceptable time period ranged between 10–20 years, allowing the countries that started measuring weather data from (2002–2012) to conduct drought evaluation and assessment. Based on both statistical metrics and IDCM, the 10-year time period can be used with an 80–90% confidence level for short timescales. However, for long timescales, the 20-year time period is better, with a 75–85% confidence level. The IDCM addressed that time period scenarios often underestimated the SPI values, which agreed with the negative RB results.

Drought evaluation and assessment depend on several steps, from selecting the time period and data set, selecting and fitting a cumulative distribution function (CDF), and transforming the fitted CDF into a normal CDF. In general, using the longest available time period is recommended and gives the most accurate results. The importance of the time period and data set came from the time period affecting all following analyses and evaluation processes. Despite its importance, the existing literature within our current knowledge does not adequately cover the effect of time periods on drought evaluation and assessment, leading to a noticeable gap in the available knowledge base. Consequently, the absence of relevant studies addressing this subject minimizes our ability to grasp the full framework of its impact. For that reason, investigating the difference between several time period scenarios and RTP scenarios allows us to fill the gap and conduct drought evaluation and assessment in countries facing data availability challenges. Using 10 years of qualified and continuous data for drought evaluation and assessment is better than doing nothing in these countries (Karbasi et al. 2023; Vaheddoost et al. 2023).

The acceptable/minimum and optimal time period scenario differs from region to region and is based on climate. Nevertheless, this research used different stations and climates to generalize the results, and it can be accepted that the 10-year time period is the acceptable/minimum time period for short timescales. And the 20-year time period is the acceptable/minimum time period for long timescales. For example, continuous data of 20 years is vital for hydrological droughts and studies. For example, a longer time period is preferable to study the deficits in water availability in rivers, lakes, and groundwater. Also, a longer time scale, such as a 12-month time scale, is also vital for hydrological drought evaluations. But, for meteorological and agricultural drought evaluation and assessment, 10 years is sufficient. Regarding the optimal time period, 30–60 years are optimal. These time periods give very similar results compared to the RTP scenario. Abu Arra and Şişman (2023) and Şen (2021) mentioned that drought evaluation and assessment are vital for drought mitigation and adaptation plans and for achieving sustainable development goals (SDGs). Based on the main outcomes of this research, the drought evaluation and assessment can be conducted with high reliability in countries facing data availability problems, allowing researchers to comprehensively understand the importance and differences of various time period scenarios for different climates.

The newly proposed matrix serves as an integral component within the comprehensive framework and processes employed for drought assessment and evaluation. IDCM facilitates the evaluation and comparison of various scenarios, different locations, and different drought indices using drought classification. In traditional approaches, drought assessment relies on the drought index and characteristics. However, the IDCM goes beyond this conventional methodology by systematically comparing different scenarios based on drought classification. Unlike classical approaches, where the assessment is predominantly focused on individual drought indices and their characteristics, the IDCM provides a structured means to discern and quantify differences between two distinct drought indices. This enhancement in the evaluation process contributes to a better understanding of drought dynamics, allowing for informed decision-making and resource allocation in the face of evolving climatic conditions.

5 Conclusion

Assessing and evaluating drought is paramount in managing water resources and tackling the impacts of drought and climate change. Drought indices, such as SPI, are pivotal tools in this evaluation, relying on the time period and datasets used. Understanding the significance and implications of this time period is critical for a comprehensive understanding and evaluation of drought occurrences. This comprehension aids decision-makers in developing effective strategies and policies. It holds particular importance for regions facing challenges in data availability, offering them a means to conduct drought evaluations based on the acceptable/minimum time period. Investigating the relevance and effects of these time periods based on statistical metrics and the newly proposed drought classification allows for a better understanding of drought dynamics, fostering resilience and preparedness in water scarcity and climate change. To implement the IDCM and find its effectiveness, as well as determine the acceptable/minimum and optimal time period for drought studies, three different climatic regions were selected: Karapinar station, Florya station in Türkiye, and Durham station in the United Kingdom. The key findings of the research are as follows:

1- The time period scenarios aligned considerably with the RTP scenario across various stations and climates, exhibiting strong CC and a high R^2.
2- The newly proposed IDCM allows for a comprehensive comparison between any two scenarios, presenting versatility in its applicability within drought and climate change studies. It allows for various applications, such as comparing different temporal and spatial scenarios and different drought indices.
3- The IDCM revealed that the SPI values were frequently underestimated in time period scenarios, aligning with the observed negative RB outcomes.
4- Based on the outcomes from diverse stations and climates in this research, it is evident that a 10-year time period is sufficient as an acceptable/minimum for short timescales. Conversely, for longer timescales, a 20-year time period is deemed acceptable/minimum time period.
5- Considering the main findings of this research, including acceptable/minimum time period, countries encountering challenges with data availability can rely on shorter time periods for drought assessment.

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Declarations

Ethical Approval Compliance with Ethical Standards.

Consent for Publication Not applicable.

Consent to Participate Not applicable.

Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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