Tellus A
Dynamic Meteorology and Oceanography

ORIGINAL RESEARCH PAPER

STOCKHOLM UNIVERSITY PRESS

Probabilistic Assessment of Future Drought Characteristics under the Quality Boosted Regional Drought Index

VEYSI KARTAL
MUHAMMAD AHMAD
OLAYAN ALBALAWI
ZULFIQAR ALI
SAAD SH. SAMMEN
MIKLAS SCHOLZ
AAMINA BATOOL

*Author affiliations can be found in the back matter of this article

ABSTRACT

Water is one of the most essential components for sustaining human and other forms of life; thus, it must be supplied to meet life's necessities. Understanding the consequences of global warming and the trends in climate change is essential for the effective operation and strategic planning of water resource projects. Consequently, accurately and efficiently characterizing drought at the regional level constitutes a more complicated and challenging obstacle. The primary goal of this study is to predict future drought characteristics in Turkey's Konya Closed Basin (KCB) region by employing the Quality Boosted Regional Drought Index (QBRDI) framework. This study uses precipitation time series data from nine sites spanning 57 years to examine drought features in Turkey's KCB. The validity of the weighting procedure in QBRDI is compared with the findings of the simple model average (SMA) using statistical measures: root mean square error (RMSE) and relative absolute error (RAE). It is observed that the RMSE value (6.282) for the weighting procedure in QBRDI is lower than the RMSE value (15.158) computed within SMA. Similarly, the value of RAE across weighting procedure in QBRDI is 0.08525, while that for SMA is 1.409. The lower values of both RMSE and RAE indicate that the weighting procedure utilized in QBRDI is more reliable than that used in the SMA. Consequently, these measurements suggest that the weighting procedure utilized in QBRDI possesses higher reliability and validity for drought assessment than that in the SMA. For application, the long-term phenomenon of drought is determined using the steady-state probability of Markov chain. The findings from steady-state probabilities show that extreme drought tends to have a higher probability than extreme wet across most timescales. This pattern suggests that drought events are marginally more probable than extreme wet events, reinforcing the need for drought-related risk evaluation and mitigation measures. In addition, the Mann–Kendall test is employed to assess the presence of a monotonic trend, while Sen's slope estimator is used to quantify the magnitude of that trend, as it serves as a complement to the Mann–Kendall test by providing a robust estimate of the trend slope.

CORRESPONDING AUTHOR:
Zulfiqar Ali
College of Statistical Sciences, University of the Punjab, Lahore, Pakistan
zulfiqar.stat@pu.edu.pk

KEYWORDS:
Global Warming; Water Resource; Quality Boosted Regional Drought Index (QBRDI); Monotonic Trend

TO CITE THIS ARTICLE:
Kartal, V., Ahmad, M., Albalawi, O., Ali, Z., Sammen, S.S., Scholz, M. and Batool, A. (2025) Probabilistic Assessment of Future Drought Characteristics under the Quality Boosted Regional Drought Index. *Tellus A: Dynamic Meteorology and Oceanography*, 77(1): 240–253. DOI: https://doi.org/10.16993/tellusa.4066

1. INTRODUCTION

Global warming, combined with changing climate change, stands as the main industrial revolution outcome, influencing energy demand, environmental sustainability, and economic stability (Lorente *et al.*, 2023). Multiple deadly effects, including mortality rates, droughts, heat waves, glacier melting, and floods, result from global climate change (Rajak, 2021). Over the past few years, concerns have arisen that global climate change may lead to an increased risk of droughts. Droughtis defined as a deficit of water over certain years, and is a major consequence of global warming (Cook *et al.*, 2020; Jehanzaib *et al.*, 2020). Therefore, immediate attention is essential to accurately and precisely notify decision-makers, environmentalists, and hydrologists about drought characteristics (Batool *et al.*, 2023). Studies have analyzed the effects of drought on the economy, agriculture, and water resources (Dost and Kasiviswanathan, 2023). The National Drought Mitigation Center (NDMC) defines drought through its official description as 'a prolonged period of deficient rainfall leading to water scarcity' (Yihdego, Vaheddoost and Al-Weshah, 2019). This is a multidimensional natural event that has serious effects on ecosystems, agriculture, water supplies, and entire populations. The manifestation of drought results from complex climate-related interplay that extends over broad geographical regions and longer periods than other climate-based natural hazards. Drought stands as one of the most damaging natural events economically (Mukherjee, Mishra and Trenberth, 2018; Ali *et al.*, 2022). Drought events fall into four climatological classifications: hydrological, meteorological, agricultural, and socioeconomic (Wang *et al.*, 2016). The management of drought impacts needs proper identification and evaluation of drought dynamics. Drought assessment and characterization require standardized toolkits as part of their process (Erhardt and Czado, 2018). Therefore, many researchers have developed numerous drought monitoring tools and indices (Ali *et al.*, 2020; Ahmad *et al.*, 2023). Svoboda and Fuchs (2016) discussed the most widely utilized drought indices in drought-prone regions for making informed decisions in early warnings. Furthermore, predicting drought attributes relies on probabilistic techniques combined with machine-learning approaches (Niaz *et al.*, 2022). The use of a copula for drought assessment has been explored in earlier studies (Won *et al.*, 2020; Tian *et al.*, 2023).

More recently, Saha *et al.* (2023) developed a new drought monitoring strategy by using a deep learning algorithm in the West Bengal region of India. The development of a hybrid index based on an advanced machine-learning copula and a probability model is considered an accurate technique for monitoring drought characteristics (Jiang *et al.*, 2023).

The accurate determination of drought characteristics remains one of the most difficult operations for local-level assessment. Previous studies have primarily focused on station-based drought assessments, which are often time-consuming and limited in scope due to resource constraints. Understanding climate characteristics by monitoring and evaluating droughts within specific areas is vital. Recently, Batool *et al.* (2023) introduced a novel index—the Standardized Composite Index for Climate Extremes (SCICE)—for regional drought assessment. Thus, aggregating individual distributions provides a more comprehensive representation of drought-related variables. The variability in extreme climate events, particularly the dynamic patterns of precipitation, remains one of the most challenging issues globally. To the best of our knowledge, no study has been conducted at the regional level in Turkey for an accurate and long-term assessment of drought behavior. The research aim is to correctly forecast upcoming drought profiles within the Konya Closed Basin (KCB), Turkey. Therefore, this study developed a new index, the Quality Boosted Regional Drought Index (QBRDI). The methodology of QBRDI is based on the research conducted by Ali *et al.* (2023). The implementation of QBRDI relies on ensemble data from nine stations to decrease the uncertainty that occurs with individual stations. Numerous statistical techniques, including non-parametric standardization, Mann–Kendall (MK) trend analysis and other approaches, have been used for drought assessment and consequence evaluation. In this application, nine meteorological stations in the Konya region of Turkey have been analyzed.

The structural outline of this paper is documented as follows: Section 2 presents the materials and methods, including the framework of study and different existing methods. Section 3 contains a summary of the obtained results alongside their subsequent evaluation. Section 4 provides the conclusion.

2. MATERIALS AND METHODS

2.1. STUDY AREA AND DATA COLLECTION

This study presents a thorough investigation of the KCB in Turkey. The central Anatolian semi-arid area in Turkey occupies an area of 53,850 km^2 and holds special climatic conditions and ecological elements. The KCB region contains multiple drainage basins, while Tuz (Salt) Lake and Beysehir Lake achieve top status as Turkey's largest freshwater lakes, serving as the region's main water reservoirs. Drought monitoring tools are helpful for early warnings and mitigation policies. Several authors have suggested numerous drought indicators and monitoring tools to determine drought severity (Citakoglu & Coşkun, 2022; Soylu Pekpostalci *et al.*, 2023). This study developed a new drought index (QBRDI) to assess the spatial-temporal distribution of drought in Turkey's KCB region. The temporal dataset from nine meteorological stations in Turkey was collected and standardized before. Analyzed data originated from the General Directorate of Meteorology (MGM) of Turkey. Outliers were removed through a weighting scheme, where high weights were given to low values and low weights to high values, among other adjustments. Each station has 696 observations with a time frame of 57 years from 1965 to 2022. The spatial geographical distribution of these stations is provided in Figure 1 with geographic attributes—latitude, longitude, and altitude—while the observational view of these stations is shown in Figure 2. Table 1 presents details about the nine KCB stations in Turkey with geographic attributes—latitude, longitude, and altitude. This spread encompasses the expansive landscapes of the KCB, from vast plains to mountainous regions, in addition to its topographical shapes.

2.2. PROBABILISTIC APPROACH

Fitting an accurate and precise approach is essential for developing standardized drought indicators (Batool *et al.*, 2024). Numerous methodologies have been employed in prior studies to achieve standardization objectives, with the most familiar ones being parametric and non-parametric techniques. In this study, two approaches, parametric and non-parametric, are utilized for standardization. Parametric approaches are the K-Component Gaussian Mixture Model (K-CGMM) (McLachlan & Peel, 2000) and univariate probability models. The univariate probability models are evaluated using the 'fitDistr' (Spiess, 2018) function from the Propagate package in R software. Univariate probability models are suitable for unimodal data. Previously, Abbas *et al*. (2022) used the 'fitdistrplus' and 'Propagate' package to fit distinct univariate distributions and selected the best one. Univariate probability models are not appropriate for fitting and computing cumulative distribution function (CDF) in the case of multimodal data. K-CGMM is an unsupervised technique utilized for modeling the multimodal data (Batool *et al.*, 2025). K-CGMM is suitable for data that have numerous peaks. K-CGMM splits data into distinct components and fits a Gaussian distribution to each component of the data. It contains two parameters: weights and mean (or variance). For a concise and extensive overview of K-CGMM, see Batool *et al*. (2023). In some cases, the *k*th component shows zero variability, causing problems with K-CGMM. Then, determining CDF using a non-parametric technique leads to an accurate inference. The ultimate objective of each approach is to standardize QBRDI data by estimating the CDF from the underlying probability distributions. Hao and AghaKouchak (2014) employed non-parametric techniques to develop a multivariate standardized drought index (MSDI) for assessing drought behavior. Similarly, Ali *et al*. (2020) deployed the parametric approach in the context of drought assessment. After estimating the CDF using parametric or non-parametric techniques, standardization is performed based on the transformation outlined by Ali *et al*. (2017).

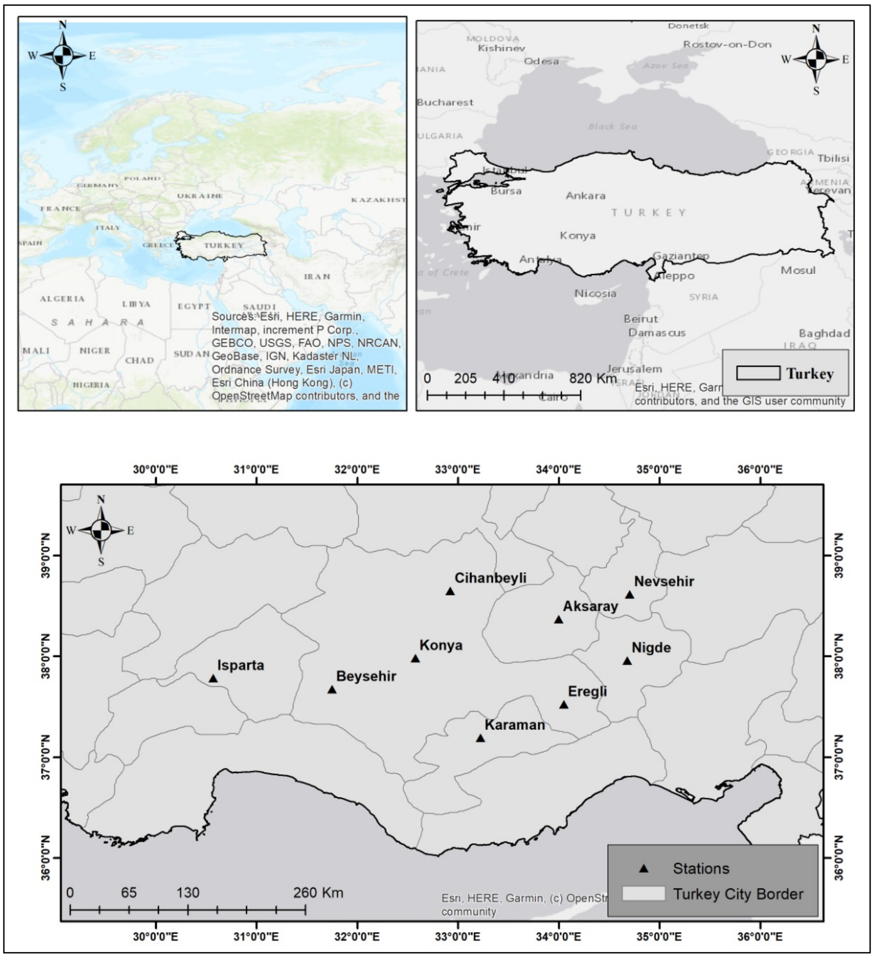

Figure 1 Map of the study site showing nine selected meteorological stations in the Konya Closed Basin located in Turkey.

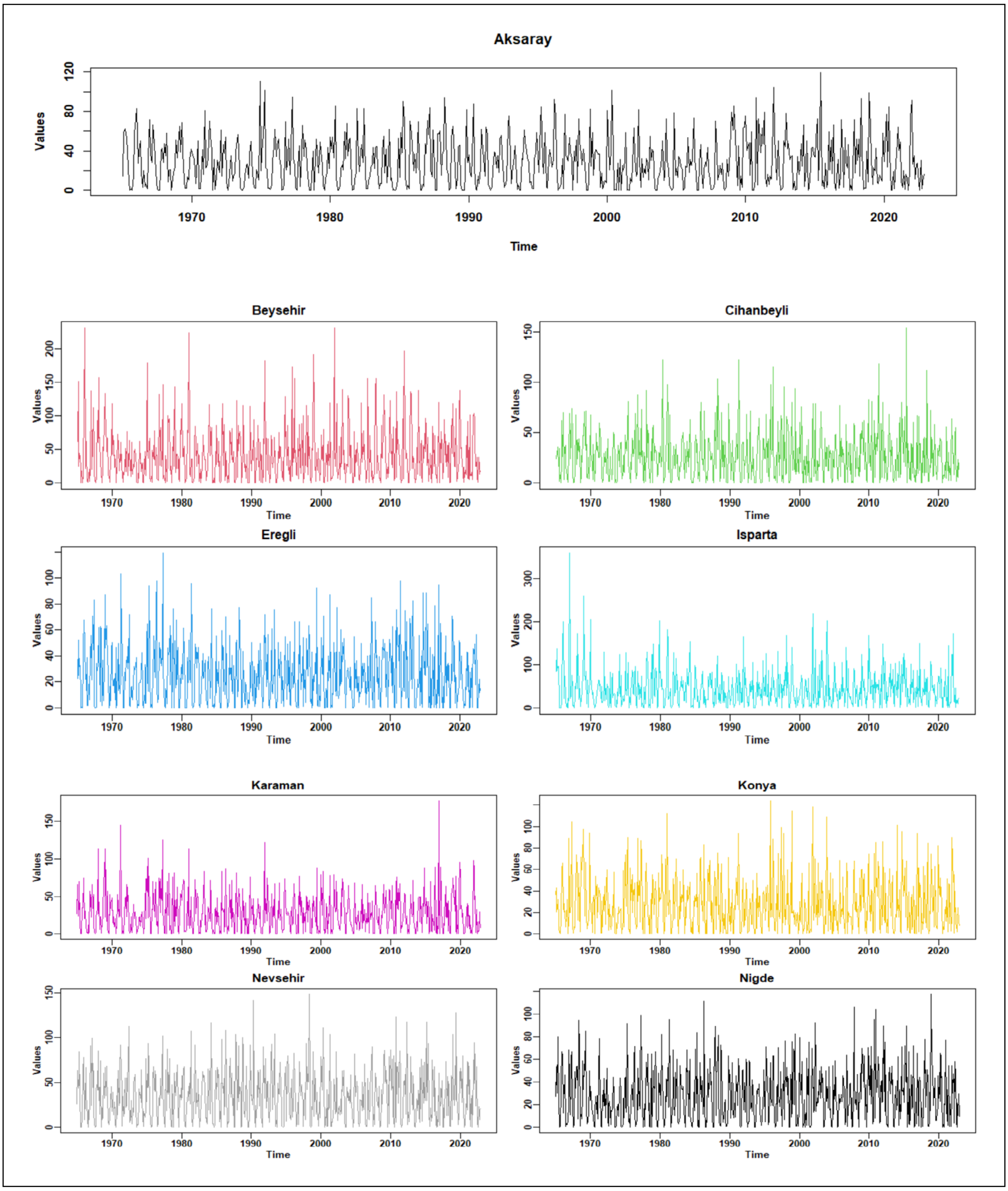

Figure 2 Temporal representation of selected nine meteorological stations in the Konya Closed Basin located in Turkey.

STATION NAME	LATITUDE (°N)	LONGITUDE (°E)	ALTITUDE (M)
Aksaray	38.3705	33.9987	970
Beysehir	37.6777	31.7463	1141
Cihanbeyli	38.650578	32.92186	973
Eregli	37.5255	34.0485	1046
Isparta	37.7848	30.5679	997
Karaman	37.1932	33.2202	1018
Konya	37.9837	32.574	1031
Nevsehir	38.6163	34.7025	1260
Nigde	37.9587	34.6795	1211

Table 1 Information about the nine meteorological stations in the Konya Closed Basin, Turkey.

2.3. TREND ANALYSIS

2.3.1. Steady-state probability of Markov chain

Andrey Markov introduced the concept of Markov chains, a method involving steady-state probabilities (Markov, 1906). This study employed a first-order Markov chain, a discrete-time stochastic process that models how a random variable evolves at discrete points in time. In a first-order Markov chain, the probability of the future state depends solely on the present state, without considering earlier states. Therefore, this method is known as memoryless. The concept of compensating probabilities in Markov chains, developed by Keilson and Syski (1974), has received considerable attention in probability theory. It has broad applications across various real-world domains, including computer science, biology, and physics (Rajwar, Deep & Das, 2023). Markov chains have been employed to optimize the performance of different algorithms and to analyze population dynamics (Wang *et al.*, 2020). A Markov chain examines the past transitory behavior of a process and contributes significantly to predicting uncertain phenomena. The mathematical framework of this method is built upon the transaction probability matrix (P), which plays a significant role in describing the behavior and transitions of Markov chains. This matrix captures the probabilities of transitioning from one state to another in the chain. In a Markov chain with k states, matrix P has an order of $n \times n$, where each entry represents the probability of transitioning from state i to j in a one-time step (see Equation 1). The rows correspond to the current states, and the columns represent the possible subsequent states. Each value within the matrix ranges between 0 and 1, and the sum of each row or column should be equal to 1:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix}. \tag{1}$$

The elements in the matrix can be leveraged to quantify the stochastic state space's transient probabilities. The long-term progression of system states is determined by the process's limiting distribution or stationary probabilities, also known as steady-state probabilities.

2.3.2. MK test statistics

MK test, a widely used non-parametric method for detecting trends in temporal data, was originally developed by Mann (1945) and later refined by Kendall (1975) for more accurate trend assessment. This method compares both positive and negative trends in data collected over time. The MK test serves as an alternative to the parametric linear regression test, which fits a linear model to data and determines trend significance through model coefficients. The MK test has wide applications in economics, hydrology, and environmental sciences (Katipoğlu, 2023; Kheyruri *et al.*, 2023). Researchers employ this technique to analyze temperature, precipitation, river flow, and stock market data trends (Reddy and Saravanan, 2023). The mathematical foundation of the test lies in the $\mathcal{S}$ statistic, which represents the signs of pairwise differences between each data point in the temporal series. The variance of this statistic is computed from the tied groups within the data, as illustrated in the equations below:

$$Z_{MK} = \begin{cases} 0 & \mathcal{S} = 0 \\ \dfrac{\mathcal{S}-1}{\sqrt{\mathrm{VAR}(\mathcal{S})}} & \mathcal{S} > 0 \\ \dfrac{\mathcal{S}+1}{\sqrt{\mathrm{VAR}(\mathcal{S})}} & \mathcal{S} < 0 \end{cases} \tag{2}$$

$$\mathcal{S} = \sum_{l=1}^{n-1} \sum_{k=l+1}^{n} \mathrm{sgn}(x_k - x_l) \tag{3}$$

$$\mathrm{sgn}(x_l - x_k) = \begin{cases} 1 & \text{if } (x_l - x_k) > 0 \\ 0 & \text{if } (x_l - x_k) = 0 \\ 1 & \text{if } (x_l - x_k) < 0 \end{cases} \tag{4}$$

$$\mathrm{VAR}(\mathcal{S}) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{\mathcal{G}} \mathcal{T}_p(\mathcal{T}_p - 1)(2\mathcal{T}_p + 5)\right]. \tag{5}$$

In the aforementioned calculations, x_k and x_l represent a time series that consists of n time points each. The parameter $\mathcal{G}$ is used to denote the total count of distinct groups existing within the dataset, whereas $\mathcal{T}_p$ specifically signifies the count of data points within the pth group.

2.3.3. Sen's slope estimator

Sen's slope is used to determine the magnitude of trends introduced by Sen. It was introduced for the first time by Sen (1968) also known as Sen's estimator. This test has gained attention across various fields, including economics, ecological studies, and geophysics (Dost and Kasiviswanathan, 2023; Karanja *et al.*, 2023). Furthermore, this test finds wide applications in analyzing groundwater levels and long-term economic indicators (Swain *et al.*, 2022). In the environmental context, it monitors gradual changes in groundwater levels over time, providing insights into aquifer health (Fu *et al.*, 2022). The calculation involves determining the median of slopes between data points. This is achieved by computing pairwise differences and dividing them by the time lag. The resulting median of these slopes provides a robust estimate of the trend, making it a suitable method for detecting trends even in the presence of outliers. The method uses a linear model to determine the slopes of residuals that remain constant throughout time. Mathematically,

$$f(t) = Qt + C, \tag{6}$$

where $f(t)$ represents the function of the time series under the time period t, Q is the median of Sen's slope estimator, and C represents the constant term.

The formula for Q_i calculation is as follows:

$$Q_i = \text{median}\left(\frac{T_l - T_m}{l-m}\right), \quad (7)$$

where Q is the median of the slope at time l and m ($m < l$), and for M data points, the value of Q can be in two forms:

$$Q = \begin{cases} \frac{M+1}{2}, & \text{if } M \text{ is odd,} \\ \dfrac{M/2 + (M+2)/2}{2}, & \text{if } M \text{ is even.} \end{cases} \quad (8)$$

The positive value of the estimator implies a growing trend, while the negative value suggests a decrease in the trend, and the zero value indicates that no trend happened.

2.4. A FRAMEWORK OF THE STUDY

The current study generates a drought monitoring index called the Quality Boosted Regional Drought Index (QBRDI) for the Konya region of Turkey, covering nine meteorological stations. The methodology of QBRDI is based on the previous study conducted by Ali *et al.* (2023). In QBRDI, we used an X-bar chart to identify out-of-control points (OCP). To aggregate regional data, weights are integrated based on the total number of OCP (TOCP). QBRDI is integrated into four different stages. The integration of each stage is presented below.

2.4.1. Stage 1. Implication of X-bar control chart to detect the OCP

The first stage of QBRDI examines the OCP based on an X-bar control chart. The upper control limit (UCL) and lower control limit (LCL) on the X-bar control chart are based on the averaged temporal data from meteorological stations in certain regions. The mathematical representation of this stage is as follows: let M_i be the temporal data of mean of selected stations. Let ¥ ∈ (LCL, UCL) be the lower and upper limits determined from M_i within X-bar chart. Let Ω ∈ (Total (OCP1), Total (OCP2), Total (OCP3), ..., Total (OCPk)) signify the total values outside the control limits. Mathematically,

$$\text{Total}(\text{OCPk}) = \begin{cases} \sum_{i=1}^{n} h, \; h = 0, \; if\; x_i \text{ lies within UCL and LCL,} \\ \qquad 1, \quad \text{otherwise.} \end{cases} \quad (9)$$

Here, n denotes the total number of points in the time series, and k represents the number of meteorological stations.

2.4.2. Stage 2. Determination of weights

This stage determines the weights for the mean of temporal data of selected meteorological stations. Weights are estimated based on the TOCP of each meteorological station. Let Ω ∈ (Total (OCP1), Total (OCP2), Total (OCP3), ..., Total (OCPk)) signify the vector of total values outside the control limits within each station. It assigns lower weights to observations having a higher number of OCPs and vice versa. Mathematically,

$$e_i = 1 - \frac{\text{Total}(\text{OCP}_i)}{\text{sum}(\text{Total}(\text{OCP}_i))} \quad (10)$$

$$\text{weight}_i = \frac{e_i}{\sum_{i=1}^{k} e_i} \quad (11)$$

where $\Sigma_{i=1}^{k} weight_i$ should be equal to 1, and k is the total number of meteorological stations.

2.4.3. Stage 3. Aggregation

In this stage, weights are assigned to the temporal data of precipitation for the aggregation. Let D_i represent the time series data of precipitation at the ith meteorological station. The aggregated regional temporal precipitation data are obtained by weighting each station's time series data according to their assigned weight. Mathematically,

$$Ac = \sum_{i=1}^{k} D_i * \text{weight}_i, \quad (12)$$

where Ac represents the regional temporal data of precipitation within weight assignments, and D_i is the time series precipitation data of the ith meteorological station.

2.4.4. Stage 4. Development of QBRDI standardization

After assigning weights to the datasets from all nine stations and constructing an ensemble model, the standardization of the QBRDI is assessed. The below mathematical expressions describe the structure of standardization (Ali *et al.*, 2022):

$$\text{QBRDI} = -\left(g + \frac{d_o + d_1 k + d_2 k^2}{1 + e_1 k + e_2 k^2 + e_3 k^3}\right), \quad (13)$$

where

$$g = \sqrt{ln\left(\frac{1}{\{P(x)\}^2}\right)} \quad (14)$$

when

$$0 \le P(x) \le 0.5 \quad (15)$$

and

$$\text{QBRDI} = +\left(g + \frac{d_o + d_1 k + d_2 k^2}{1 + e_1 k + e_2 k^2 + e_3 k^3}\right), \quad (16)$$

where

$$g = \sqrt{ln\left(\frac{1}{\{1 - P(x)\}^2}\right)} \quad (17)$$

when

$$0.5 \le P(x) \le 1, \quad (18)$$

where

$$P(x) = \begin{cases} F(x_i), & \text{if CDF of K–CGMM has smallest BIC,} \\ T(x_i), & \text{if CDF of univariate method has smallest BIC,} \\ P(x_i), & \text{if CDF of non-parametric method has smallest BIC,} \end{cases} \quad (19)$$

where d_o = 2.515517, d_1 = 0.802, d_2 = 0.010328, e_1 = 1.432788, e_2 = 0.189269, and e_3 = 0.001308 are the constants. The standardized data are classified into seven categories based on their values, ranging from extremely dry to extremely wet conditions. These classes are used to categorize drought severity based on standardized values. The classification provides a structured way to interpret drought conditions. The detailed information of seven standardized classes is as follows: extreme drought (ED): –2.00 and less, severe drought (SD): –1.50 to –1.99, moderate drought (MD): –1.00 to –1.49, near normal (NN): –0.99 to 0.99, moderate wet (MW): 1.00 to 1.49, severe wet (SW): 1.50 to 1.99, and extreme wet (EW): 2.00 and above.

2.5. COMPARATIVE METHODS AND METRICS

The weighting procedure in the development of QBRDI undergoes relative assessment within the utilization of the simple model average (SMA) procedure in this research. The cumulative index of the SMA follows this mathematical format:

$$SMA = \frac{1}{N}\sum_{i=1}^{N} S_i, \tag{20}$$

where S_i represents the ith precipitation observation at the meteorological station. The SMA method serves as a performance assessment approach, utilized by numerous researchers (Jose, Vincent & Dwarakish, 2022; Rhymee *et al*., 2022; Ombadi *et al*., 2021). This method is preferred due to its simplicity and ability to combine multiple results into a single index. Previous studies have discussed the limitations of SMA in comparison to more advanced, statistically rigorous methods, highlighting the need for approaches that account for the distribution and variance of the data. Therefore, we justify the use of SMA in this study as a baseline comparison for performance.

In this study, we have utilized the RMSE to determine the relative performance of weighted procedure utilized in QBRDI. Below is the presentation of mathematical expressions that define RMSE:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{K}\left(P_i - \hat{P}_i\right)^2}{n}}, \tag{21}$$

where P_i is the vector of the original dataset of precipitation, $\hat{p}_i$ is the vector of predicted behavior, and k is the total number of selected stations.

The second performance metric is relative absolute error (RAE), which is also extensively employed in the literature. Mathematically,

$$\text{RAE} = \sum_{i=1}^{K}\left|P_i - \hat{P}\right| / \sum_{i=1}^{K}\left|P_i - \overline{P}\right|, \tag{22}$$

where P_i is a vector of an actual data of precipitation and $\hat{p}_i$ is the projection values. When comparing indexes, the lower RAE values indicate the superiority of one index over the other index.

3. RESULTS AND DISCUSSION

3.1. IMPLICATION OF WEIGHTS AND THE VALIDATION OF QBRDI

In this section, the results of weights under QBRDI and the validation of this index are defined. QBRDI aims to reduce bias and outliers and increase data reliability. Table 2 shows the monthly weights for all nine stations from January to December. QBRDI gives more weight to stations having lower number of OCP and less weight to stations having larger numbers of OCP and normalizes the dataset to investigate the drought characteristics. Figure 3 shows the temporal variation of all nine station weights QBRDI. It takes time on the x-axis (1965–2022) and weight values on the y-axis and shows the time difference between each model. The results presented in Table 3 demonstrate the superior performance of the deployed weighting procedure (Ali *et al*., 2023) compared to the SMA method. The RMSE values for the weighting procedure (Ali *et al*., 2023) are consistently lower across all three statistics—minimum, average, and maximum—indicating more accurate predictions. Specifically, the average RMSE under the weighting procedure (Ali *et al*., 2023) is 6.282, whereas SMA produces a much higher average RMSE of 15.158. Additionally, the maximum

STATIONS	JAN.	FEB.	MAR.	APR.	MAY	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
Aksaray	0.125	0.122	0.115	0.109	0.121	0.121	0.121	0.119	0.117	0.117	0.12	0.121
Beysehir	0.094	0.093	0.104	0.115	0.115	0.117	0.11	0.103	0.098	0.095	0.09	0.085
Cihanbeyli	0.114	0.119	0.115	0.103	0.114	0.115	0.113	0.113	0.113	0.114	0.117	0.12
Eregli	0.118	0.124	0.12	0.114	0.119	0.114	0.117	0.113	0.121	0.121	0.121	0.124
Isparta	0.069	0.085	0.099	0.094	0.086	0.103	0.088	0.087	0.096	0.096	0.087	0.076
Karaman	0.121	0.11	0.111	0.116	0.115	0.115	0.112	0.117	0.118	0.119	0.11	0.122
Konya	0.12	0.116	0.115	0.119	0.116	0.114	0.116	0.116	0.117	0.112	0.12	0.119
Nevsehir	0.116	0.111	0.102	0.111	0.097	0.09	0.106	0.113	0.106	0.107	0.116	0.112
Nigde	0.122	0.12	0.119	0.12	0.117	0.112	0.117	0.119	0.114	0.12	0.119	0.121

Table 2 Monthly weights under QBRDI based on data from nine meteorological stations in the Konya Closed Basin, Turkey.
Abbreviation: QBRDI, Quality Boosted Regional Drought Index.

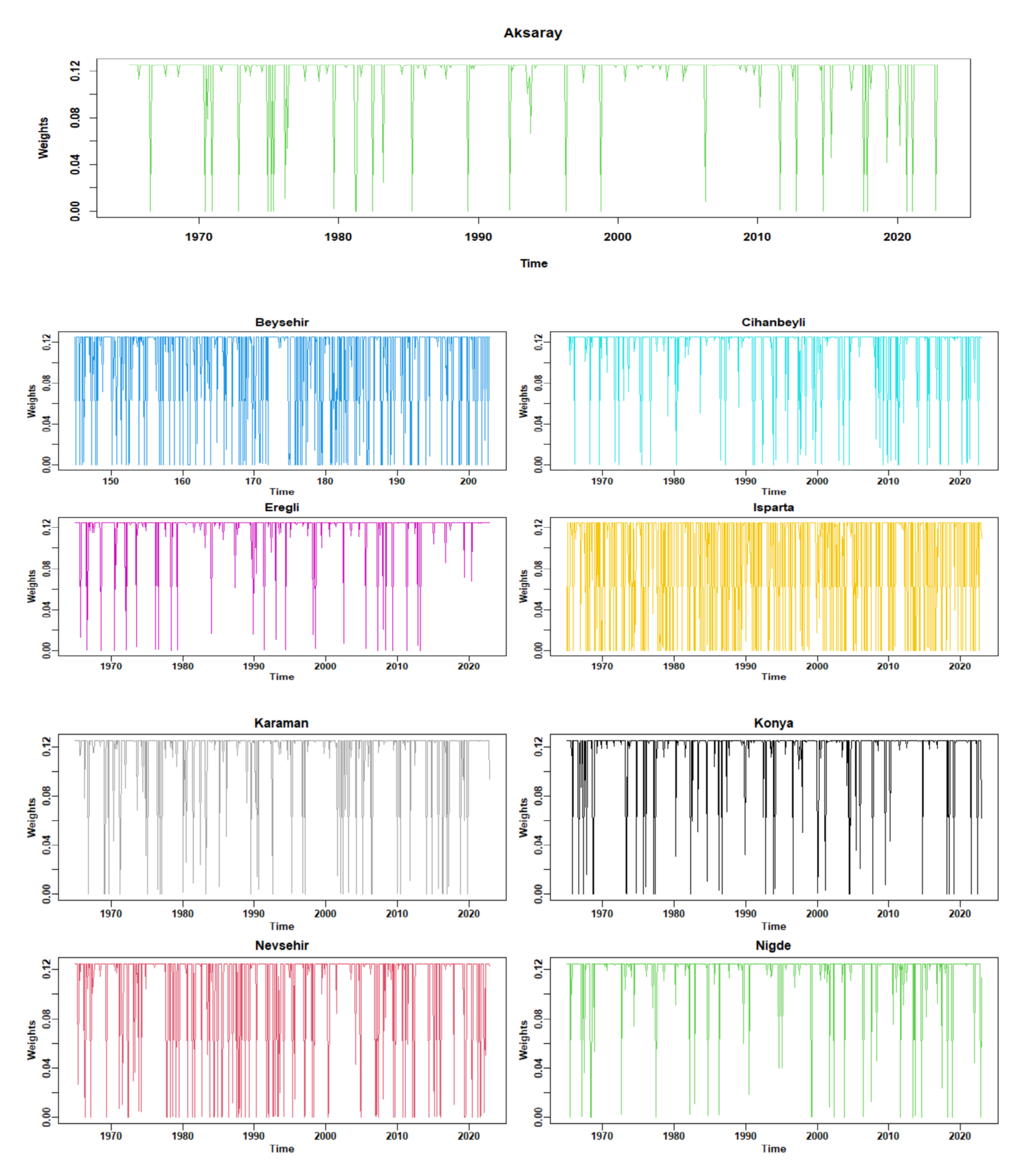

Figure 3 Temporal representation of weights of all nine meteorological stations in the Konya Closed Basin located in Turkey.

COMPARATIVE MEASURES	PROPOSED			SMA		
	MINIMUM	AVERAGE	MAXIMUM	MINIMUM	AVERAGE	MAXIMUM
RMSE	2.618	6.282	8.618	7.333	15.158	27.752
RAE	0.043	0.085	2.266	0.679	1.409	2.712

Table 3 Validation of the deployed weighting procedure (Ali *et al.*, 2023) using SMA.

Abbreviations: RAE, relative absolute error; RMSE, root mean square error; SMA, simple model average.

RMSE observed in QBRDI (8.618) is even lower than the minimum RMSE in SMA (7.333), highlighting the substantial improvement in predictive accuracy. Similarly, the RAE values show a significant reduction under the weighting procedure (Ali *et al.*, 2023). The average RAE for the weighting procedure (Ali *et al.*, 2023) is 0.085, while SMA results in an average RAE of 1.409, suggesting that the weighting procedure (Ali *et al.*, 2023) provides more precise estimations and effectively captures variations in observed data. The superior performance of the weighting procedure (Ali *et al.*, 2023) is attributed to its unequal weighting scheme, which assigns larger weights to stations having lower numbers of OCP and less weight to stations having larger numbers of OCP. Unlike SMA, which gives equal importance to all regions regardless of their reliability, QBRDI prioritizes more accurate regional analysis, leading to enhanced predictive accuracy. This dynamic weighting approach ensures that the ensemble is not influenced by poorly performing regions, reducing overall error. The significant reduction in RMSE and RAE validates the effectiveness of this method in improving drought index estimation. Thus, QBRDI emerges as a more robust and reliable alternative to SMA for ensemble modeling by incorporating a refined weighting strategy based on regional observation proximity.

3.2. THE IMPLICATION OF K-CGMM AND NON-PARAMETRIC TECHNIQUE FOR STANDARDIZATION

In the present study, parametric and non-parametric approaches are used in the standardization process. The results presented in Table 4 highlight the superior performance of the K-CGMM compared to the univariate probability distributions in terms of the Bayesian Information Criterion (BIC) at various timescales. K-CGMM consistently outperforms univariate probability models, demonstrating its robustness in capturing the underlying behavior across most timescales. For instance, at timescale 1, the BIC for the univariate generalized normal distribution is –143.91, while K-CGMM achieves a significantly lower BIC of –645.13. Similarly, at scale 6, the univariate Johnson SB distribution has a BIC of –336.78, whereas K-CGMM drastically improves the fit with a BIC of –2608.2. These results confirm that K-CGMM provides a more efficient and accurate representation of the data distribution compared to traditional univariate models. However, at timescale 9, K-CGMM does not perform well, as evidenced by its higher BIC value (967.636) compared to the univariate Johnson SU model (–73.06). This suggests that the standard parametric approach for K-CGMM is not suitable at this timescale. To address this limitation, the CDF is determined non-parametrically, ensuring that the model remains flexible and accurately represents the distribution without imposing restrictive parametric assumptions. This adaptive approach allows K-CGMM to maintain its effectiveness across different timescales, even when standard parametric modeling does not provide an optimal fit. Overall, the results demonstrate that K-CGMM is a more effective modeling approach, as it consistently achieves lower BIC values, signifying better goodness-of-fit compared to univariate probability distributions. As depicted in Figure 4, the standardized data illustrate the temporal fluctuations during dry and wet conditions across seven distinct monthly timescales (1, 3, 6, 9, 12, 24, and 48). The y-axis represents standardized values, while the x-axis represents time. It signifies that data values from 0 to –2 show dryness and data values ranging from 0 to 2 show wetness.

3.3. ASSESSMENT OF LONG-TERM PROBABILITIES OF DROUGHT AND TREND ANALYSIS

This section presents an overview of the long-term drought probability in Turkey's KCB region, using a Markov chain steady-state probability model. The analysis is based on seven distinct classes representing varying drought and wet conditions. Table 5 presents the steady-state probability of seven classes at seven distinct timescales (1, 3, 6, 9, 12, 24, and 48). These values

SCENARIOS	QBRDI		
TIMESCALES	**UNIVARIATE PROBABILITY MODEL**		**K-CGMD**
Scale 1	Generalized normal	–143.91	–645.13
Scale 3	Johnson SU	–371.36	–694.17
Scale 6	Johnson SB	–336.78	–2608.2
Scale 9	Johnson SU	–73.06	967.636
Scale 12	Weibull	–470.35	–1230.8
Scale 24	Generalized normal	–209.57	–2134.6
Scale 48	4P Beta	–172.36	–235.02

Table 4 Evaluating appropriate distribution based on BIC under univariate distribution and K-CGMD at various timescales over single locations.

Abbreviations: BIC, Bayesian Information Criterion; QBRDI, Quality Boosted Regional Drought Index.

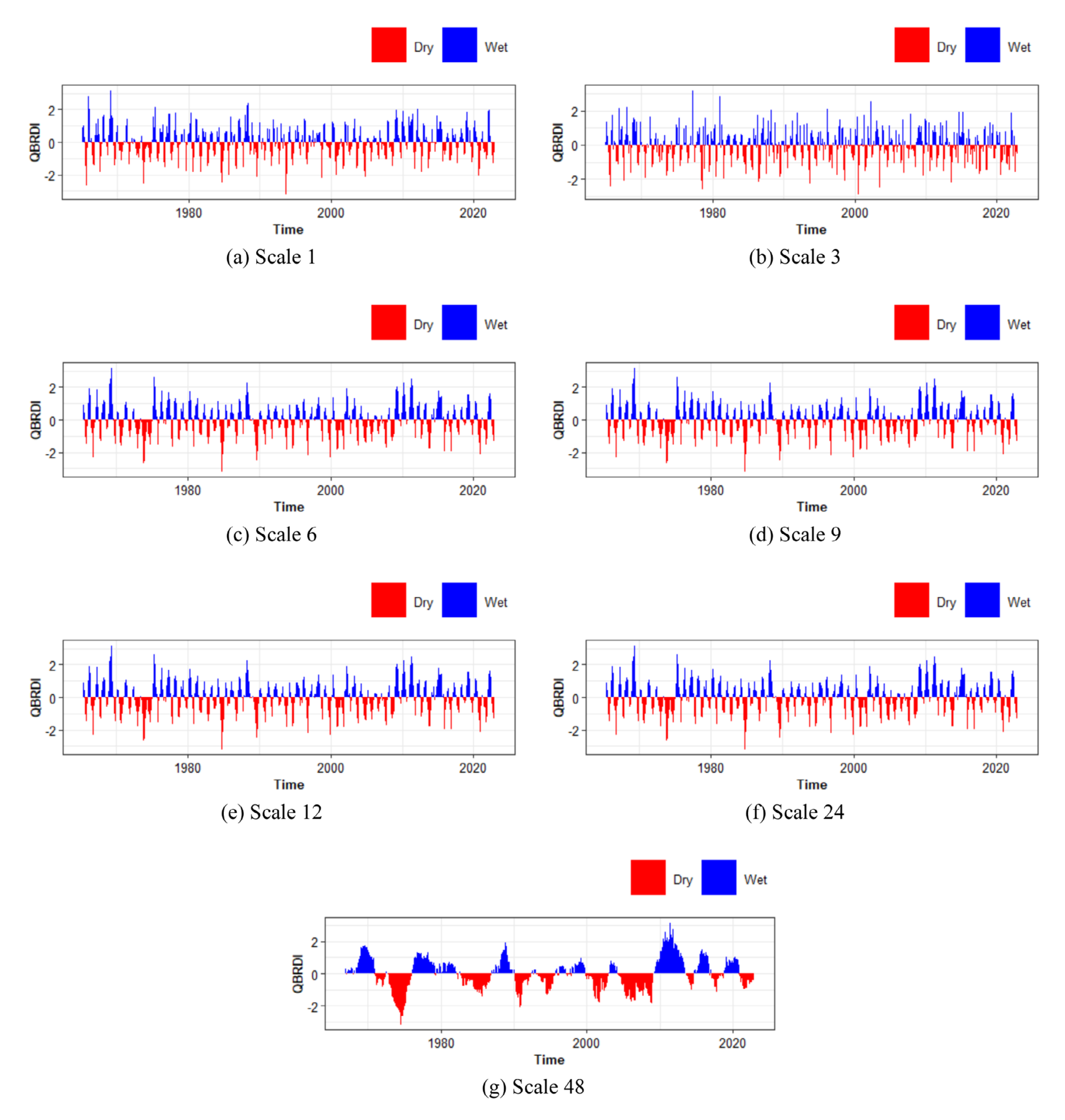

Figure 4 Temporal dry and wet fluctuation of QBRDI under seven different monthly timescales.
Abbreviation: QBRDI, Quality Boosted Regional Drought Index.

TIMESCALES	ED	EW	MD	MW	NN	SD	SW
1	0.023022	0.023022	0.090847	0.090647	0.683453	0.046604	0.044604
3	0.024089	0.023088	0.097352	0.092352	0.682540	0.043290	0.043290
6	0.023598	0.023102	0.093498	0.092408	0.680065	0.044014	0.043316
9	0.024100	0.023155	0.093031	0.091171	0.680164	0.044965	0.043415
12	0.023395	0.023392	0.095105	0.092105	0.681287	0.045860	0.043860
24	0.022324	0.022321	0.097262	0.092262	0.681548	0.047643	0.044643
48	0.023399	0.021836	0.093584	0.087345	0.689404	0.043673	0.040761

Table 5 Steady-state probabilities for various drought classes under seven different timescales.
Abbreviations: ED, extreme drought; EW, extreme wet; MD, moderate drought; MW, moderate wet; NN, near normal; SD, severe drought; SW, severe wet.

TIMESCALES	KENDAL *Z*	SLOPE	*P* VALUE	SIGNIFICANCE	DIRECTION
1	0.42407789	0.000776753	0.671509	$P > 0.10$	Increasing
3	0.4530965	0.000812574	0.6504793	$P > 0.10$	Increasing
6	0.21919571	5.00E–04	0.8264976	$P > 0.10$	Increasing
9	0.0059095	0.000126628	0.9952849	$P > 0.10$	Increasing
12	–0.20621246	–0.0007875	0.836625	$P > 0.10$	Decreasing
24	–0.34809441	–0.00112587	0.7277693	$P > 0.10$	Decreasing
48	0.97762014	0.003484615	0.3282622	$P > 0.10$	Increasing

Table 6 Increasing and decreasing trend of drought under seven different monthly timescales.

indicate the probability of various events occurring at each timescale. As we examine the probabilities from timescales 1 to 48, it becomes clear that the probabilities of ED and EW fluctuate slightly, with EW generally having lower probabilities.

Meanwhile, MD and MW also exhibit fluctuations, with MD probabilities tending to be slightly higher than MW. NN shows a relatively stable probability of around 0.68 across all timescales. SD and SW exhibit similar patterns; both decrease as monthly timescales increase, and SW decreases continuously. Overall, the probabilities show that distinct timescales have varying impacts on these events, with some showing more stability than others. From these results, it can be concluded that KCB in Turkey may face drought problems in the future. To know the presence of a trend using two non-parametric techniques, Mann–Kendall and Sen's slope. According to the MK test, a *P* value above the significance level (0.05) signifies an insignificant trend. Sen's slope estimates this trend value; its sign indicates the direction of the trend. Table 6 provides trend analysis results for distinct timescales (i.e., 1, 3, 6, 9, 12, 24, and 48). For monthly timescales 1, 3, 6, and 9, the Kendall *Z* values and slopes are positive, indicating an increasing trend over time. However, these trends are generally relatively weak, as the slope values are small. For the 12- and 24-month timescales, both the Kendall *Z* values and slopes are negative, indicating a decreasing trend. Interestingly, at the 48-month timescale, the Kendall *Z* value and slope are positive, suggesting an increasing trend, but this time, the trend appears more prominent as the slope value is higher. These results suggest that there may be some fluctuations in the data, with both weak increasing and decreasing trends, but the most robust trend is observed with a significant positive slope at the 48-month timescale.

4. CONCLUSION

Water is a vital element for human life and all other living creatures. Due to a lack of water, natural calamities such as droughts occur, which have devastating effects on various aspects of life. Therefore, there is an urgent need to develop new hybrid standardized methods to fully grasp the global effects of drought and water scarcity. In this regard, the present study used a newly developed regional drought index, QBRDI, to understand the drought consequences due to water shortage. In implementing QBRDI, this study utilized meteorological data spanning 57 years from nine stations to assess the drought characteristics within the KCB, located in Turkey. Furthermore, we employed the steady-state probabilities of the Markov chain to know the long-term evaluation of drought in the KCB region located in Turkey. The probability values obtained from this analysis were alarming, indicating the need to implement robust policies in this region to address future drought challenges. Two non-parametric techniques, namely the Mann–Kendall test and Sen's slope estimator are employed to assess both the presence of a monotonic trend and the magnitude of that trend. Overall, the results show that while periods of SD have occurred, normal levels of drought are observed on average. Identification of wet and dry periods, along with trend analysis of meteorological data in the region, may assist in planning and managing regional water resources.

DATA ACCESSIBILITY STATEMENT

The datasets used and/or analyzed in the present study are available from the corresponding author upon reasonable request.

ACKNOWLEDGEMENTS

A special thank you to Turkey's General Directorate of Meteorology (MGM) for supplying the database utilized in this study.

FUNDING INFORMATION

Authors receive no funding for preparing this manuscript.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR AFFILIATIONS

Veysi Kartal orcid.org/0000-0003-4671-1281
Civil Engineering, Engineering Faculty, Siirt University, Siirt, Turkey

Muhammad Ahmad
College of Statistical Sciences, University of the Punjab, Lahore, Pakistan

Olayan Albalawi
Department of Statistics, Faculty of Science, University of Tabuk, Tabuk, Saudi Arabia

Zulfiqar Ali orcid.org/0000-0001-9291-8342
College of Statistical Sciences, University of the Punjab, Lahore, Pakistan

Saad Sh. Sammen
Department of Civil Engineering, College of Engineering, University of Diyala, Diyala Governorate, Iraq

Miklas Scholz orcid.org/0000-0001-8919-3838
Department of Civil Engineering Science, School of Civil Engineering, and the Built Environment, Faculty of Engineering and the Built Environment, University of Johannesburg, Kingsway Campus, Auckland Park, Johannesburg, South Africa

Aamina Batool orcid.org/0009-0005-3101-5402
College of Statistical Sciences, University of the Punjab, Lahore, Pakistan

REFERENCES

Abbas, S.A., Xuan, Y., Al-Rammahi, A.H. and **Addab, H.F.** (2022) A comparison study of observed and the CMIP5 modelled precipitation over Iraq 1941–2005. *Atmosphere*, 13(11): 1869. DOI: https://doi.org/10.3390/atmos13111869

Ahmad, M., Ali, Z., Ilyas, M., Mohsin, M. and **Niaz, R.** (2023) A common factor analysis based data mining procedure for effective assessment of 21st century drought under multiple global climate models. *Water Resources Management*, 37: 1–20. DOI: https://doi.org/10.1007/s11269-023-03581-2

Ali, S., Liu, D., Fu, Q., Cheema, M.J.M., Pal, S.C., Arshad, A. and **Zhang, L.** (2022) Constructing high-resolution groundwater drought at spatio-temporal scale using GRACE satellite data based on machine learning in the Indus Basin. *Journal of Hydrology*, 612: 128295. DOI: https://doi.org/10.1016/j.jhydrol.2022.128295

Ali, Z., Almanjahie, I.M., Hussain, I., Ismail, M. and **Faisal, M.** (2020) A novel generalized combinative procedure for multi-scalar standardized drought indices-The long average weighted joint aggregative criterion. *Tellus A: Dynamic Meteorology and Oceanography*, 72(1): 1–23. DOI: https://doi.org/10.1080/16000870.2020.1736248

Ali, Z., Qamar, S., Khan, N., Faisal, M. and **Sammen, S.S.** (2023) A New Regional Drought Index under X-bar chart based weighting scheme – The Quality Boosted Regional Drought Index (QBRDI). *Water Resources Management*, 37(5): 1895–1911. DOI: https://doi.org/10.1007/s11269-023-03461-9

Ali, Z., Hussain, I., Faisal, M., Nazir, H.M., Moemen, M.A.E., Hussain, T. and **Shamsuddin, S.** (2017) A novel multi-scalar drought index for monitoring drought: the standardized precipitation temperature index. *Water resources management*, 31(15): 4957–4969. DOI: https://doi.org/10.1007/s11269-017-1788-1

Batool, A., Ali, Z., Mohsin, M., Masmoudi, A., Kartal, V. and **Satti, S.** (2024) Assessing the generalization of forecasting ability of machine learning and probabilistic models for complex climate characteristics. *Stochastic Environmental Research and Risk Assessment*, 38(8): 2927–2947. DOI: https://doi.org/10.1007/s00477-024-02721-3

Batool, A., Ali, Z., Mohsin, M. and **Shakeel, M.** (2023) A generalized procedure for joint monitoring and probabilistic quantification of extreme climate events at regional level. *Environmental Monitoring and Assessment*, 195(10): 1223. DOI: https://doi.org/10.1007/s10661-023-11717-5

Batool, A., Kartal, V., Ali, Z., Scholz, M. and **Ali, F.** (2025) A novel regional forecastable multiscalar standardized drought index (RFMSDI) for regional drought monitoring and assessment. *Agricultural Water Management*, 308: 109289. DOI: https://doi.org/10.1016/j.agwat.2025.109289

Citakoglu, H. and **Coşkun, Ö.** (2022) Comparison of hybrid machine learning methods for the prediction of short-term meteorological droughts of Sakarya Meteorological Station in Turkey. *Environmental Science and Pollution Research*, 29(50): 75487–75511. DOI: https://doi.org/10.1007/s11356-022-21083-3

Cook, B.I., Mankin, J.S., Marvel, K., Williams, A.P., Smerdon, J.E. and **Anchukaitis, K.J.** (2020) Twenty-First Century Drought Projections in the CMIP6 Forcing Scenarios. *Earth's Future*, 8: e2019EF001461. DOI: https://doi.org/10.1029/2019EF001461

Dost, R. and **Kasiviswanathan, K.S.** (2023) Quantification of water resource sustainability in response to drought risk assessment for Afghanistan river basins. *Natural Resources Research*, 32(1): 235–256. DOI: https://doi.org/10.1007/s11053-022-10129-5

Erhardt, T.M. and **Czado, C.** (2018) Standardized drought indices: A novel univariate and multivariate approach. *Journal of the Royal Statistical Society Series C: Applied Statistics*, 67(3): 643–664. DOI: https://doi.org/10.1111/rssc.12242

Fu, G., Rojas, R. and **Gonzalez, D.** (2022) Trends in groundwater levels in alluvial aquifers of the Murray–Darling basin and their attributions. *Water*, 14(11): 1808. DOI: https://doi.org/10.3390/w14111808

Hao, Z. and **AghaKouchak, A.** (2014) A nonparametric multivariate multi-index drought monitoring framework. *Journal of Hydrometeorology*, 15(1): 89–101. DOI: https://doi.org/10.1175/JHM-D-12-0160.1

Jehanzaib, M., Sattar, M.N., Lee, J.H. and **Kim, T.W.** (2020) Investigating effect of climate change on drought propagation from meteorological to hydrological drought using multi-model ensemble projections. *Stochastic Environmental Research and Risk Assessment*, 34: 7–21. DOI: https://doi.org/10.1007/s00477-019-01760-5

Jiang, T., Su, X., Zhang, G., Zhang, T. and **Wu, H.** (2023) Estimating propagation probability from meteorological to ecological droughts using a hybrid machine learning copula method. *Hydrology and Earth System Sciences*, 27(2): 559–576. DOI: https://doi.org/10.5194/hess-27-559-2023

Jose, D.M., Vincent, A.M. and **Dwarakish, G.S.** (2022) Improving multiple model ensemble predictions of daily precipitation and temperature through machine learning techniques. *Scientific Reports*, 12(1): 1–25. DOI: https://doi.org/10.1038/s41598-022-08786-w

Karanja, J., Svoma, B.M., Walter, J. and **Georgescu, M.** (2023) Southwest US winter precipitation variability: Reviewing the role of oceanic teleconnections. *Environmental Research Letters*, 18(5): 053003. DOI: https://doi.org/10.1088/1748-9326/accd84

Katipoğlu, O.M. (2023) Revealing the trend and change point in Hargreaves equation based on potential evapotranspiration values with various statistical approaches. *Environmental Science and Pollution Research*, 30: 1–17. DOI: https://doi.org/10.1007/s11356-023-27417-z

Keilson, J. and **Syski, R.** (1974) Compensation measures in the theory of Markov chains. *Stochastic Processes and Their Applications*, 2(1): 59–72. DOI: https://doi.org/10.1016/0304-4149(74)90012-X

Kendall, M.G. (1975) *Rank correlation methods*. London: Charles Griffin.

Kheyruri, Y., Sharafati, A. and **Shahid, S.** (2023) Evaluation of the impact of large-scale atmospheric indicators and meteorological variables on drought in different regions of Iran. *Environmental Earth Sciences*, 82(12): 317. DOI: https://doi.org/10.1007/s12665-023-11015-w

Lorente, D.B., Mohammed, K.S., Cifuentes-Faura, J. and **Shahzad, U.** (2023) Dynamic connectedness among climate change index, green financial assets and renewable energy markets: Novel evidence from sustainable development perspective. *Renewable Energy*, 204: 94–105. DOI: https://doi.org/10.1016/j.renene.2022.12.085

Mann, H.B. (1945) Nonparametric tests against trend. *Econometrica: Journal of the Econometric Society*, 13: 245–259. DOI: https://doi.org/10.2307/1907187

Markov, A.A. (1906) Generalization of the law of large numbers to dependent quantities. *Russian. Izvestiia Fiz. Mat. Obschestva Kazan Univ., 2nd. Ser*, 15(135): 339.

McLachlan, G.J. and **Peel, D.** (2000) *Finite mixture models*. John Wiley & Sons. DOI: https://doi.org/10.1002/0471721182

Mukherjee, S., Mishra, A. and **Trenberth, K.E.** (2018) Climate change and drought: A perspective on drought indices. *Current Climate Change Reports*, 4(2): 145–163. DOI: https://doi.org/10.1007/s40641-018-0098-x

Niaz, R., Almazah, M., Hussain, I., Al-Ansari, N. and **Sammen, S.S.** (2022) Assessing the probability of drought severity in a homogeneous region. *Complexity*, 2022: Article ID 3139870, 8 pages. DOI: https://doi.org/10.1155/2022/3139870

Ombadi, M., Nguyen, P., Sorooshian, S. and **Hsu, K.L.** (2021) Retrospective analysis and Bayesian model averaging of CMIP6 precipitation in the Nile River Basin. *Journal of Hydrometeorology*, 22(1): 217–229. DOI: https://doi.org/10.1175/JHM-D-20-0157.1

Rajak, J. (2021) A preliminary review on impact of climate change and our environment with reference to global warming. *International Journal of Environmental Sciences*, 10: 11–14.

Rajwar, K., Deep, K. and **Das, S.** (2023) An exhaustive review of the metaheuristic algorithms for search and optimization: Taxonomy, applications, and open challenges. *Artificial Intelligence Review*, 56: 1–71. DOI: https://doi.org/10.1007/s10462-023-10470-y

Reddy, N.M. and **Saravanan, S.** (2023) Extreme precipitation indices over India using CMIP6: A special emphasis on the SSP585 scenario. *Environmental Science and Pollution Research*, 30(16): 47119–47143. DOI: https://doi.org/10.1007/s11356-023-25649-7

Rhymee, H., Shams, S., Ratnayake, U. and **Rahman, E.K.A.** (2022) Comparing statistical downscaling and arithmetic mean in simulating CMIP6 multi-model ensemble over Brunei. *Hydrology*, 9(9): 161. DOI: https://doi.org/10.3390/hydrology9090161

Saha, S., Kundu, B., Saha, A., Mukherjee, K. and **Pradhan, B.** (2023) Manifesting deep learning algorithms for developing drought vulnerability index in monsoon climate dominant region of West Bengal, India. *Theoretical and Applied Climatology*, 151(1–2): 891–913. DOI: https://doi.org/10.1007/s00704-022-04300-4

Sen, P.K. (1968) Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63(324): 1379–1389. DOI: https://doi.org/10.1080/01621459.1968.10480934

Soylu Pekpostalci, D., Tur, R., Danandeh Mehr, A., Vazifekhah Ghaffari, M.A., Dąbrowska, D. and **Nourani, V.** (2023) Drought monitoring and forecasting across Turkey: A contemporary review. *Sustainability,* 15(7): 6080. DOI: https://doi.org/10.3390/su15076080

Spiess, A.N. (2018) Package 'propagate'. Available at https://mirror.las.iastate.edu/CRAN/web/packages/propagate/propagate.pdf

Svoboda, M.D. and **Fuchs, B.A.** (2016) *Handbook of drought indicators and indices*, vol. 2. Geneva, Switzerland: World Meteorological Organization. DOI: https://doi.org/10.1201/b22009-11

Swain, S., Sahoo, S., Taloor, A.K., Mishra, S.K. and **Pandey, A.** (2022) Exploring recent groundwater level changes using innovative trend analysis (ITA) technique over three districts of Jharkhand, India. *Groundwater for Sustainable Development*, 18: 100783. DOI: https://doi.org/10.1016/j.gsd.2022.100783

Tian, Q., Wang, F., Tian, Y., Jiang, Y., Weng, P. and **Li, J.** (2023) Copula-based comprehensive drought identification and evaluation over the Xijiang River Basin in South China. *Ecological Indicators*, 154: 110503. DOI: https://doi.org/10.1016/j.ecolind.2023.110503

Wang, W., Ertsen, M.W., Svoboda, M.D. and **Hafeez, M.** (2016) Propagation of drought: from meteorological drought to agricultural and hydrological drought. *Advances in Meteorology*, 2016, Article ID 6547209, 5 pages. DOI: https://doi.org/10.1155/2016/6547209

Wang, X., Chen, H., Heidari, A.A., Zhang, X., Xu, J., Xu, Y. and **Huang, H.** (2020) Multi-population following behavior-driven fruit fly optimization: A Markov chain convergence proof and comprehensive analysis. *Knowledge-Based Systems*, 210: 106437. DOI: https://doi.org/10.1016/j.knosys.2020.106437

Won, J., Choi, J., Lee, O. and **Kim, S.** (2020) Copula-based Joint Drought Index using SPI and EDDI and its application to climate change. *Science of the Total Environment*, 744: 140701. DOI: https://doi.org/10.1016/j.scitotenv.2020.140701

Yihdego, Y., Vaheddoost, B. and **Al-Weshah, R.A.** (2019) Drought indices and indicators revisited. *Arabian Journal of Geosciences*, 12: 1–12. DOI: https://doi.org/10.1007/s12517-019-4237-z

TO CITE THIS ARTICLE:
Kartal, V., Ahmad, M., Albalawi, O., Ali, Z., Sammen, S.S., Scholz, M. and Batool, A. (2025) Probabilistic Assessment of Future Drought Characteristics under the Quality Boosted Regional Drought Index. *Tellus A: Dynamic Meteorology and Oceanography*, 77(1): 240–253. DOI: https://doi.org/10.16993/tellusa.4066

Submitted: 21 February 2024 **Accepted:** 19 March 2024 **Published:** 14 November 2025

COPYRIGHT:
© 2025 The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC-BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. See http://creativecommons.org/licenses/by/4.0/.

Tellus A: Dynamic Meteorology and Oceanography is a peer-reviewed open access journal published by Stockholm University Press.