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# Impact of climate change on the severity, duration, and frequency of drought in a semi-arid agricultural basin

Atie Hosseinizadeh<sup>1</sup>, Hesam SeyedKaboli<sup>2</sup>, Heidar Zareie<sup>1</sup>, Ali Akhondali<sup>1</sup> and Babak Farjad<sup>3\*</sup>

# **Abstract**

**Background:** Climate change is one of the greatest threats facing the world today and future generations. A change in climate can alter the frequency and duration of drought especially in arid and semi-arid regions. This study aims at investigating the impact of climate change on the severity, duration, and frequency of drought in a semi-arid agricultural basin in Khuzestan, Iran.

**Results:** The largest increases in duration of drought occur for the normal (SPI < -0.5) and extreme (SPI < -2) conditions while the largest increases in frequency of drought occur under the warmer and drier climate scenario in the western portion of the basin. The frequency of moderate (SPI < -1) and severe (SPI < -1.5) droughts decreases under all scenarios whereas most scenarios show an increase in the frequency of extreme (SPI < -2) drought.

**Conclusions:** This study applied the Standardized Precipitation Index (SPI) along with a combination of GCM-scenarios to create the severity-duration-frequency (SDF) curves of drought for the period 2020-2044. An average period of six months (ending in May) was used for the SPI, corresponding to the agricultural growing season of the region, to assess drought conditions under five plausible climate scenarios. The selected GCM-scenarios were GISS-ER A1B (warmer and drier), CSIROMk3.5 B1 (cooler and drier), INGV-SXG A1B (median conditions), ECHO-G A2 (warmer and wetter) and ECHAM5 B1 (cooler and wetter) and they were downscaled with an Artificial Neural Network (ANN) approach. Results reveal that most scenarios exhibit an increase in the duration of extreme drought while the duration of moderate drought decreases under all scenarios. The largest increases in the frequency of extreme droughts occur in the western portion of the basin in response to the warmer and drier climate scenario. An increase in the number of extreme (SPI < -2) drought conditions with a longer duration can influence the growing season.

Keywords: Drought; Climate change; ANN; Severity; Duration; Frequency; SPI

# **Background**

Climate change is one of the greatest threats facing the world today and future generations (Van Pelt and Swart 2011; Ranjan et al. 2006). According to the latest Intergovernmental Panel on Climate Change (IPCC) report, the global surface temperature will increase between 1.5 to 2°C by the end of the 21st century relative to the period from 1850 to 1900 (IPCC 2013). Climate change can alter the hydrological cycle which may result in extreme events

such as floods and droughts (Quevauviller 2011; Wilhite et al. 2014; Pulwarty and Sivakumar 2014; Farjad et al. 2015; Woznicki et al. 2015). Therefore, understanding the influence of climate change on the frequency and severity of extreme hydrological events is of crucial importance in order to better guide sustainable management of water resources. Numerous studies have investigated the impact of climate change on extreme hydrological events (Lamond and Penning-Rowsell 2014). However, much of these studies have focused on the impact of climate change on floods (Shi et al. 2013; Braga et al. 2013; Kobierska et al. 2013) and not enough attention has been given to the relationship

Full list of author information is available at the end of the article



<sup>\*</sup> Correspondence: bfarjad@ucalgary.ca

<sup>&</sup>lt;sup>3</sup>Department of Geomatics Engineering, University of Calgary, Calgary, AB, Canada

between drought and climate change at the watershed scale (Muller 2014; Kiem and Austin 2013).

General Circulation Models (GCMs) are one of the primary instruments for projecting future changes in climate variables (IPCC 2007). However, there is an inherent uncertainty in using only one GCM-scenario. In order to cover a range of plausible changes in future climate it is necessary to use multiple GCMs (Prudhomme et al. 2003; Zhao et al. 2005; Charlton et al. 2006; Grillakis et al. 2011; Taylor et al. 2013).

In this study the impact of climate change on the severity, duration and frequency of drought was investigated in the Dezful basin, in Khuzestan, Iran for the period 2020-2044. To achieve this, the Standardized Precipitation Index (SPI) was used along with a combination of fifteen GCMs and three scenarios of greenhouse gas emissions to address the uncertainties in future projected climate.

# **Methods**

In this section the case study is described followed by the methodology of the study.

# Case study

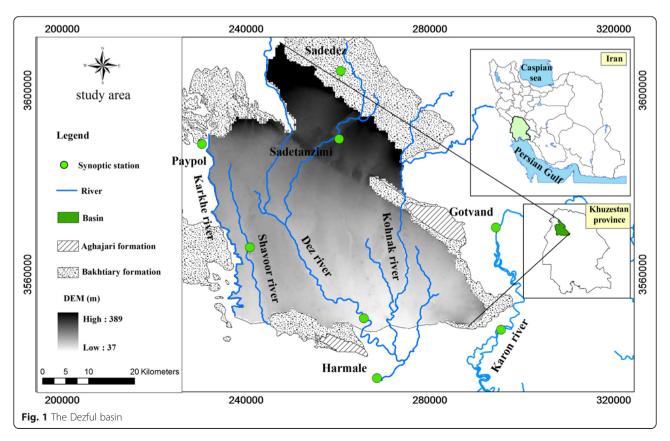
The Dezful basin is one of the largest agricultural basins in Khuzestan province in south-west Iran (Fig. 1). This basin has a semi-arid climate and is located in the Northern Province which has the largest irrigation

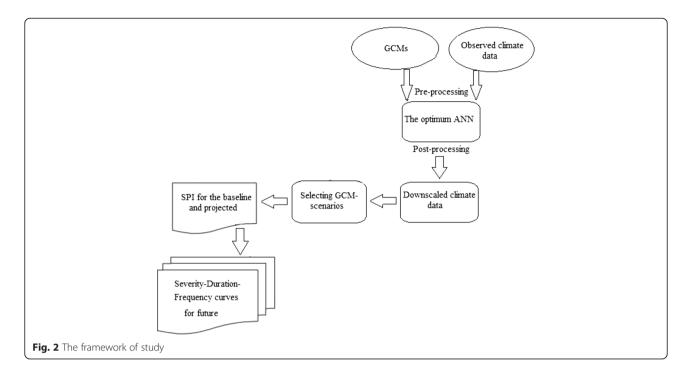
network in the country (Dez irrigation network). The basin covers an area of  $2073~\rm{km}^2$  with elevations ranging from  $37~\rm{m}$  to  $389~\rm{m}$ .

The land-use/cover of the basin consists of agricultural lands and urban areas including three cities: Dezful, Andimeshk and Shoosh. The major crops in the study area include Wheat (32 %), sugarcane (21 %) and maize (16 %). The following four rivers flow southward in the basin and include: Dez, Karkhe, Kohnak and Shavoor. The observed climate data such as precipitation and temperature were obtained from five climate index stations namely Paypol, Gotvand, Harmale, Sadetanzimi, and Sadedez (Dez-Dam) for the period 1985-2009. The Mann-Whitney test along with a homogeneous random test were used to verify the quality of the data at each station (McCuen 2002).

# Methodological framework

Figure 2 illustrates the methodological framework of this study. Observed and projected precipitation data were considered for the period of 1985-2009 and 2020-2044, respectively. The projected climate data were obtained from GCMs and were downscaled using the ANN in the basin. GCMs-scenarios were evaluated to select the most suitable climate scenarios for the basin. The selected scenarios were employed to create severity-duration-frequency (SDF) curves of





drought at five different climate index stations. The methodology is described in details as follows.

# Severity and return period of drought

There are several indicators to investigating drought situations. One of the widely used indicators is the Standardized Precipitation Index (SPI) which has been developed by McKee et al. (1993) from the Colorado Climate Center, the Western Regional Climate Center, and the National Drought Mitigation Center to define and monitor the status of the drought in the United States. This index is suitable for both agricultural purposes (which generally consider short-term time scales) and hydrological purposes (which can be applied for long-term time scales) (Edwards and McKee 1997). Precipitation is the primary input for the SPI (Caccamo et al. 2011). The SPI was implemented based on fitting a suitable probability distribution to rainfall data and then it was

**Table 1** The SPI Drought classification (McKee et al. 1993)

Values of SPI	SPI category
values of 311	
≥2	Extremely wet
1.5–1.99	Severely wet
1–1.49	Moderately wet
-0.99 to +0.99	Normal
-1.49 to -1	Moderately drought
-1.99 to -1.5	Severely drought
≤-2	Extremely drought

transferred to a standard normal distribution (Duggins, et al. 2010). The gamma distribution was most appropriate to fit the rainfall data (McKee et al. 1993). The calculated SPI values were classified in different drought conditions based on the proposed SPI classification (Table 1).

The SPI was calculated for a time scale of six months (ending in May) in a year corresponding to the growth period of common crops (wheat) in the study area

**Table 2** Attribute of the selected GCM-scenarios

Table 2 Attribute of the selected GCM-scenarios			
Number	Model	Emission scenarios	Organizer
1	CGCM3T47	A1B, A2, B1	CCCma (Canada)
2	CNRMCM3	A1B, A2, B1	CNRM (France)
3	CSIROMk3.5	A1B, A2, B1	CSIRO (Australia)
4	ECHAM5	A1B, A2, B1	Max Planck Ins (Germany)
5	ECHO-G	A1B, A2, B1	Meteorological Ins (Germany)
6	FGOALS-g1	A1B, B1	IAP (China)
7	GFDMCL2.1	A1B, A2, B1	GFDL (USA)
8	GISS-ER	A1B, A2, B1	GISS (USA)
9	HadCm3	A1B, A2, B1	UK Met.Office
10	HadGEM1	A1B, A2	UK Met.Office
11	INGV-SXG	A1B, A2	NIGV (Italy)
12	INMCM3	A1B, A2, B1	INM (Russia)
13	MIROC3.2	A1B, A2, B1	NIES (Japan)
14	MRI CGCM2.3	A1B, A2, B1	Japan AM
15	NCARPCM	A1B, A2, B1	NCAR (USA)

(Vergni and Todisco 2011). The spatial distribution of severity and frequency of droughts was examined by calculating the SPI for each station in the region.

In order to determine the drought return periods for each climate station, a frequency analysis was performed on projected climate scenarios. This was done using the Weibull cumulative probability distribution function since it performs better than other distribution functions when there is a small sample size of data (Park et al. 2014). The return period and duration of drought were estimated in different severity categories using this distribution function which is formulated as follows:

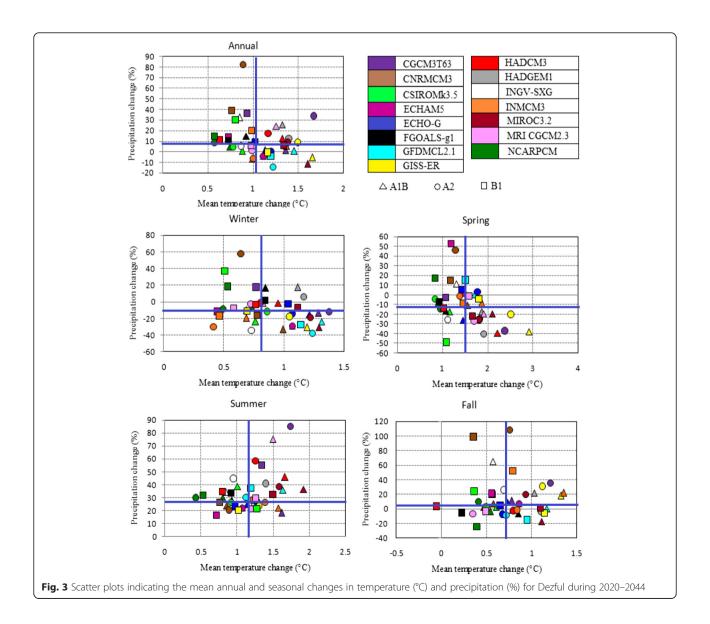
$$F(x) = 1 - \exp\left(-\left(\frac{x}{a}\right)^{b}\right)$$

where F(x) is the cumulative frequency at normalized time x, a is the scale parameter, and b is the parameter of curve shape.

# Climate change scenarios

In this study, a combination of fifteen GCMs and three greenhouse gas emissions scenarios were used, as summarized in Table 2. Five GCM-scenarios were selected which represented a range of changes in future climate; four representing the more extreme changes in mean temperature and precipitation, and one representing median conditions.

The selected GCM-scenarios were GISS-ER A1B (warmer and drier), CSIROMk3.5 B1 (cooler and drier), INGV-SXG A1B (median condition), ECHO-G A2 (warmer and wetter)



and ECHAM5 B1 (cooler and wetter). The selection of GCM-scenarios was based on the average annual and seasonal variations of temperature and precipitation over the study area (Barrow and Yu 2005). Scatter plots of average annual and seasonal precipitation and temperature were created to make the selection (Fig. 3). This assessment was done for the spring season, since GCM-scenarios showed both decreases and increases in precipitation during this season and also it is the agricultural growing season of the study area.

# Downscaling approach

Since the spatial resolution of GCMs is too coarse (250 to 600 km), and not applicable for direct use in local climate impact studies (Aerts and Droogers 2004; Semenov and Stratonovitch 2010; Green et al. 2011), the output of GCMs were downscaled using an artificial neural network.

Artificial Neural Networks (ANNs) are mathematical models resembling the structure of the brain and central nervous system that can be used in the modeling of complex systems (Maier and Dandy 2001). One of the most popular and robust tools in the training of ANNs is the Back Propagation (BP) algorithm, in combination with a supervised error-correction learning rule. In this algorithm, neurons or nodes are structured in layers, starting with an input layer and ending with the output layer. The input layer is applied to the network and the effects on the output layer are transferred by the hidden layer. The input to each neuron is calculated with the following equation:

$$\zeta_i^n = \sum\nolimits_{j=1}^m W_{ji}^n \cdot O_j^{n-1}.$$

Where  $\zeta_i^n$  is input to neuron i in layer n,  $W_{ji}^n$  is the tap weight from the neuron i in layer n to neuron j in layer

(n-1),  $O_j^{n-1}$  is the output of neuron j in layer (n-1), and m is the total number of neurons in the layer (n-1).

The BP algorithm is basically a gradient descent technique that can minimize the network error function. This can achieve in two steps. First, the effect of the input is passed forward through the network. Second, an error between the observed and the predicted values is calculated at the output layer, and consequently is backpropagated toward the input layer through each hidden node to adjust the network weights.

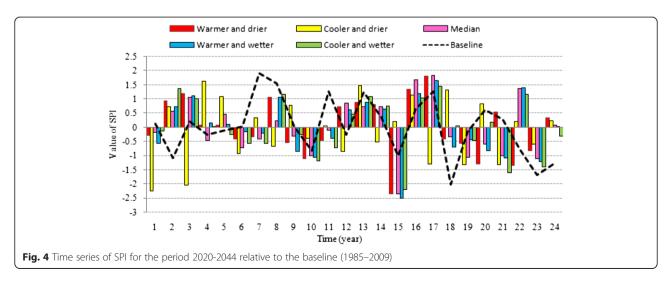
$$\Delta W_{ji}^{n}(m+1) = \eta \frac{\partial(E)}{\partial W_{ji}^{n}} + \mu \Delta W_{ji}^{n}(m)$$

Where  $\Delta W_{ji}^n$  is the increasing weight,  $\eta$  is the learning rate, and  $\mu$  is the momentum parameter. The BP algorithm is repeated its forward and backward ways to reach an acceptable error.

In this study the structure of the network is built in the Neurosolution 5 software. GCMs output as predictors and observed local data (predictands) were imported to the network. Several ANN models with different combinations of transfer functions and number of neurons in the hidden layer are conducted until the optimum network is identified. Finally a Multiple Layer Perception (MLP) with one hidden layer and linear TanhAxon transfer function was selected for downscaling in this study. The r-value and RMSE are 0.65 and 0.32 for precipitation and 0.9 and 0.2 for temperature respectively.

# Results and discussion

Time series of the SPI are illustrated for the Sadetanzimi station under the five GCM-scenarios during the period of 2020-2044 relative to the baseline (Fig. 4). There is no consistency in increases or decreases in the SPI for the Sadetanzimi station for the 2020-2044. However, the SPI



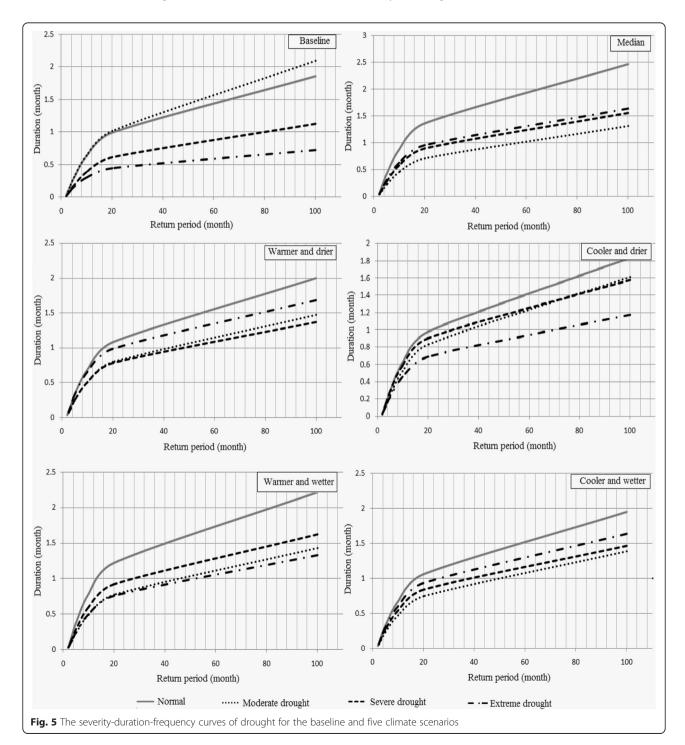
reaches -2 which represents extreme droughts in the future.

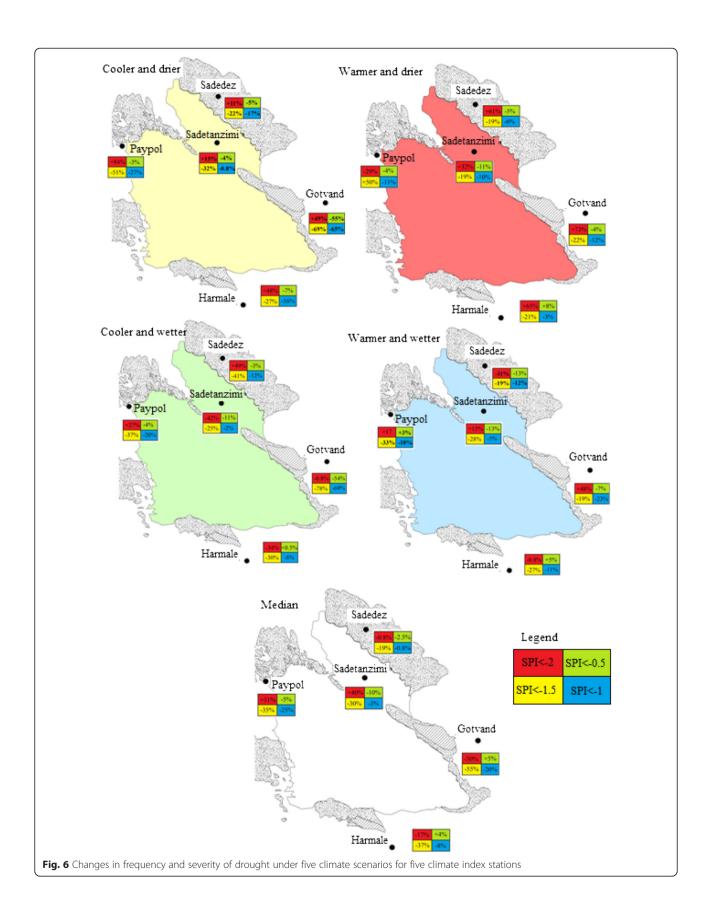
The duration and return period of droughts are shown in Figure 5. Moderate droughts (SPI < -1) occur with a longer duration than the other categories of droughts for the baseline period while extreme droughts (SPI < -2) occur with a shorter duration. On the other hand, the duration of moderate droughts (SPI < -1) decreases whereas

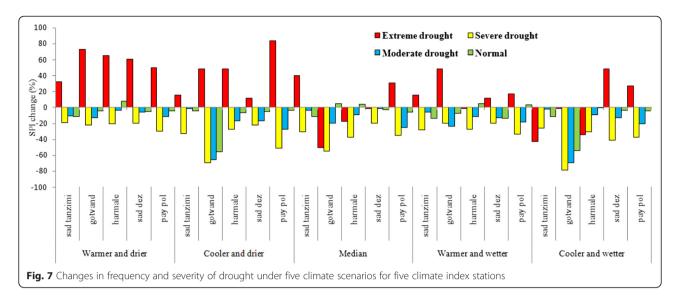
the duration of normal condition (SPI < -0.5) increases in the future period under all scenarios.

Normal and extreme droughts occur with a longer duration under the warmer-drier and cooler-drier scenarios. The extreme droughts with a shorter duration are exhibited only for the cooler-wetter climate scenario.

Figures 6 and 7 show changes in the frequency and severity of droughts for the five climate scenarios at each







station. The majority of changes in drought frequency occur at the Gotvand station which is located in the western portion of the basin. The drought frequency for the moderate (SPI < -1) and severe condition (SPI < -1.5) decrease under all scenarios whereas the drought frequency for the extreme condition (SPI < -2) increases under warmer-drier and cooler-drier climate scenarios at all stations. The largest decline in moderate and severe drought conditions occurs under the cooler-wetter climate scenario.

#### Conclusion

In this study, climate change impacts on the severity, duration and frequency of drought were investigated in a semi - arid basin in south-west Iran. A combination of fifteen GCMs and three scenarios of greenhouse gas emissions were employed in order to address the uncertainties in both the forcing of the GCM parameters and future emissions. The GCM-scenarios were examined and eventually five scenarios (warmer and drier, cooler and drier, warmer and wetter, cooler and wetter, and median conditions) were selected which represent plausible changes in future climate during 2020-2044. These scenarios were used to create the severity-durationfrequency curves of drought for the period 2020-2044. Results reveal that the duration of moderate droughts decreases and the duration of normal condition increases under the five future climate scenarios. The largest increases in duration of drought occur for the normal (SPI < -0.5) and extreme (SPI < -2) conditions while the largest increases in frequency of drought occur under the warmer and drier climate scenario in the western portion of the basin. The frequency of moderate (SPI < -1) and severe (SPI < -1.5) droughts decreases under all scenarios whereas most scenarios show an increase in the frequency of extreme (SPI < -2) drought. An increase in the number of extreme (SPI < -2) drought conditions with a longer duration can influence the growing season. This study provides insight into the future droughts conditions under climate change which can be used to protect and manage water and agricultural resources.

#### Competing interests

The authors declare that they have no competing interests.

## Authors' contributions

AH collected data, designed and implemented the methodological framework of this study, and prepared the manuscript. HSK supervised the project. HZ and AMA gave technical support and conceptual advice. BF made substantial contributions to the conception, design, implementation, analysis of the study. All authors discussed the content of the manuscript, method and results. All authors read and approved the final manuscript.

# Author details

<sup>1</sup>Department of Hydrology, ShahidChamran University of Ahvaz, Ahvaz, Khuzestan, Iran. <sup>2</sup>Department of Civil Engineering, Jondishapur University (Dezful campus), Dezful, Khuzestan, Iran. <sup>3</sup>Department of Geomatics Engineering, University of Calgary, Calgary, AB, Canada.

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