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Susceptibility Assessment of Winter Wheat, Barley and Rapeseed to Drought Using Generalized Estimating Equations and Cross-Correlation Function

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Abstract

Due to the impact of drought on crop yield, the aim of this research is the susceptibility assessment of winter wheat, barley and rapeseed species to drought using Generalized Estimating Equations (GEE) and Cross-Correlation Function (CCF). For this objective, the climatic data of 10 synoptic stations in Iran from 1968 to 2017 (i.e., 50 years) were used. Then, the AquaCrop model was adopted to simulate annual yield (A_v) of the above-mentioned species. Also, the standardized precipitation evapotranspiration index (SPEI) was applied to assess drought conditions in selected constant and progressively increasing reference time periods, including 1-month, 3-month, 6-month and 12-month time scales (27 reference time periods) starting in October. For evaluating the accuracy of the GEE model, the correlation coefficients (CC) between simulated and predicted annual yields in selected species through the AquaCrop model and GEE model were used, respectively. The accuracy test of the GEE model showed that the CC between simulated and predicted annual yield of barley almost in all stations and all-time scales were signifcant at 0.01 level. Only in Birjand and Kerman stations the CC between simulated and predicted annual yield were signifcant at 0.05 level in 3.7% and 66.67% of time scales, respectively. Based on the GEE and CCF models in all stations, the susceptibility of rapeseed to drought was more than that of wheat, and the susceptibility of wheat was more than that of barley.

Keywords Rapeseed · Winter wheat · Barley · SPEI · GEE · Cross-correlation function

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1 Introduction

Over the last few decades, meteorological droughts have been one of the natural disasters that have had negative impacts on agriculture productions and food security in the world, especially in arid and semi-arid regions. The drought, which can occur in various regions with any climates, has diferent impacts on various sections, especially those with greater dependency on water; for example: environment section, rangelands, surface and sub-surface water resources, agricultural productions especially rain-fed farming section, etc. (Hamal et al. [2020](#page-33-0); Iqbal et al. [2020](#page-33-1); Schierhorn et al. [2020](#page-34-0); Otkin et al. [2019;](#page-33-2) Wine [2019;](#page-34-1) Zarei [2018](#page-34-2)). Therefore, it is important to evaluate the drought conditions in diferent regions properly and determine the severity of various droughts. The Standardized Precipitation Evapotranspiration Index (SPEI), introduced by Vicente-Serrano et al. [\(2010](#page-34-3)), is one of the newest and the most applied indices used to monitor drought conditions in diferent time scales (Danandeh Mehr et al. [2020](#page-32-0); Shen et al. [2019](#page-34-4)). There have been a lot of studies (e.g., Ayantobo et al. [2019](#page-32-1); Bhuyan-Erhardt et al. [2019](#page-32-2); Khoshoei et al. [2019;](#page-33-3) Wable et al. [2019;](#page-34-5) Wang et al. [2019a](#page-34-6)) conducted on drought around the world by using the SPEI.

Li et al. [\(2019](#page-33-4)) compared the Standardized Precipitation Index (SPI), SPEI based on Penman-Monteith (SPEI-PM) and SPEI based on Thornthwaite (SPEI-TH) by using data series of 35 stations in Yangtze River Basin during 1959–2017. The results indicated that the SPEI-PM was the best index to assess drought conditions. Wable et al. ([2019\)](#page-34-5) compared fve drought indices in River Basin (Western India) with semi-arid climate conditions and found that the SPEI 9-month was the most suitable index for evaluating the drought conditions. Tian et al. [\(2018](#page-34-7)) evaluated 6 drought indices to assess agricultural drought in the south-central United States; the study revealed that there is a relatively higher CC between the SPEI and Z-score and all the crop yields. Labudová et al. [\(2017](#page-33-5)) compared the SPI and SPEI indices to evaluate drought effect on crop yield in the East Slovakian. The results showed that there is the highest CC between 3-monthly SPEI and maize yield.

On the other hand, regarding the drought efects on the annual yield of crops, many researchers have tried to evaluate the sensitivity of various plant species to drought (e.g., Chen et al. [2020](#page-32-3); Huang et al. [2020;](#page-33-6) Gao et al. [2019;](#page-33-7) Leng and Hall [2019;](#page-33-8) Meise et al. [2019;](#page-33-9) Peña-Gallardo et al. [2019;](#page-33-10) Peña-Gallardo et al. [2018\)](#page-33-11). Peña-Gallardo et al. [\(2019](#page-33-10)) evaluated the response of the annual crop yield to drought (based on SPEI) in 5 main dryland cultivations in the United States. The results showed that the CC between drought and crop yield in regions with humid climate conditions was less than other regions. On the other hand, the winter wheat responded to drought at medium to long SPEI timescales, while soybean and corn responded to short or long drought time-scales. Samarah ([2005\)](#page-34-8) evaluated the drought efects on growth and yield of barley. The results showed that drought stress was detrimental to grain yield, regardless of the stress severity. Marček et al. ([2019\)](#page-33-12) assessed the metabolic response to drought in six winter wheat genotypes.

Chen et al. (2018) (2018) assessed the drought and flood effects on crop production in China during 1949–2015 using the Bayesian hierarchical model. The results showed a signifcant reduction in the grain yields in 90.32% of provinces of the study region. Páscoa et al. [\(2017](#page-33-13)) evaluated the drought efects on wheat yield in the Iberian Peninsula during 1929–2012. They found a strong control on wheat yield in May and June. Li et al. [\(2018](#page-33-14)) evaluated the response of vegetation to drought in diferent time scales in Mongolia plateau. Results indicated that vegetation in steppe regions is more sensitive to shorter timescales of droughts, while it is more sensitive to longer drought time-scales in the forest regions. Zhao et al. ([2019\)](#page-34-9) assessed the drought efects on vegetation dynamics in China's Loess Plateau. The study showed that the severe and extreme drought (SPEI<−1.5) has reduced the normalized diference vegetation index (NDVI) of the region studied in 2001 and 2005. Jalil et al. [\(2020](#page-33-15)) revealed that the AquaCrop model was able to accurately simulate the water productivity of crop in Kabul. Using the GEE and CCF models in hydrological studies has been less considered. Zarei et al. ([2020\)](#page-34-10) and Chakraborty [\(2020](#page-32-5)) are some of the researchers that used the GEE and CCF models.

This study aims at evaluating the susceptibility of winter wheat, barley and rapeseed to drought because of the following reasons: a) the necessity of sustainably feeding the rapidly growing population; b) the important role of wheat, barley and rapeseed in food security of humans and livestock worldwide; c) the occurrence of successive droughts and the increase in their intensity afected by human-activities-related changes; and d) the impacts of drought occurrence on the yield of wheat, barley and rapeseed. To accurately and comprehensively achieve this aim, the impact of drought on all plant growth periods (in 27 diferent time periods) was investigated using two new statistical models (in agricultural science) including GEE and CCF models.

2 Material and Methods

2.1 Study Region

The study region corresponds to Iran covering an area about 168 million hectares extending from 25.56 \degree to 39.77 \degree N and 44.02 \degree to 63.36 \degree E (Fig. [1](#page-3-0)). The average height of Iran varies from less than −10 m at Caspian Sea coasts to about 5333 m above sea level at the Damavand Mountain. Based on Modifed De-Martonne index, the climate conditions of Iran vary from hyper-humid to hyper-arid in the northwest (such as Bandar Anzali) and central regions (such as Yazd) of Iran, respectively (Zarei and Moghimi [2019b](#page-34-11); Zarei [2018](#page-34-2)). The statistical population of the study included 10 synoptic stations with the suitable spatial distribution and adequate time duration of meteorological data series with hyper-arid (Esfahan) to semi-arid (Arak, Ghazvin, Sanandaj and Shiraz) climate conditions during 1968–2017. Based on the data collected from the selected stations, the mean of monthly precipitation of the study area varies from 10.75 mm at Esfahan station to 36.49 mm at Sanandaj station, while the mean of the monthly potential evapotranspiration of the study area varies from 115.92 mm at Ghazvin station to 171.39 mm at Sabzevar station. Geographic location and climatic properties of the selected stations are presented in Table [1.](#page-4-0)

2.2 Methods

2.2.1 Data Collection and Selection of the Appropriate Time Period

In this research, climatic data series of 10 stations including Arak, Brjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran synoptic stations from 1968 to 2017, prepared by the Iran Meteorological Organization (IMO), were used to calculate values of drought index in diferent time scales (SPEI index), and simulate the *Ay* of winter wheat, barley and rapeseed. To estimate missing values and to evaluate the homogeneity of data series in all stations, the multiple imputation and Mockus methods were adopted, respectively (Rezazadeh Jodi and Sattari [2016](#page-34-12)). The appropriate time periods were selected in accordance with planting to harvesting time of winter

Fig. 1 Location of selected stations in the study area (Iran)

wheat, barley and rapeseed species at the selected stations, according to the diference in planting to harvesting time in selected species and selected station. Accordingly, constant and progressively increasing appropriate time periods include the following periods: 1-month (11 time periods), 3-month (9 time periods), 6-month (6 time periods), and 12-month (1 time period). These time periods started in October (Zarei et al. [2019;](#page-34-13) Tigkas et al. [2018](#page-34-14); Tigkas et al. [2016\)](#page-34-15) and are presented in detail in Table [5.](#page-13-0)

2.2.2 SPEI Calculation

To calculate the SPEI, first, the differences (Di) between the rainfall (R_i) and potential evapotranspiration or PET (to calculate PET the FAO Penman-Monteith or FAO-56 was used) for month *i* were calculated and aggregated at different time scales (D^k) :

$$
Di = R_i - PET_i \tag{1}
$$

$$
D^{k} = \sum_{i=0}^{k-1} R_{n-i} - PET_{n-i}
$$
 (2)

then based on the L-moment procedure, the probability density function of a three-parameter log-logistic distribution was applied to take into account the negative values of D^k :

if MDM index ≤5 climate condition is Hyper-Arid (HA), climate condition was classifed Arid if 5<MDM index ≤10, and climate condition was classifed Semi-Arid if

10<MDM index ≤20

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Table 1 Characteristics of the selected meteorological synoptic stations

Table 1 Characteristics of the selected meteorological synoptic stations

$$
F(x) = \frac{\lambda}{k} \left(\frac{x-\mu}{k}\right)^{\lambda-1} \left[\left(1 + \frac{x-\mu}{k}\right)^{\lambda} \right]^{-2} \tag{3}
$$

where k , λ and μ are scale parameters.

Finally, to compute the original SPEI, the calculated values of $F(x)$ were converted into corresponding Z-standardized normal values (Vicente-Serrano et al. [2010](#page-34-3)). Drought classes based on SPEI are presented in Table [2](#page-5-0). For Further information about SPEI, one can refer to some studies (e.g., Barbosa et al. [2019;](#page-32-7) Li et al. [2019;](#page-33-4) Wang et al. [2019b;](#page-34-16) Zarei and Moghimi [2019a\)](#page-34-17).

2.2.3 Simulation Annual Yield (Ay) of Winter Wheat, Barley and Rapeseed

The AquaCrop model was employed to simulate *Ay* of winter wheat, barley and rapeseed in all stations during 50 years (from 1968 to 2017). The AquaCrop model is one of the most applied models to simulate crop yield in diferent regions because the AquaCrop model needs low input data and has a user-friendly structure (Zarei et al. [2019\)](#page-34-13). In this research, the climatic parameters in each station (such as precipitation, temperature and potential evapotranspiration) and the AquaCrop model which was calibrated and validated for winter wheat, Barley and rapeseed species by Shirshahi et al. ([2018\)](#page-34-18), Ramezani et al. ([2019\)](#page-33-16) and Mousavizadeh et al. ([2016\)](#page-33-17) were used in order to simulate the *Ay* of the mentioned species in each station, respectively.

2.2.4 Statistical Analysis

Generalized Estimating Equations (GEE) To model and predict the response variable (*Ay* of winter wheat, barley and rapeseed) based on the predictive variables (SPEI in diferent time scales), we have a panel dataset. Fixed or random efects techniques or generalized estimating equations (GEE), in abbreviation are suggested to analyze the panel dataset. Based on the nature of samples and also favorable study's focus, each of these approaches has particular privileges (Hu et al. [1998](#page-33-18)). The GEE techniques have many privileges, especially this approach intends robust estimations for the regression parameters when there is a high correlation between repeated measurements (Ballinger [2004;](#page-32-8) Ghisletta and Spini [2004;](#page-33-19) Hu et al. [1998\)](#page-33-18). This advantage guides us to apply the GEE technique in the present study. The simple GEE formula is written by:

$$
Y_t = \beta_0 + \beta_1 X_t + \epsilon_t \tag{4}
$$

[2019\)](#page-34-13)

where β_0 and β_1 are regression parameters (coefficients) and ϵ_t is a zero-mean random variable.

To create this predictive regression model, the GEE technique uses a link function which depends on the distribution of the response variable (Y_t) . In this research, because the normality assumption was satisfied for Y_t , the non-transforming identity link function was used. Also, GEE needs a working correlation matrix; because of the signifcant Pearson's correlation between the current and previous samples, the frst-order autoregressive, AR (1), was considered as the working correlation matrix. The GEE method estimates the model parameters through an iterative procedure that optimizes the ft of the model to the dataset.

Ability Assessment of the GEE Model In the GEE model, the absolute values of Beta coeffcients (|*B*|) between SPEI in diferent time scales and *Ay* of diferent species were utilized to evaluate the relationship between drought and *Ay* of selected species in each station. It is shown that the higher the values of $|B|$ coefficient, the higher the impact of SPEI on A_{ν} . In addition, in this research, the correlation coefficients (CC) between simulated A_v using the AquaCrop model and predicted *Ay*using GEE methods, were used to assess the ability of the GEE model in predicting *Ay* of selected species based on SPEI in diferent time scales.

Cross-Correlation Function (CCF) The CCF is a measure that can be applied as a rate of similarity between two functions or datasets (Shumway and Stofer [2017](#page-34-19); Venables and Ripley [2002](#page-34-20)). Let *f* and *g* be two continuous functions; then the CCF in a given lag τ is defned by:

$$
(f * g)(\tau) = \int_{-\infty}^{\infty} f^*(t)g(t + \tau)dt
$$
\n(5)

where f^* denotes the complex conjugate of f , τ is any arbitrary integer and t is time.

In the discrete case, the cross-correlation is defned as

$$
(f * g)(\tau) = \sum_{t=-\infty}^{\infty} f^*(t)g(t+\tau)
$$
\n(6)

As it can be observed, the cross-correlation measures the similarity of $f(t)$ and $g(t+\tau)$. Let (X_t, Y_t) represent a pair of stationary time series. The mean (μ_X) and the standard deviation (σ_X) of the time series X_t are defined by

$$
\mu_X = E(X_t) = \int_{-\infty}^{\infty} x f_X(x) dx, \tag{7}
$$

and

$$
\sigma_X^2 = E(X_t - \mu_X)^2 = \int_{-\infty}^{\infty} (x - \mu_X)^2 f_X(x) dx,
$$
\n(8)

where $f_X(x)$ is the density function of the time series X_t at point *x*.

Similarly, the mean (μ_Y) and the standard deviation (σ_Y) of the time series Y_t are defined by

$$
\mu_Y = E(Y_t) = \int_{-\infty}^{\infty} y f_Y(y) dy,
$$
\n(9)

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and

$$
\sigma_Y^2 = E(Y_t - \mu_Y)^2 = \int_{-\infty}^{\infty} (y - \mu_Y)^2 f_Y(y) dy,
$$
\n(10)

where $f_Y(y)$ is the density function of the time series Y_t at point *y*.

In addition, the covariance function of the time series (X_t, Y_t) in lag τ is defined by

$$
\gamma_{X,Y}(\tau) = E\big[\big(X_t - \mu_X\big)\big(Y_{t+\tau} - \mu_Y\big)\big] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \big(X_t - \mu_X\big)\big(Y_{t+\tau} - \mu_Y\big)f_{X,Y}(x,y)dxdy,
$$
\n(11)

where $f_{X, Y}(x, y)$ is the density function of the time series (X_t, Y_t) at point (x, y) .

Then, the CCF of X_t and Y_t in lag τ is given as:

$$
\rho_{X,Y}(\tau)\rho_{X,Y}(\tau) = \frac{\gamma_{X,Y}(\tau)}{\sigma_X \sigma_y} \tag{12}
$$

The above-mentioned Eq. ([12](#page-7-0)) is the cross-covariance function, and μ and σ are the mean and standard deviation of the time series, respectively. The CCF of two stationary processes can be estimated by sample cross-correlation function given as

$$
\hat{\rho}_{X,Y}(\tau) = \frac{\hat{\gamma}_{X,Y}(\tau)}{S_X S_Y} \tag{13}
$$

where

$$
\overline{X} = \frac{1}{n} \sum_{t=1}^{n} X_t,
$$
\n(14)

$$
\overline{Y} = \frac{1}{n} \sum_{t=1}^{n} Y_t,
$$
\n(15)

$$
S_X^2 = \frac{1}{n-1} \sum_{t=1}^n \left(X_t - \overline{X} \right)^2, \tag{16}
$$

$$
S_Y^2 = \frac{1}{n-1} \sum_{t=1}^n \left(Y_t - \overline{Y} \right)^2,\tag{17}
$$

and

$$
\hat{\gamma}_{X,Y}(\tau) = \frac{1}{n} \sum_{t=1}^{n-|\tau|} \left(X_t - \overline{X} \right) \left(Y_{t+\tau} - \overline{Y} \right) \tag{18}
$$

The above-mentioned Eq. [\(18\)](#page-7-1) is the sample cross-covariance function and s_x and s_y are the sample standard deviation of the process. The CCF is a useful tool to determine the rate of similarity (which can be between -1 to $+1$) and the time delay between two processes.

Fig. 2 Calculated 12-month SPEI (October to September) in Arak, Shiraz and Tehran stations

3 Results and Discussion

3.1 The Calculated SPEI

The results of the calculated SPEI showed that the normal class of drought severity (with SPEI between −1 to 1) had the highest frequency at all stations and all-time scales. Results showed that during 1968–2017 the highest values of the 12-month SPEI at Arak, Brjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations had occurred in 1969, 2002, 1996, 1995, 1996, 1984, 2015, 1986, 1992 and 1996, respectively, and the lowest values of the 12-month SPEI at Arak, Brjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations had occurred in 1973, 1980, 2013, 1973, 1973, 1969, 2008, 1999, 1983 and 2014 respectively (Table [3](#page-8-0) and Fig. [2](#page-8-1)).

3.2 The Simulated Annual Yield (*Ay***) of Winter Wheat, Barley and Rapeseed**

For diferent species, diferent results were obtained which are presented in the following. The results of simulated A_v in winter wheat using the AquaCrop model showed that the mean of simulated *Ay* at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations were 0.40, 0.55, 0.31, 2.37, 0.61, 0.25, 0.66, 0.67, 1.79 and 0.79, respectively (Fig. [3\)](#page-9-0). In barley, the mean of simulated *Ay* at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations were 0.74, 0.05, 0.14, 0.59, 0.58, 0.05, 0.26, 0.59, 0.24 and 0.56, respectively (Fig. [4\)](#page-10-0). In rapeseed, the mean of simulated *Ay* at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations were 0.79, 0.66, 0.35, 3.46, 1.2, 0.17, 0.82, 1.36, 2.95 and 1.34, respectively (Fig. [5\)](#page-11-0). Some properties of simulated *Ay* in mentioned species using the AquaCrop model from 1968 to 2017 are presented in Table [4.](#page-12-0)

Fig. 3 Simulated and predicted annual yield of winter wheat using AquaCrop model and GEE method in Arak and Shiraz stations

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Fig. 4 Simulated and predicted annual yield of barley using AquaCrop model and GEE method in Arak and Shiraz stations

3.3 Susceptibility Test of Winter Wheat, Barley and Rapeseed to Drought Using GEE

The results of the susceptibility test of winter wheat, barley and rapeseed to drought using the GEE model showed that at all stations, rapeseed with the highest values of Beta coefficients (*IB*) was the most sensitive species, and barley with the lowest values of Beta coefficients (*IB*) was the most resistant species to drought, respectively. The results also showed that the rapeseed had the highest values of $|B|$ coefficients at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations in 81.48%, 100%, 92.59%, 96.30%, 85.18%, 62.96%, 96.30%, 81.48%, 85.18% and 92.59% of reference periods, respectively. However, barley had the lowest values of *|B|* coefficients at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations in 62.96%, 100%, 66.67%, 96.30%, 55.56%, 81.48%, 92.59%, 81.48%, 81.48% and 85.18% of reference periods, respectively. The general results of Tables [5,](#page-13-0) [6](#page-15-0) and [7](#page-17-0) show that the level of the absolute values of B coefficients for rapeseed (Table τ) is higher than wheat (Table [5](#page-13-0)), and for wheat it is higher than barley (Table [6\)](#page-15-0), which indicates that barley is less susceptible to drought. The results showed that at all stations winter wheat had moderate drought sensitivity compared to barley and rapeseed. In other words, among the

Fig. 5 Simulated and predicted annual yield of rapeseed using AquaCrop model and GEE method in Arak and Shiraz stations

selected species, the susceptibility of rapeseed to drought was more than wheat and the susceptibility of wheat was more than barley. The reasons of these results can be shorter growth period in barley than winter wheat and rapeseed, less evapotranspiration in barley than winter wheat and rapeseed and the larger canopy cover in rapeseed.

3.4 Ability Assessment of the GEE Model to Predict *Ay*

The correlation coefficients (CC) between simulated and predicted A_v of the winter wheat, barley and rapeseed using the AquaCrop model and GEE method (respectively) indicated that in winter wheat the CC between simulated and predicted A_v at all stations and all-time scales were signifcant at 0.01 level (Table [8](#page-19-0)). Table [8](#page-19-0) showed that the average of CC was 0.771, 0.860, 0.815, 0.949, 0.787, 0.781, 0.825, 0.755, 0.926 and 0.841, at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations, respectively. In barley, the CC between simulated and predicted A_v were significant at 0.01 level at Arak, Esfahan, Fasa, Ghazvin, Sabzevar, Sanandaj, Shiraz and Tehran stations in alltime scales (Table [9](#page-21-0)). The CC in 33.33% and 96.30% of reference periods were signifcant at 0.01 level, respectively and in 66.67% and 3.7% of reference periods were signifcant at 0.05 level at Kerman and Birjand stations, respectively. Table [9](#page-21-0) showed that the mean of

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CC coefficients in all station and all-time scales were significant at 0.01 level *CC* coefficients in all station and all-time scales were significant at 0.01 level

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at 0.01 level

CC was 0.929, 0.374, 0.518, 0.782, 0.831, 0.369, 0.615, 0.840, 0.552 and 0.794 at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz and Tehran stations, respectively. In rapeseed the CC between simulated and predicted *Ay* at all stations and all-time scales were significant at 0.01 level (Table [10](#page-24-0)). According to Table 10, the average of CC was 0.730, 0.777, 0.714, 0.899, 0.779, 0.536, 0.753, 0.776, 0.896 and 0.811 at Arak, Birjand, Esfahan, Fasa, Ghazvin, Kerman, Sabzevar, Sanandaj, Shiraz, and Tehran stations, respectively. Therefore, it can be concluded that the GEE model was highly capable of predicting *Ay* at all stations and all under-evaluated species.

3.5 Susceptibility Test of Winter Wheat, Barley and Rapeseed to Drought Using CCF

According to the result of susceptibility test of winter wheat, barley and rapeseed to drought using CCF method at Arak, Birjand, Esfahan, Ghazvin, Sabzevar, Sanandaj, Shiraz and Tehran stations, it can be concluded that rapeseed with the highest values of |*CCF*| between simulated A_v using the AquaCrop model and SPEI in more selected time scales was the most sensitive species to drought. In addition, barley with the lowest values of |*CCF*| in more selected time scales was the most resistant species to drought (Tables [11](#page-26-0), [12](#page-28-0) and [13](#page-30-0)). The results indicated that at Arak, Birjand, Esfahan, Ghazvin, Sabzevar, Sanandaj, Shiraz and Tehran stations in 14 out of 27, 15 out of 27, 16 out of 27, 16 out of 27, 22 out of 27, 14 out of 27, 17 out of 27and 22 out of 27 of reference periods, respectively, rapeseed had the highest values of |*CCF*| and in 15 out of 27, 27 out of 27, 19 out of 27, 15 out of 27, 25 out of 27, 20 out of 27, 21 out of 27and 23 out of 27 of reference periods, respectively, barley had the lowest values of |*CCF*|. Winter wheat with the highest values of |*CCF*| in more selected time scales was the most sensitive species to drought, and barley with the lowest values of *CCF* in more selected time scales was the most resistant species to drought at Fasa and Kerman stations (Tables [11,](#page-26-0) [12](#page-28-0) and [13\)](#page-30-0). The results indicated that winter wheat had the highest values of *ICCF* in 17 out of 27 and 14 out of 27 of reference periods, and barley had the lowest values of |*CCF*| in 26 out of 27 and 20 out of 27 of reference periods at Fasa and Kerman stations, respectively. Therefore, it can be concluded that based on the CCF method, rapeseed and barley were the most sensitive and the most resistant species to drought at almost all stations, respectively, and winter wheat had moderate drought sensitivity compared to barley and rapeseed. Some factors such as shorter growth period in barley than winter wheat and rapeseed, less evapotranspiration in barley than winter wheat and rapeseed, etc. play an efective role on the results of the study. Katerji et al. [\(2009](#page-33-20)) assessed the sensitivity of wheat and barley to drought. The results of this research indicated that the sensitivity of wheat to drought is more than barley. It seems that the results of this paper are comparable to our results.

4 Conclusions

Given the importance of sustainable food security in the world and the central role of wheat, barley, and rapeseed in this feld, recognizing the efective parameters on the yield of the above-mentioned species can help to reduce the risk of food security. Drought occurrence is one of the efective parameters on the yield of the mentioned species. Therefore, in the present study, we tried to assess the susceptibility of winter wheat, barley and rapeseed to drought using GEE and CCF models. The results of this study indicated that based on the GEE model used at all stations, rapeseed was the most sensitive species to drought

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and barley was the most resistant species to drought. The CCF analysis to susceptibility assessment of mentioned species to drought showed that rapeseed and barley were the most sensitive and the most resistant species to drought at Arak, Birjand, Esfahan, Ghazvin, Sabzevar, Sanandaj, Shiraz and Tehran stations, respectively, while winter wheat and barley were the most sensitive and the most resistant species to drought at Fasa and Kerman stations. Finally, based on the results, it is suggested that barley can be the frst choice of cultivation, wheat can be the second and rapeseed can be the third for farmers in order to reduce the negative efects of drought on the annual yield of the mentioned species, and reduce economic losses, especially in the central and southern parts of Iran where the occurrence of drought is more frequent.

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Data Availability The data used in this research are available by the corresponding author upon reasonable request.

Declarations

Ethics Approval The authors confrm that this article is original research and has not been published or presented previously in any journal or conference in any language (in whole or in part).

Consent to Participate and Consent to Publish not applicable.

Competing Interests The authors have no confict of interest.

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