Drought monitoring and prediction using SPI, SPEI, and random forest model in various climates of Iran

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ABSTRACT

The aim of this study is to select the best model (combination of different lag times) for predicting the standardized precipitation index (SPI) and the standardized precipitation and evapotranspiration index (SPEI) in next time. Monthly precipitation and temperature data from 1960 to 2019 were used. In temperate climates, such as the north of Iran, the correlation coefficients of SPI and SPEI were 0.94, 0.95, and 0.81 at the time scales of 3, 12, and 48 months, respectively. Besides, this correlation coefficient was 0.47, 0.35, and 0.44 in arid and hot climates, such as the southwest of Iran because potential evapotranspiration (PET) depends on temperature more than rainfall. Drought was predicted using the random forest (RF) model and applying 1–12 months lag times for next time. By increasing the time scale, the prediction accuracy of SPI and SPEI will improve. The ability of SPEI is more than SPI for drought prediction, because the overall accuracy (OA) of prediction will increase, and the errors (i.e., overestimate (OE) and underestimate (UE)) will reduce. It is recommended for future studies (1) using wavelet analysis for improving accuracy of predictions and (2) using the Penman-Monteith method if ground-based data are available.

Key words: drought indices, drought monitoring, drought prediction, random forest

HIGHLIGHTS

• Use of SPI and SPEI drought indices and determination of correlation between them.
• Prediction of meteorological drought by a random forest model.
• Increasing of prediction accuracy by increasing of time scale.
• SPEI performed better than SPI for drought prediction.
• Increasing of OA and decreasing of OE and UE with increasing time scale.

INTRODUCTION

In recent years, climatic change has led to various meteorological changes around the world. In the arid and semi-arid regions such as the Middle East, climatic change has increased severity and duration of meteorological droughts. Therefore, using appropriate methods and meteorological drought indices is necessary for predicting short-term and long-term droughts. Numerous studies have been performed to assess meteorological droughts in arid and semi-arid regions such as Zhang et al. (2021) and Tayfur (2021). Iran is located in the sub-tropical high-pressure belt or horse latitudes. Iran has a large area (over 1,600,000 km²) and a great variety of different climates. This country is a good example for assessing and forecasting meteorological droughts in arid and semi-arid regions.

Iran lies in an arid and semi-arid climate far from moisture sources. Rain clouds have already lost a large portion of their moisture when they arrive in Iran, and they cannot induce rainfall in Central and Eastern Iran (Adib et al. 2021). The distribution of precipitation is uneven in Iran. The temporal and spatial precipitation pattern causes severe and long-lasting droughts that affect various sectors including agriculture and industry. Consequently, the economical situation of people whose income relies on these resources is unstabilized (Mahmoudi et al. 2019).

Drought is part of the nature of different climates that occasionally occurs in a region or regions. Therefore, although it is a normal phenomenon, many consequences and damages are now more than the past. Along with the increasing trend of...
drought occurrence must be considered the vulnerability of communities to it. Also, factors such as population growth, increasing consumption, changing lifestyle patterns, and the arrival of new water competitors have played an influential role in increasing drought. On the other hand, changes in climatic and hydrological processes such as increasing temperature, reducing the ratio of snowfall to total precipitation, and reducing runoff in the basins have somehow increased the adverse effects of drought.

Meteorological drought is a decrease in rainfall compared to normal. This change could be due to Earth processes such as oceanic and geophysical interactions, biosphere interactions, or solar energy fluctuations. Due to the conditions of recent decades and climate change, Iran has faced various climatic hazards, the first consequence of these changes is shown in meteorological droughts. Therefore, meteorological assessment of drought conditions is of particular importance.

The present study is about meteorological drought. The following are some studies that have been conducted to monitor and predict drought:

Bazrafshan (2017) indicated increasing trend for temperature and decreasing trend for precipitation and intensity of long-term droughts in most of the regions of Iran. He used SPI and SPEI and showed the superiority of the SPEI for monitoring droughts. Abbasi et al. (2019) monitored and predicted drought in the Urmia Lake area in northwestern Iran. They used the Urmia synoptic station data to calculate SPI and SPEI at different time scales. Drought characteristics, period, and frequency according to SPI and SPEI indices were presented in different time scales. In predicting drought, the SPEI index was used. By delaying the SPEI time series up to 5 months, the next step predicted the drought situation. The accuracy of the forecast was evaluated presenting Overall Accuracy (OA), Producer’s Accuracy (PA), and User’s Accuracy (UA) indices. The result indicates that the forecast performance improves with increasing drought time scale from 1 month to 48 months. Bahrami et al. (2019) calculated the seasonal SPI index for prediction of seasonal drought. They used 38 synoptic stations data throughout Iran. According to their results, the highest frequency is related to the normal and mild wet season, and the lowest class is related to severe drought and extreme drought. The best model for forecasting Moving Average (MA) (5) and Hannan-Rissanen MA (5) is 60.53 and 15.79%, respectively. Also, Ghamhami & Irannejad (2019) analyzed droughts in Iran during 1988–2017. They used the principal component analysis, copula functions, and Mann–Kendall test for this purpose. Mahmoudi et al. (2019) examined seven precipitation-based drought indices, including standardized precipitation index (SPI), percent of normal index (PN), China-Z index (ZSI), Deciles index (DI), China-Z index (CZI), effective drought index (EDI), and modified CZI (MCZI) at 41 synoptic stations throughout Iran during the period (1985–2013). They reported that SPI and EDI indices have the best performance in drought monitoring in Iran, respectively. Sharafati et al. (2020) calculated the trend and characteristics of meteorological droughts in regions with different climates in Iran by calculating the SPI index. SPI index was calculated in 1, 3, 6, 9, and 12 scales, and drought events were classified based on the characteristics of severity, duration, and peak to evaluate the spatial variation of drought in different regions. Their results showed that the highest frequency and severity of short-term droughts (6 months and less) occurred in the Caspian Sea’s northwestern and southern shores. The highest frequency and severity of long-term droughts occurred in the southern, southeastern, and southwestern regions. In general, the northwestern regions of Iran are more exposed to drought in severity, duration, and peak. The highest increase in the severity and duration of droughts is related to the central arid regions. Sobhani et al. (2019) used SPEI for drought monitoring in the Lake Urmia basin of Iran. They observed an increasing trend for drought and temperature. Karimi et al. (2020) examined the trend of variables: atmospheric evaporative demand (AED) and meteorological drought from 1988 to 2018 in southwestern Iran’s Karkheh river basin. AED was calculated based on the FAO-56 Penman–Monteith equation using the variables of precipitation, air temperature, wind speed, and sunshine duration. Their results showed an increasing trend in the AED. The trend of SPEI and SPI indices was also declining. The magnitude of this decrease was more remarkable for SPEI, which indicates an increase in the severity of the drought is associated with an increase in AED. Nouri & Homae (2020) have assessed different characteristics of drought from 1966 to 2012 in Iran by applying the Mann–Kendall test, SPI, and SPEI. These indices showed a declining trend.

Data mining is the most momentous technology for the effective use of large data (Esmaeili-Gisavandani et al. 2021). Its importance is increasing; random forest (RF) is an easy-to-use machine learning algorithm that often provides excellent results even without adjusting its parameters. This algorithm is one of the most widely used machine learning algorithms for both classification and regression due to its simplicity and usability. The RF model can model nonlinear problems well.

Based on predicting drought indices presented in the literature review, SPI and SPEI indices have not been predicted using the RF model. Therefore, this study uses the RF model in six stations throughout Iran for predicting drought.
The purpose of this study is to compare the performance of SPI and SPEI indices in different climatic conditions and to present the best model (combination of different lag times) in predicting drought in each of these climatic regions. For finding the best model and predicting drought, the RF model was used. Then, a comparison between SPI and SPEI performance shows the superior meteorological drought index in each climatic region and time scale.

Previous similar studies (Abbasi et al. 2019; Kisi et al. 2019; Zhang et al. 2020) used the gene expression programming (GEP) method based on a tree structure and artificial neural network (ANN) and an adaptive network-based fuzzy inference system (ANFIS) based on the black box. Meanwhile the RF model used in this study, which is based on the decision-trees and classification, showed better performance than the methods used in previous studies. Also, Mahmoudi et al. (2019) and Sharafati et al. (2020) have studied indices based on the precipitation variable (SPI, PN, ZSI, DI, CZI, EDI), whereas in the present study, in addition to the SPI index, SPEI was used, which is related to precipitation and temperature. The advantage of using SPEI is that two important climatic variables (precipitation and temperature) will be given importance; the SPEI index in hot regions such as southwestern Iran where the maximum temperature is more than 50 °C is more useful than SPI, this point illustrated by Bazrafshan (2017).

Considering the importance of drought studies in a country like Iran where the predominant climate is arid and semi-arid, the objectives we pursue in this study are (1) calculation of SPI and SPEI meteorological drought indices for six synoptic stations throughout Iran with different climates; (2) analysis of drought characteristics in these regions according to SPI and SPEI indices; (3) investigating the correlation between SPEI and SPI meteorological drought indices in different regions of Iran; (4) determining the frequency of drought classes according to both indices and comparing them; (5) predicting SPI and SPEI drought indices with RF for creating combinations of these indices with lag time and (6) determining the accuracy of drought class prediction related to each of the indices created by the RF model.

Therefore, the novelties and differences between this study with previous studies:

1. Dividing a large region (Iran) to six climate regions based on the Köppen-Geiger classification and evaluating the performance of different meteorological drought indices based on their adaption with features of these regions.
2. To predict drought, the RF model was used as a robust machine learning technique. The RF model is a classification model. Most previous studies used regression relations, regression machine learning models such as support vector machine (SVM) and different ANNs for this purpose.
3. Applying 1–12 months lag times for predicting SPI or SPEI in next time and selecting the best model (combination of different lag times) based on different accuracy indices for each region and time scale. Previous studies used fewer lag times and most of them applied this procedure for a climate region.

MATERIALS AND METHODS

Case study

In this study, drought in Iran has been studied. Regions in the country with different climates were selected in terms of Köppen-Geiger climate classification (Kottek et al. 2006). Aridity indices such as the de Martonne aridity index are related to the climatic characteristics of temperature and precipitation, but the Köppen-Geiger climate classification also pays attention to precipitation regime, seasonality of precipitation and vegetation and is generally divided into five main categories: tropical and humid, dry, moderately warm, moderately cold, and cold and subcategories. Therefore, the accuracy of this climate classification is more than other aridity indices.

The studied regions include Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan. These stations are selected based on the prevailing climate, location, and appropriate data sequence. Abadan station has a very hot and humid climate and is located in southwestern Iran. Babolsar station has a rainy climate and is located in northern Iran. Isfahan station has a cold and dry climate and is located in the center of Iran. Khoy station has a cold climate and is located in the west and northwest of Iran. Mashhad station has a cold and dry climate and is located in northeastern Iran. Zahedan station has a hot and dry climate and is located in southeastern Iran. These six synoptic stations are in different parts of Iran and the distance between some stations such as Khoy and Zahedan is more than 2,000 km. Also, they represent different climates and do not belong to a specific region. Then, obtained results can be used for different climates in arid and semi-arid regions.

Monthly temperature and precipitation data of these stations over a period of 60 years (1960–2019) were obtained from the Meteorological Organization of Iran. (The data for 2020 have not yet been approved by the Meteorological Organization of Iran.)
Iran, and usually this organization submits the data with a delay of 1 year after the final review. Also, in 2020, nothing significant has happened that has not been considered in this 60-year period.)

The specifications of the stations used are shown in Figure 1.

Iran is a country in Western Asia, with an area of $1.65 \times 10^6$ km$^2$, at latitude 25–40° and longitude 44–63°. Iran has a rich and diverse topography and climates; the Alborz and Zagros Mountains lie in the northern and western parts of Iran at an elevation of over 5,500 m. Also, the southern Caspian Sea shores have an elevation of −23 m (below the mean sea level). The rainfall rate reduces from the western areas to the eastern parts, and the temperature rises from the northwest to the southeast (Rahimi et al. 2013). This study investigates drought across Iran. Regions with different climates (based on the Köppen-Geiger climate classification) in Iran were selected. The Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan Stations were studied. The monthly temperature and precipitation data of these stations in a 60-year period (1960–2019) were obtained from the Iran Meteorological Organization. Figure 1 and Table 1 represent the locations and climatic conditions of the stations.

Standardized precipitation index

The SPI was introduced by Mckee et al. (1993). SPI values can be calculated at different time scales (for example, 1, 3, 6, 9, 12, 24, and 48 months). For example, SPI-3 suggests that the 3-month moving average has been used for the initial time series. The probability distribution of precipitation followed the Pearson III distribution. The SPI values of the stations were calculated in the R-environment using the SPI package (http://www.R-project.org).

Using 1-, 3-, 6-, 9-, 12-, 24-, and 48-month time scales was recommended by McKee et al. (1993) and Vicente-Serrano et al. (2010). In addition, in many studies around the world, including Iran, these time scales have been used. For example, Abbasi et al. (2019), Bahrami et al. (2019), Bazrafshan (2017), Nabaei et al. (2019), and Sharafati et al. (2020) used these time scales.

![Figure 1](image_url) | The spatial distribution of the study stations located in Iran.

<table>
<thead>
<tr>
<th>Station</th>
<th>Latitude (N)</th>
<th>Longitude (E)</th>
<th>Elevation (m.a.s.l)</th>
<th>Precipitation (mm)</th>
<th>Temperature (°C)</th>
<th>Köppen-Geiger climate classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abadan</td>
<td>30.38</td>
<td>48.21</td>
<td>7</td>
<td>151</td>
<td>26</td>
<td>BWh</td>
</tr>
<tr>
<td>Babolsar</td>
<td>36.72</td>
<td>52.65</td>
<td>−21</td>
<td>896</td>
<td>17</td>
<td>Cfb</td>
</tr>
<tr>
<td>Isfahan</td>
<td>32.52</td>
<td>51.71</td>
<td>1,550</td>
<td>122</td>
<td>17</td>
<td>BWk</td>
</tr>
<tr>
<td>Khoy</td>
<td>38.56</td>
<td>45.00</td>
<td>1,103</td>
<td>290</td>
<td>13</td>
<td>Dfa</td>
</tr>
<tr>
<td>Mashhad</td>
<td>36.24</td>
<td>59.63</td>
<td>999</td>
<td>246</td>
<td>15</td>
<td>BSk</td>
</tr>
<tr>
<td>Zahedan</td>
<td>29.47</td>
<td>60.90</td>
<td>1,370</td>
<td>80</td>
<td>19</td>
<td>BWk</td>
</tr>
</tbody>
</table>
1-, 3-, 6-, and 12-month time scales can show monthly, seasonal, semi-annual, and annual droughts. In Iran, the dry period is 9 months at each year. Then, considering the 9-month time scale is necessary. Also, 24- and 48-month time scales can show long-term droughts.

**Standardized precipitation evapotranspiration index**

The SPEI was proposed by Vicente-Serrano et al. (2010). SPEI is calculated in the same way as SPI; however, SPEI uses the difference between precipitation and potential evapotranspiration (PET). PET was calculated using the Thornthwaite method (Thornthwaite 1948).

\[
\text{PET} = 16 \times \left( \frac{10T}{I} \right)^m \tag{1}
\]

\[
m = 6.75 \times 10^{-7} I^3 - 7.71 \times 10^{-5} I^2 + 1.79 \times 10^{-2} I + 0.49 \tag{2}
\]

\[
I = \sum_{i=1}^{12} \left( \frac{T_i}{\bar{T}} \right)^{1.5} \tag{3}
\]

\[
\text{PET}_c = \text{PET} \times \left( \frac{D \times N}{360} \right) \tag{4}
\]

In the Thornthwaite method, \( T \) is the average monthly temperature (°C), \( m \) is the I-dependency coefficient, \( I \) is the heat index or the total of the 12-month index, \( \text{PET}_c \) is corrected PET, \( N \) is the number of days in a month, and \( D \) is the average month of the maximum number of sunshine hours in the desired latitude. Thus, having PET in hand, the difference between precipitation (\( P \)) and PET is obtained for month \( i \) (Sellinger 1996).

\[
D_i = P_i - \text{PET}_i \tag{5}
\]

For SPEI, the log-logistic distribution is used.

\[
f(x) = \beta \left( \frac{x - \gamma}{\alpha} \right)^{\beta-1} \left[ 1 + \left( \frac{x - \gamma}{\alpha} \right)^{\beta} \right]^{-2} \tag{6}
\]

where \( \alpha, \beta, \) and \( \gamma \) are the scale, shape, and origin parameters for \( D \) values in the domain \( D < \gamma < \infty \) (Vicente-Serrano et al. 2010; Alam et al. 2017). The probability distribution function of \( D \) series is obtained by:

\[
f(x) = \left[ 1 + \left( \frac{x}{x - \gamma} \right)^{\beta} \right]^{-1} \tag{7}
\]

The SPEI index as standardized values (\( x \)) \( F \) can be easily calculated.

\[
\text{SPEI} = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \tag{8}
\]

where \( w = \sqrt{-2 \ln(p)} \) for \( p \leq 0.5 \), and \( P \) is the probability of \( D \) overestimation. Also, \( C_0, C_1, C_2, d_1, d_2, \) and \( d_3 \) are constants. A zero SPEI represents matching with a 50% \( D \) cumulative probability (Vicente-Serrano et al. 2010).

SPI and SPEI use probability distribution functions while other meteorological indices such as PN, ZSI, DI, CZI, EDI, and MCZI do not use these functions. Therefore, SPI and SPEI can show features of meteorological drought well. These two indices are conventional indices for studying meteorological drought in different regions of the world. The SPI index considers only the precipitation variable, but the SPEI index, in addition to precipitation, also uses the temperature variable, which is an important factor in the climate. These indices have been used in similar studies such as Bazrafshan (2017), Abbasi et al. (2019), and Sharafati et al. (2020) in Iran.
The reason for using the Thornthwaite method in calculating SPEI is:
In order to increase the accuracy of the calculations, this study used the ground-based data of synoptic stations, which are the most reliable data recorded in Iran. To apply the Penman–Monteith method, the existence of minimum temperature, maximum temperature, precipitation, humidity, wind speed, and radiation are essential in all six study areas. Among these phenomena, wind speed and radiation data were not recorded in the synoptic stations.
On the other hand, reanalysis data such as Climatic Research Unit (CRU) data has not the accuracy of ground-based data and definitely requires bias correction.

Drought feature extraction
To investigate the drought of the six selected stations in the 60-year statistical period, SPI and SPEI were calculated at the time scales of 1, 3, 6, 9, 12, 24, and 48 months. Both SPI and SPEI have high fluctuations in short periods, and these fluctuations reduce as the time scale increases. In addition, increased drought time scale reduces drought severity and increases its duration. The run theory was used to determine the severity, duration, and peak of each drought event (Mishra & Singh 2010). The run theory method is one of the most usable methods for extracting drought characteristics. Another similar method is the copulas method. Wang et al. (2020) compared the two methods (run theory and copulas), and the obtained results showed the similar performance of the two methods. Because of the simplicity of the run theory method, this study used it. This method was used in authoritative articles such as Šen (1989), Moyé & Kapadia (1995), and Mishra & Singh (2010).
Drought indices are time series whose values represent the intensity of drought. In this study, a zero threshold was used to detect drought events, extracting the characteristics of each drought event, such as severity, duration, and peak. There are various methods for determining the drought threshold, including determining the threshold, but selecting zero is one of the most usable and simplest methods for determining the drought threshold. Sharafati et al. (2020) applied this drought threshold. Also, values below zero SPI and SPEI indicate drought and compatibility of the zero threshold with this issue can simplify the diagnosis of drought.

Random forest model
The forest mechanism is flexible enough to house both supervised classification and regression tasks. However, to keep things simple, we specialize in this introduction on multivariate analysis and only briefly survey the classification case. Our objective during this section is to produce a concise but mathematically precise presentation of the algorithm for building an RF. The overall framework is nonparametric regression estimation, during which an input random vector \( X \in X \subseteq \mathbb{R}^p \) is observed, and also the goal is to predict the square-integrable random response \( Y \in \mathbb{R} \) by estimating the regression function \( m(x) = \mathbb{E}[Y | X = x] \). With this aim in mind, we assume that we are given a training sample \( D_n = ((X_1, Y_1), \ldots, (X_n, Y_n)) \) of independent random variables distributed because of the independent prototype pair \( (X, Y) \). The goal is to use the info set \( D_n \) to construct an estimate \( mn: X \to \mathbb{R} \) of the function \( m \). In this respect, we are saying that the regression function estimate \( mn \) is (mean squared error) consistent if \( \mathbb{E}[mn(X) - m(X)]^2 \to 0 \) as \( n \to \infty \) (the expectation is evaluated over \( X \) and therefore the sample \( D_n \)). An RF could be a predictor consisting of a group of \( M \) randomized regression trees. For the \( j \)th tree within the family, the expected value at the query point \( x \) is denoted by \( mn(x; \Theta_j, D_n) \), where \( \Theta_1, \ldots, \Theta_M \) are independent random variables, distributed as a generic stochastic variable \( \Theta \) and independent of \( D_n \). In practice, the variable \( \Theta \) is employed to resample the training set before the expansion of individual trees and to pick out the successive directions for splitting – more precise definitions are going to be given later. In mathematical terms, the \( j \) tree estimate takes the shape

\[
mn(x; \Theta_j, D_n) = \sum_{i(\in D_n(\Theta_j))} 1_{x \in An(x; \Theta_j, D_n)} Y_i / \text{Nn}(x; \Theta_j, D_n) \]

where \( D_n(\Theta_j) \) is that the set of knowledge points selected before the tree construction, \( An(x; \Theta_j, D_n) \) is that the cell containing \( x \), and \( \text{Nn}(x; \Theta, D_n) \) is that the number of (preselected) points that represent \( An(x; \Theta_j, D_n) \).

The RF machine learner may be a meta-learner, meaning it consists of the many individual learners (trees). The RF uses multiple random trees classifications to votes on an overall classification for the given set of inputs. In general, each individual machine learner vote is given equal weight. In Breiman’s later work, this algorithm was modified to perform both unweighted and weighted voting. The forest chooses the individual classification that contains the foremost votes. Figure 2 shows the un-weighted RF algorithm (Breiman 2001; Ferretzakis et al. 2020).
The reason for using the RF model in this study is:

The theoretical foundations of evaluation algorithms such as GEP and AI are different. For example, GEP uses a tree structure and AI techniques such as ANFIS are black box models that have been constructed from a set of nodes. The used RF model in this study is one of the classification based machine learning techniques and has better performance than other models for predicting meteorological droughts in different climate regions. For example, according to the results (Abbasi et al. 2019), the GEP model could not predict short-term droughts well, whereas the RF model predicts these droughts well. (The obtained Nash–Sutcliffe (NS) values for predicted SPI-1 and SPEI-1 are above 0.85 in this study, while the proposed GEP model by Abbasi et al. (2019) could not predict SPEI-1 well.) Other advantages of RF are high speed and operational accuracy compared to other methods such as the GEP method.

**Evaluation criteria**

To evaluate the performance of the models, the statistical indices of NS and root-mean-square error (RMSE) were used to determine the accuracy and error of the modeling (Nash & Sutcliffe 1970; Adib et al. 2019).

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum (X_{\text{pred}} - X_{\text{obs}})^2}
\]

\[
\text{NS} = 1 - \frac{\sum (X_{\text{pred}} - X_{\text{obs}})^2}{\sum (X_{\text{pred}} - X_{\text{obs}})^2}
\]

These statistical indices evaluate the accuracy and error of predictions. NS as a representative of accuracy indices and RMSE as a representative of error indices. There were other indices such as \( R, R^2 \), and the mean absolute error (MAE), but these indices have been used and approved in many articles. The reason for selecting these criteria are:

1. The range of NS values is more than other accuracy error (\(-\infty \) to 1).
2. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors.

**Prediction error analysis**

This study used three criteria for prediction error analysis. (1) Overall Accuracy (OA), (2) User’s Accuracy (UA), and (3) Producer’s Accuracy (PA). The relationships of these criteria are expressed in relationships (11) to (13).

\[
\text{OA} = \frac{\sum_i X_{ii}}{N}
\]

Figure 2 | Meta Learners (White 2005).
where \( N \) is the total number of observations during the statistical period; \( X_{ii} \) is the number of events in which the drought class is correctly predicted. \( X_{ij} \) represents events where the prediction value differs from the observational value (Abbasi et al. 2019).

Using these criteria is a conventional method for evaluating the accuracy of RF classification (Jhonnerie et al. 2015). Abbasi et al. (2019) used these criteria to determine the accuracy of the RF model in estimating the drought class prediction. These criteria show different aspects of the accuracy of RF classification.

Figure 3 describes steps of this study.

**Figure 3** | Schematic of applied methods.
RESULTS

Drought monitoring

SPI and SPEI were calculated at the time scales of 1, 3, 6, 9, 12, 24, and 48 months. Figure 4 illustrates the SPI and SPEI variations of the Babolsar Station in the 60-year statistical period. According to Figure 4, the indices had large fluctuations at short time scales, which reduced as the time scale increased. In other words, an increase in the time scale reduced the number of drought events and enhanced the drought duration. In this section, changes in SPI and SPEI indices of Babolsar station are presented; similar charts for other stations are provided in the Supplementary material.

In this section, the drought results are presented based on the 48-month time scale. According to the SPI results, Abadan experienced drought in the initial and last decades of the statistical period (i.e., 1960–2019). According to the SPEI results, Abadan has often experienced drought since the 1980s. Babolsar had the longest drought period in the initial 15 years of the statistical period, based on the SPI results. Also, Babolsar has experienced alternatively occurring drought events in the recent decade. Based on the SPEI results, Babolsar underwent drought at the beginning, middle, and end of the statistical period. Moreover, based on the SPEI results, Babolsar experiences alternatively occurring drought events, and the drought intensity of Babolsar has been more extensive in the recent decade than the other decades. Based on the SPI results, Khoy experienced drought from 1986 to 2018. Based on the SPEI results, Khoy has alternatively occurring drought events, whose duration has increased in the recent decade. The Khoy Station is located in the north of Urmia Lake. Enhanced drought, improper water resources planning management, and the nonobservance of Urmia Lake water rights, which used to be the largest saltwater lake in the Middle East, have significantly decreased the area of Urmia Lake. However, suitable rainfall and management measures have somewhat shifted the lake far from the critical circumstances in recent years. This improvement is not stabilized, and critical circumstances may return.

Based on the SPI results, Mashhad experienced drought in the initial decade and last quarter of the statistical period. Based on the SPEI results, Mashhad often experienced drought in the last quarter of the statistical period. Based on the SPI and SPEI results, Zahedan experienced drought in the two last decades of the statistical period.

Tables 2 and 3 list the drought characteristics based on the SPI and SPEI results at the time scales of 3, 12, and 48 months. According to Table 2, the highest number of drought events occurred in the Babolsar and Khoy stations, the longest drought periods happened in the Khoy, Isfahan, and Abadan stations, and the most intense peak was −4.46 in the Babolsar station under SPI-3 in March 2001. The highest drought severity occurred at −149.9 during March 1995–April 2005 in the Khoy station under SPI-48. The drought severity of the Abadan station was found to be −148.4 under SPI-48 from January 2009 to November 2019.

According to Table 3, the highest numbers of drought events occurred in the Khoy and Babolsar stations, the longest drought periods happened in the Zahedan and Mashhad stations, and the most intense peak was −2.64 under SPEI-3 in the Zahedan station in August 1960. The highest drought severity was −290.8 under SPEI-48 at the Mashhad station from December 1996 to the end of the statistical period (i.e., December 2019).

According to Table 4, the high correlation between SPI and SPEI at stations such as Babolsar indicates that SPI can alone represent drought situations. At the Abadan and Zahedan stations with very high evaporation rates, there is a small correlation between SPI and SPEI. Therefore, SPI cannot be employed in place of SPEI.

Figures 5 and 6 show and compare the relative frequencies of drought classes based on SPI and SPEI, respectively, in the 60-year period. The results suggest the overall similarity of the relative frequencies of the drought classes based on SPI and SPEI at all six stations (Figures 5 and 6). For both indices, the normal class has the highest frequency; the SPI frequency of the normal class is larger than the SPEI frequency of the normal class.

Drought prediction

In modeling, drought indices with a lag-time of 1–12 months were used to predict the meteorological drought index in the next time step. Therefore, this study has used the RF model to predict drought indices. By using the RF model, short, medium, and long-term severe or extreme meteorological droughts can be predicted. This method is similar to the used method by Abbasi et al. (2019).

In the RF model, 13 combinations with time lags of 1–12 months were used for SPI and SPEI prediction in the next time step. For example, the predicted SPI-12 and SPEI-12 could indicate the occurrence of meteorological drought in the next year.
Figure 4 | Time series of SPI and SPEI indices in Babolsar station in time scales of 1–48 months. (continued).
Tables 5 and 6 show the optimal combinations for the prediction of SPI and SPEI, respectively.

Model 1: $X_{t+1} = f(X_t)$
Model 2: $X_{t+1} = f(X_t, X_{t-1})$
Model 3: $X_{t+1} = f(X_t, X_{t-1}, X_{t-2})$

Model 13: $X_{t+1} = f(X_t, X_{t-1}, X_{t-5}, X_{t-4}, X_{t-5}, X_{t-6}, X_{t-7}, X_{t-8}, X_{t-9}, X_{t-10}, X_{t-11}, X_{t-12})$ \( (14) \)

where $X$ represents SPI and SPEI, in the 60-year period of SPI and SPEI, 70% of the drought index data were employed as the training data, whereas the remaining 30% were used as the test data.

For each time scale, SPI is sensitive to SPI at months ago. The correlation coefficient between SPI and SPEI is less than the correlation coefficient between SPIs at different months. This situation can be observed for SPEI too. Therefore, Equation (14) contains a type of index (SPI or SPEI). Using different indices in this equation reduces NS and increases RMSE.

This study used the lag time to 12 months ago to predict drought in the next step. The results showed that in optimal models, the maximum lag time is 11 months (Tables 5 and 6). So considering 12 months for the lag time is the right choice. Therefore, long-term drought modeling (i.e., longer time scale) is more accurate than short-term drought modeling. This is due to the lower fluctuations and higher smoothness of long-term drought times series than short-term ones. In
other words, the efficiency enhancement of prediction models is directly associated with the time scale of the adopted drought index in the model. As shown in Tables 5 and 6, an increase in the time scale improves the prediction models. This was mentioned by Abbasi et al. (2019) and Hosseini-Moghari & Araghinejad (2015).

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Drought characteristics based on SPEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought characteristics</td>
<td>Time scale</td>
</tr>
<tr>
<td>Number of dry periods</td>
<td>3 months</td>
</tr>
<tr>
<td></td>
<td>12 months</td>
</tr>
<tr>
<td></td>
<td>48 months</td>
</tr>
<tr>
<td>Max duration of drought period (month)</td>
<td>3 months</td>
</tr>
<tr>
<td></td>
<td>12 months</td>
</tr>
<tr>
<td></td>
<td>48 months</td>
</tr>
<tr>
<td>Average of drought periods (month)</td>
<td>3 months</td>
</tr>
<tr>
<td></td>
<td>12 months</td>
</tr>
<tr>
<td></td>
<td>48 months</td>
</tr>
<tr>
<td>Standard deviation of drought periods (month)</td>
<td>3 months</td>
</tr>
<tr>
<td></td>
<td>12 months</td>
</tr>
<tr>
<td></td>
<td>48 months</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Correlation coefficient between SPI and SPEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation between SPI and SPEI</td>
<td>Abadan</td>
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<tr>
<td>1 month</td>
<td>0.49</td>
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<tr>
<td>3 months</td>
<td>0.47</td>
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<tr>
<td>6 months</td>
<td>0.43</td>
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<tr>
<td>9 months</td>
<td>0.37</td>
</tr>
<tr>
<td>12 months</td>
<td>0.35</td>
</tr>
<tr>
<td>24 months</td>
<td>0.37</td>
</tr>
<tr>
<td>48 months</td>
<td>0.44</td>
</tr>
</tbody>
</table>
According to Table 5, the best NS at the time scales of 1, 3, 6, 9, 24, and 48 months belong to the Abadan, Khoy, Khoy, Khoy, Mashhad, and Khoy stations, respectively, and the best RMSE at the time scales of 1, 3, 6, 9, 24, and 48 months belong to the Zahedan, Zahedan, Mashhad, Mashhad, Mashhad, and Khoy, respectively. According to Table 6, the best
### Table 5 | The best models in drought prediction based on the SPI index

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Abadan</th>
<th>Babolsar</th>
<th>Isfahan</th>
<th>Khoy</th>
<th>Mashhad</th>
<th>Zahedan</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>Model 12</td>
<td>Model 12</td>
<td>Model 10</td>
<td>Model 8</td>
<td>Model 12</td>
<td>Model 11</td>
</tr>
<tr>
<td></td>
<td>NS = 0.894</td>
<td>NS = 0.859</td>
<td>NS = 0.87</td>
<td>NS = 0.855</td>
<td>NS = 0.87</td>
<td>NS = 0.887</td>
</tr>
<tr>
<td></td>
<td>RMSE = 0.278</td>
<td>RMSE = 0.361</td>
<td>RMSE = 0.297</td>
<td>RMSE = 0.356</td>
<td>RMSE = 0.319</td>
<td>RMSE = 0.265</td>
</tr>
<tr>
<td>3 months</td>
<td>Model 5</td>
<td>Model 7</td>
<td>Model 5</td>
<td>Model 10</td>
<td>Model 9</td>
<td>Model 5</td>
</tr>
<tr>
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<td>NS = 0.93</td>
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<td>NS = 0.93</td>
<td>NS = 0.938</td>
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<td>NS = 0.927</td>
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<tr>
<td></td>
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<td>RMSE = 0.243</td>
<td>RMSE = 0.264</td>
<td>RMSE = 0.234</td>
</tr>
<tr>
<td>6 months</td>
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<td>Model 8</td>
<td>Model 6</td>
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<td>Model 8</td>
</tr>
<tr>
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<td>NS = 0.942</td>
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<td>NS = 0.965</td>
<td>NS = 0.957</td>
<td>NS = 0.953</td>
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<tr>
<td></td>
<td>RMSE = 0.23</td>
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<td>RMSE = 0.213</td>
<td>RMSE = 0.203</td>
<td>RMSE = 0.213</td>
</tr>
<tr>
<td>9 months</td>
<td>Model 10</td>
<td>Model 10</td>
<td>Model 12</td>
<td>Model 12</td>
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<tr>
<td></td>
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<td>NS = 0.971</td>
<td>NS = 0.974</td>
<td>NS = 0.973</td>
<td>NS = 0.971</td>
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<tr>
<td></td>
<td>RMSE = 0.192</td>
<td>RMSE = 0.193</td>
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<td>RMSE = 0.159</td>
<td>RMSE = 0.17</td>
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<td>12 months</td>
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<td>Model 12</td>
</tr>
<tr>
<td></td>
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<td>NS = 0.981</td>
<td>NS = 0.981</td>
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<tr>
<td></td>
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<td>RMSE = 0.135</td>
<td>RMSE = 0.135</td>
<td>RMSE = 0.143</td>
</tr>
<tr>
<td>24 months</td>
<td>Model 11</td>
<td>Model 11</td>
<td>Model 10</td>
<td>Model 7</td>
<td>Model 11</td>
<td>Model 8</td>
</tr>
<tr>
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<td>NS = 0.986</td>
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<td>NS = 0.991</td>
<td>NS = 0.987</td>
</tr>
<tr>
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<td>RMSE = 0.095</td>
<td>RMSE = 0.113</td>
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<tr>
<td>48 months</td>
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<td>Model 9</td>
<td>Model 5</td>
<td>Model 8</td>
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<tr>
<td></td>
<td>NS = 0.992</td>
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<td>NS = 0.995</td>
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<tr>
<td></td>
<td>RMSE = 0.087</td>
<td>RMSE = 0.123</td>
<td>RMSE = 0.095</td>
<td>RMSE = 0.066</td>
<td>RMSE = 0.077</td>
<td>RMSE = 0.087</td>
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</table>

### Table 6 | The best models in drought prediction based on the SPEI index

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Abadan</th>
<th>Babolsar</th>
<th>Isfahan</th>
<th>Khoy</th>
<th>Mashhad</th>
<th>Zahedan</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>Model 12</td>
<td>Model 11</td>
<td>Model 11</td>
<td>Model 12</td>
<td>Model 12</td>
<td>Model 12</td>
</tr>
<tr>
<td></td>
<td>NS = 0.887</td>
<td>NS = 0.857</td>
<td>NS = 0.86</td>
<td>NS = 0.862</td>
<td>NS = 0.879</td>
<td>NS = 0.876</td>
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<tr>
<td></td>
<td>RMSE = 0.335</td>
<td>RMSE = 0.377</td>
<td>RMSE = 0.375</td>
<td>RMSE = 0.37</td>
<td>RMSE = 0.348</td>
<td>RMSE = 0.348</td>
</tr>
<tr>
<td>3 months</td>
<td>Model 8</td>
<td>Model 4</td>
<td>Model 5</td>
<td>Model 4</td>
<td>Model 5</td>
<td>Model 5</td>
</tr>
<tr>
<td></td>
<td>NS = 0.951</td>
<td>NS = 0.922</td>
<td>NS = 0.918</td>
<td>NS = 0.943</td>
<td>NS = 0.955</td>
<td>NS = 0.953</td>
</tr>
<tr>
<td></td>
<td>RMSE = 0.217</td>
<td>RMSE = 0.278</td>
<td>RMSE = 0.307</td>
<td>RMSE = 0.238</td>
<td>RMSE = 0.211</td>
<td>RMSE = 0.21</td>
</tr>
<tr>
<td>6 months</td>
<td>Model 10</td>
<td>Model 9</td>
<td>Model 7</td>
<td>Model 8</td>
<td>Model 7</td>
<td>Model 7</td>
</tr>
<tr>
<td></td>
<td>NS = 0.98</td>
<td>NS = 0.951</td>
<td>NS = 0.97</td>
<td>NS = 0.966</td>
<td>NS = 0.98</td>
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<tr>
<td></td>
<td>RMSE = 0.138</td>
<td>RMSE = 0.221</td>
<td>RMSE = 0.17</td>
<td>RMSE = 0.182</td>
<td>RMSE = 0.141</td>
<td>RMSE = 0.136</td>
</tr>
<tr>
<td>9 months</td>
<td>Model 4</td>
<td>Model 9</td>
<td>Model 11</td>
<td>Model 9</td>
<td>Model 10</td>
<td>Model 8</td>
</tr>
<tr>
<td></td>
<td>NS = 0.993</td>
<td>NS = 0.967</td>
<td>NS = 0.979</td>
<td>NS = 0.975</td>
<td>NS = 0.987</td>
<td>NS = 0.989</td>
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<tr>
<td></td>
<td>RMSE = 0.081</td>
<td>RMSE = 0.18</td>
<td>RMSE = 0.142</td>
<td>RMSE = 0.155</td>
<td>RMSE = 0.112</td>
<td>RMSE = 0.102</td>
</tr>
<tr>
<td>12 months</td>
<td>Model 7</td>
<td>Model 12</td>
<td>Model 5</td>
<td>Model 8</td>
<td>Model 11</td>
<td>Model 11</td>
</tr>
<tr>
<td></td>
<td>NS = 0.997</td>
<td>NS = 0.976</td>
<td>NS = 0.986</td>
<td>NS = 0.983</td>
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<tr>
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<td>RMSE = 0.056</td>
<td>RMSE = 0.153</td>
<td>RMSE = 0.117</td>
<td>RMSE = 0.129</td>
<td>RMSE = 0.094</td>
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</tr>
<tr>
<td>24 months</td>
<td>Model 3</td>
<td>Model 9</td>
<td>Model 6</td>
<td>Model 2</td>
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<td>Model 3</td>
</tr>
<tr>
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<td>NS = 0.998</td>
<td>NS = 0.984</td>
<td>NS = 0.995</td>
<td>NS = 0.991</td>
<td>NS = 0.997</td>
<td>NS = 0.998</td>
</tr>
<tr>
<td></td>
<td>RMSE = 0.047</td>
<td>RMSE = 0.125</td>
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<td>RMSE = 0.095</td>
<td>RMSE = 0.054</td>
<td>RMSE = 0.046</td>
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<tr>
<td>48 months</td>
<td>Model 12</td>
<td>Model 9</td>
<td>Model 7</td>
<td>Model 11</td>
<td>Model 4</td>
<td>Model 7</td>
</tr>
<tr>
<td></td>
<td>NS = 0.998</td>
<td>NS = 0.989</td>
<td>NS = 0.997</td>
<td>NS = 0.996</td>
<td>NS = 0.999</td>
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</tr>
<tr>
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<td>RMSE = 0.038</td>
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<td>RMSE = 0.064</td>
<td>RMSE = 0.035</td>
<td>RMSE = 0.037</td>
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</table>
NS at the time scales of 1, 3, 9, 12, and 48 months belong to the Abadan, Mashhad, Abadan, Abadan, and Mashhad, respectively, and the best RMSE at the time scales of 1, 3, 6, 9, 12, 24, and 48 months belong to the Abadan, Zahedan, Zahedan, Abadan, Abadan, Zahedan, and Mashhad, respectively.

The Taylor diagram provides a proper perspective on the accuracy of the RF model. In this diagram, radial values that take distance from the hallow points (observed quantities) represent the root-mean-square deviation (RMSD), and radial distances from the origin represent the standard deviation (Taylor 2001). In addition, the on-arc values indicate the correlation coefficient between the observed data and predicted results. Figure 7 illustrates the best combination in the prediction of SPI and SPEI for each time scale (1–48 months) at the six stations. As mentioned, an increased time scale is expected to improve modeling accuracy. In this study, the modeling accuracy was largest at the 48-month time scale for all stations. Moreover, a comparison of SPI and SPEI reveals that SPEI-48 is more accurate than SPI-48.

Figure 8 shows the superior models in the prediction of SPI and SPEI at different time scales. At the 1-month time scale, SPI has higher prediction accuracy than SPEI, particularly at the Abadan and Zahedan stations with relatively low precipitation and high temperatures. At the other stations, SPEI has higher prediction accuracy than SPI; the SPEI predictions at the time scales of 3, 6, 9, 12, 24, and 48 months were more accurate at the Abadan, Mashhad, and Zahedan stations than the other stations.

To evaluate accuracy in estimation of the drought class for SPI and SPEI prediction, the user accuracy (UA) and producer accuracy (PA) were presented for different drought classes. Figures 9 and 10 illustrate PA for SPI and SPEI, respectively. In addition, Figures 11 and 12 represent UA for SPI and SPEI, respectively. In general, as the SPI and SPEI time scales increase, UA and PA noticeably increase. For example, at the 48-month time scale and for all drought classes, the average PA of SPI
predictions increased from 88.2 to 93.6% at the Abadan station, from 72.4 to 87.1% at the Babolsar station, from 86.6 to 89.7% at the Isfahan station, from 82.4 to 92.1% at the Khoy station, and from 95 to 95.9% at the Zahedan station as compared to the average PA of the SPEI predictions.

At the 48-month time scale and for all drought classes, the average UA of SPI predictions increased from 92.5 to 98% at the Abadan station, from 87.8 to 92.4% at the Babolsar station, from 90.3 to 94.6% at the Isfahan station, from 62.2 to 96.6% at the Mashhad station but reduced from 95.9 to 94.3% at the Khoy station and from 95.4 to 94.8% at the Zahedan station as compared to the average UA of the SPEI predictions.

Figure 8 | Taylor diagram of top models in predicting drought in each region in time steps of 1–48 months.
Figure 9 | PA value in drought prediction based on the SPI index.

Figure 10 | PA value in drought prediction based on the SPEI index.
**Figure 11** | UA value in drought prediction based on the SPI index.

**Figure 12** | UA value in drought prediction based on the SPEI index.
Let $i$ represent the actual drought class and $j$ represent the RF-predicted class. The estimate for which $i = j$ is considered to be correct. If $i < j$, an underestimate has occurred, while if $i > j$, an overestimate has happened.

According to Figure 13, the overall accuracy (OA) of SPI predictions increased by 15, 24, 16.7, 24.2, 18.4, and 15.8% when the time scale increased from 1 month to 48 months at the Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan stations, respectively. In addition, the OA of SPEI predictions increased by 24.5, 24.7, 26.9, 27.1, 24.6, and 22% at the Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan stations, respectively, when the time scale enhanced from 1 month to 48 months. Therefore, the OA of SPEI predictions is higher than that of SPI predictions.

An increase in the time scale from 1 month to 48 months reduced OE in SPI predictions by 7.6, 11.7, 12.8, 14.6, 12.5, and 11.4% at the Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan stations, respectively, and decreased OE in SPEI predictions by 12.8, 13, 16.1, 17.1, 14.4, and 12.6% at the Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan stations, respectively. Therefore, the OE of SPEI predictions is lower than that of SPI predictions. When the time scale increased from 1 month to 48 months, UE in SPI predictions decreased by 7.4, 12.3, 4, 9.5, 5.9, and 4.4% at the Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan stations, respectively, while UE in SPEI predictions reduced by 11.7, 11.8, 10.8, 10.1, 10.2, and 9.4% at the Abadan, Babolsar, Isfahan, Khoy, Mashhad, and Zahedan stations, respectively. Therefore, the UE of SPEI predictions is lower than that of SPI predictions.

The three indicators OA, OE, and UE show good accuracy and uncertainty in predictions. The OE and UE indices show over estimate and under estimate in modeling, respectively, which form a band of uncertainty. Figure 13 illustrates this well. According to this figure, with increasing the time scale of droughts, the uncertainty in forecasts decreases.

**DISCUSSION**

This study monitors and predicts meteorological drought over a period of 60 years. The highest correlation between SPI and SPEI occurred at the Babolsar, Khoy, Mashhad, Isfahan, Zahedan, and Abadan stations, in descending order. A higher
correlation between SPI and SPEI indicates that SPI is reliable in drought monitoring, and it is not required to calculate SPEI. In other words, an SPI-SPEI comparison was performed to evaluate the effects of PET on drought in Iran and uncertainty in the SPI results. The results revealed that in an arid climate such as in Abadan, Zahedan, and Isfahan in which the average precipitation is low and the average temperature is high; the correlation between the SPI and SPEI is lower than other stations in other climates (Tirivarombo et al. (2018) demonstrated this in the Kafue Basin in northern Zambia). Therefore, these results are in contrast with the obtained results of Sharafati et al. (2020) and Mahmoudi et al. (2019) (see Table 4) that reported a high correlation amount among the SPI and SPEI in all regions with various climates. Thus, PET is a significant factor that must be regarded in drought calculations, particularly in arid areas. In other words, based on the achieved results of the present study, utilizing indices that, in addition to precipitation, are based on PET is recommended in arid regions. Based on the SPEI index, the longest and peak of the 3-month drought has occurred in the southwest and southeast. Moreover, the longest and peak of the 12-month drought has taken place in north/northwest and south/southeast, respectively. Finally, the longest and peak of the 48-month drought has happened in the center, north, east, and southeast, respectively, that are well-matched with the results of Sharafati et al. (2020).

On a 3-month period scale, the drought durability is lower in the north and northwest and higher in the southwest and southeast. Furthermore, the 3-month drought severity is lower in the northwest and higher in the southwest. On a 12-month period scale, the drought durability average is lower in the north and northwest and higher in the southwest. The 12-month drought severity is lower in the north and northwest and higher in the southeast and east. Additionally, the average drought durability is lower in the northwest and north and higher in the southwest on a 48-month scale. The 48-month drought severity is lower in the northwest and higher in the east and southeast. According to values of both SPI and SPEI indices, peak, mean, and standard deviation of drought periods, drought severity, and durability have increased by increasing the time scale in all climates. In comparison, the amplitude of drought incidents and peaks in the short-term scale (3-month) is higher than the long-term scale (48-month) in all regions according to the SPI index value. However, based on the SPEI value, these features in the short-term scale (3-month) compared to the long-term scale (48-month) in the southwest, northwest, east, and southeast regions have decreased, while they have increased in the central and northern areas in these scales. These results are consistent with Sharafati et al. (2020). The highest number of drought incidents has taken place in the north and northwest of Iran, which is well-matched with the results of Alizadeh-Choobari & Najafi (2018), Nabaei et al. (2019), and Sharafati et al. (2020).

Based on SPEI-48, drought and wet periods alternatively occurred in the 60-year period. However, drought has lasted in the past two decades in Iran. Based on SPEI-48, the longest drought periods in the past two decades occurred at the Mashhad, Abadan, Zahedan, Khoy, Isfahan, and Babolsar stations, in descending order. Also, based on SPEI, the most intense drought periods in the past two decades happened at the Zahedan, Mashhad, Isfahan, Abadan, Babolsar, and Khoy stations in descending order. The descending and ascending precipitation trends under the influence of climate change led to these drought events (Najafi & Moazami 2016; Bazrafshan 2017; Alizadeh-Choobari & Najafi 2018).

As shown in Figure 7, in RF drought prediction, an increase in the drought time scale improved modeling accuracy due to the reduced fluctuations in drought time series. With reduction of fluctuation of time series, the shape of these time series approaches the line. Linear modes are easier and more accurate to predict than nonlinear modes. In addition, the prediction accuracy of SPEI-48 was higher than that of SPI-48. The superior models at the time scales of 1, 3, 6, 9, 12, 24, and 48 months in SPI and SPEI predictions are presented in Tables 5 and 6, and prediction error analysis was performed based on these superior models. Overall, OA increased as the time scale increased. The accuracy enhancement of SPEI predictions was higher than that of SPI predictions. Abbasi et al. (2019) mentioned that a rise in the time scale improved accuracy and decreased prediction errors in the GEP model, which is based on the tree structure, while the results of the present study demonstrated that the RF, which is based on the decision tree, has better performance than the GEP model in accuracy improvement and error reduction. The advantages of the RF model include high modeling speed and the ability to make short-term drought predictions, which is excellent as compared to the GEP. Kisi et al. (2019) integrated the ANFIS with optimization algorithms such as GA and PSO. Zhang et al. (2020) used ARIMA, WNN, and SVM for drought forecasting. However, the RF model based on classification was more robust than the models used in these studies. Mahmoudi et al. (2019) were content with just seven precipitation-based drought indices and introduced the SPI index as the best index in drought monitoring. An essential point in calculating drought in arid and semi-arid countries such as Iran is the significant amount of PET included in the SPEI index but not in the SPI. OE and UE reduced as the time scale enhanced, and these OE and UE reductions were greater in SPEI predictions than in SPI predictions.
The obtained important results and highlights of this study are:

1. The nonapplicability of the SPI index, which is based only on rainfall, is in hot and dry areas (such as Abadan station).
   
   The SPI index, which uses only the precipitation variable, is not suitable for warm regions such as southwestern Iran, where the temperature is high, while the SPEI should be used for these regions. Sharafati et al. (2020) did not mention this matter but obtained results in this study are completely consistent with the results of Bazrafshan (2017). This matter was observed in hot and dry regions of other countries such as studies of Li et al. (2020) in China and Pei et al. (2020) in Inner Mongolia of China.

2. Provide accurate forecast models (combination of different lag times) for six regions with different climates (Tables 5 and 6).

3. Extraction of drought characteristics of each region according to the run theory (Tables 2 and 3).

4. Using the RF model, which with its classification ability could improve the results of forecasts (compared to previous studies); for example, according to the results (Abbasi et al. 2019), the GEP model was not able to predict short-term droughts, while the RF model did well (Tables 5 and 6).

CONCLUSION

In general, unlike flood events, drought occurs in longer periods. Thus, when drought happens in a long period, the frequent occurrence of precipitation in a short period (e.g., a year or in some months) in a region cannot easily compensate for the shortage of water resources due to long-term drought. The prediction and monitoring of drought play a vital role in the reduction of drought hazards. Due to its arid and semi-arid climate, Iran is exposed to such drought tensions. Therefore, the present study monitored drought events in Iran by using SPI and SPEI for a 60-year period (1960–2019), proposing a model for drought management to minimize drought damages by implementing drought management measures.

The obtained results indicate the high correlation of SPI and SPEI indices in the north and northwest regions of Iran that have temperate and continental climates. In contrast, a lower correlation amount has been acquired in the east, southeast, central, and southwest regions with arid climates.

The average durability of short-term and long-term droughts is lower in the north and northwest; on the other hand, the southwest and southeast represent a higher value at the short-term scale, and the southwest indicates a higher value at the long-term scale, as well. In this regard, the longest drought period of the southwest has occurred in the 1960s and 1970s.

Additionally, the drought severity at the north and northwest is lower; nevertheless, it is higher at the short-term scale in the southwest and at the long-term scale in the east and southeast. Moreover, the most extended drought period of east and south regions has occurred in the last two decades.

Using a robust RF model to predict drought in the next time step has produced extraordinary results. By increasing the time scale from short-term to long-term, the modeling accuracy is enhanced. The reason for this enhancement is the reduction of oscillation in long-term drought time-series in comparison to short-term ones. The NS and OA increase and decrease of RMSE, OE, and UE prove this claim.

On the other hand, in the present study, an optimal combination of required delays for building the most robust RF model to predict short-term to long-term droughts has been selected. The corresponding results have been illustrated in the Taylor diagram. Therefore, the drought can be predicted with high accuracy by using the RF model.

The limitation of this study was the shortage of ground-based data as the meteorological data for the Penman–Monteith method. This method can calculate potential evapotranspiration accurately. Also, using time series preprocessing techniques such as wavelet analysis can improve the accuracy of predictions such as short-term meteorological drought prediction.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

REFERENCES


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