

## Variability of time duration analysis for rainfall water using precipitation indexes in Hai town

Basima Abbas Jabir Al-Humairi<sup>a,\*</sup> and Nadhum Shamkhi Rahal<sup>b</sup>

<sup>a</sup>Middle Technical University, Kut Technical Institute, Baghdad, Iraq

<sup>b</sup>Middle Technical University, Suwaira Technical Institute, Baghdad, Iraq

\*Corresponding author. E-mail: basma.abbas@mtu.edu.iq

### ABSTRACT

Insufficient rainfall has an impact on a variety of natural resources. This work aims to determine the variability of rainfall and drought in Hai town depending on the standardized rainfall index (SRI), rainfall concentration index (RCI), index of wetness (IW), and coefficient of variation (CV). Rainfall series were taken from the Meteorological Station Directorate of Hai Town, Iraq for a period of 30 years (1989–2018). The results indicated that the years 1996 and 2014 had high SRI and were under extremely wet conditions (IW = 195.93 and 165.93, respectively). However, the lowest SRI value was in 2004, with a wetness index of 35.15, whereas the RCI was strongly irregular in rainfall distribution. Also, the CV was highly variable that ranged between 113.78 and 244.01. Mathematical models were created and confirmed for predicting the wetness index using data-fitting software. Model 1 generated best outcomes ( $R^2 = 99.99\%$ , relative error (RE) = 0.221, root mean square error (RMSE = 0.253) and standard error of estimates (SEE = 0.28). The results demonstrated that rain indicators have significant differences and alteration throughout the study period. Hence, the best model for estimating wetness and droughts in Hai town is recommended.

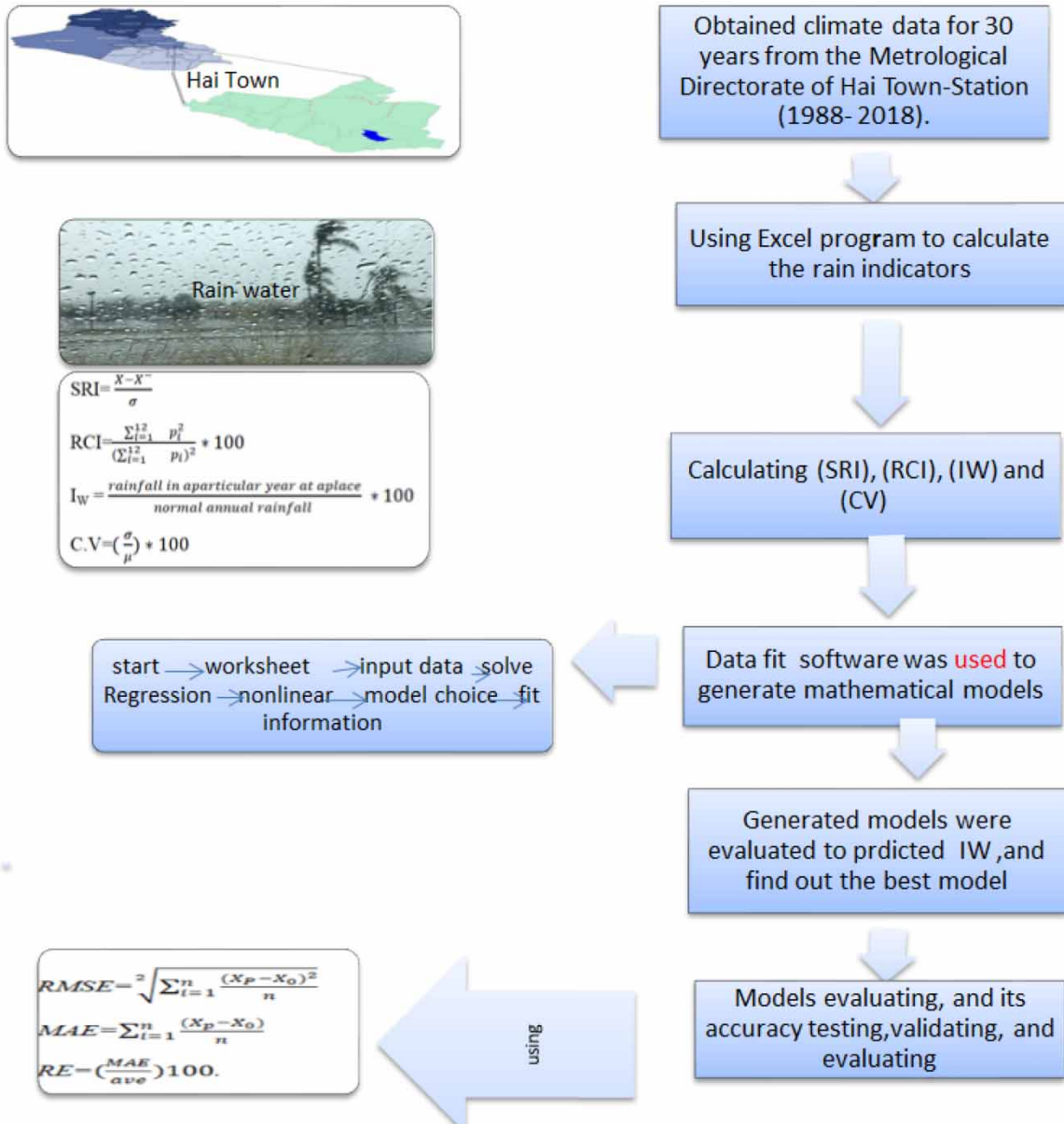
**Key words:** coefficient of variation, DataFit software, index of wetness, rainfall concentration index, standardized rainfall index, statistical analysis

### HIGHLIGHTS

- Variability of rainfall and drought monitoring in Hai town were evaluated.
- SRI, RCI, IW, and CV were used.
- DataFit program (statistically) was used to predict value index of wetness.
- Make statistical models for index of wetness by using the DataFit program, and then the best model was chosen depending on  $R^2$ , RMSE, SEE, RE.
- Differences between predicted value and measured value for index of wetness were recorded.

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GRAPHICAL ABSTRACT



1. INTRODUCTION

Rainwater is a significant atmospheric factor that is impacted by both floods and droughts. Many researchers are interested in planning management of water resources, hydrological simulation, analysis of flooding frequency, flood risk assessment, agricultural scheduling, effects of climate change, evaluations of water resources, as well as other environmental evaluations. These evaluations were done to understand the variability of temporal rainfall. Numerous studies have focused on how rainfall varies depending on precipitation indices (Zakwan & Ara 2019), and analyzed the temporal changes of rainfall in India depending on seasonal, monthly, and yearly rainfall series for the period 1950–2016. They demonstrated the result dependability of 90% from rainfall depth greater than 180 mm for the months of July and 160 mm for the months of August. Also, they noticed a reduction in overall rainfall for the years 1986–2016. Mahfouz *et al.* (2016) studied drought intervals for the duration of 1950–2014 in Lebanon based on the Standardized Precipitation Index (SPI) and found that annual precipitation increased in September–October and decreased in February, while drought conditions increased primarily in the winter–spring season. Moazzam *et al.* (2022) used the standard rainfall indicator to evaluate the wet and dry conditions for the period 1980–2020 and their results showed that extreme droughts occurred

in Pakistan during the years (1982–1983, 1985, 1990–1991, 2000–2001) and moderate droughts occurred during the years (1977, 1984, 2007, 2014–2015, and 2017–2018). According to data from rain gauges at Ghanaian meteorological stations, [Nkrumah \*et al.\* \(2014\)](#) evaluated the annual and seasonal variability of rainfall in three zones that distribute rainfall in Ghana for a period of 1990–2008 and compared the results to data obtained from the regional climate model. [Al-Shamarti \(2017\)](#) examined the rainfall seasonality index using rainfall data from 28 stations in three zones of Iraq. His study was based on the amount of rainfall, and found a significant variability of the seasonality index for rainfall between zones and between years as well.

[Saha \(2020\)](#) studied the Precipitation Concentration Index (seasonal and annual) to assess the distribution of rainwater, in Bangladesh, and showed an equally distributed rainfall during the summer monsoon. The winter rain displayed a strong predominance of irregular precipitation distribution. The annual indicator of the concentration of rainwater ranged between 14.96 and 43.82 in 2006 and 2000, respectively, and the average of 37 years was 32.22, according to research by [Rawat \*et al.\* \(2021\)](#) using the Precipitation Concentration Index to study rainfall variability (annual and seasonal) in India for the period (1982–2018).

[Pathak & Dodamani \(2020\)](#) investigated annual and seasonal rainfall trends and also investigated the Ghataprabha River Basin meteorological dryness trends in India using non-parametric Mann–Kendall and standardized rain water indicators.

The Standardized Precipitation indicators (SPI-C) were adjusted in a study by [Cerpa Reyes \*et al.\* \(2022\)](#) for the evolution of drought under conditions of zero monthly precipitation. The findings revealed that the SPI-C improved dryness detection in the Colombian Arroyo Pecheln Basin. [Mehta & Yadav \(2022\)](#) utilized Sen's slope estimator testing and the Mann–Kendall rule to analyze trends in rainfall across the Jalore region of South-West Rajasthan in the Luni river basin from 1901 to 2021, the findings indicated an increase in pre- and post-monsoon rainfall, and decline in annual rainfall, which is reflected in lower winter and S–W monsoon rainfall. [Mahrokh \*et al.\* \(2023\)](#) investigated the impact of climate change on dryness circumstances in Iran's Dez Basin by utilizing the hydro-meteorological dryness indices, which integrates the Standardized Rainfall Evapotranspiration Indicator and Standardized Runoff Factor, and their findings indicated that normal drought levels are going to continue, and in future mild and severe droughts will increase. [Mahdavi & Ghorbanizadeh \(2023\)](#) examined the effects of changing climates on droughts in Iran's Zard River Basin and demonstrated that upcoming droughts will be much more severe than they have ever been.

In order to identify the nature of variance and trends of rainwater in the West African Sahel, the researchers ([Nouaceur & Murarescu 2020](#)) utilized continuous wavelets transform and the 'Bertin Matrix' method of processing information chronologically in graphics. Their findings showed that rain had resumed recently over the Sahelian region and a significant association with the surface temperature of the Atlantic Ocean had been noticed.

[Aryal \*et al.\* \(2022\)](#) investigated the characteristics of droughts in Nepalese river basin that depend on the SPI, Rainwater Anomaly Index (RAI), and assessed their effects on yearly crop production. They demonstrated that the SPI and RAI could be utilized equally to evaluate the severity of the dryness. Additionally, the severity of the drought had a direct impact on crop yield, which included wheat, millet, barley, and paddy. Thus, planning irrigation and water resource management systems may benefit from these findings.

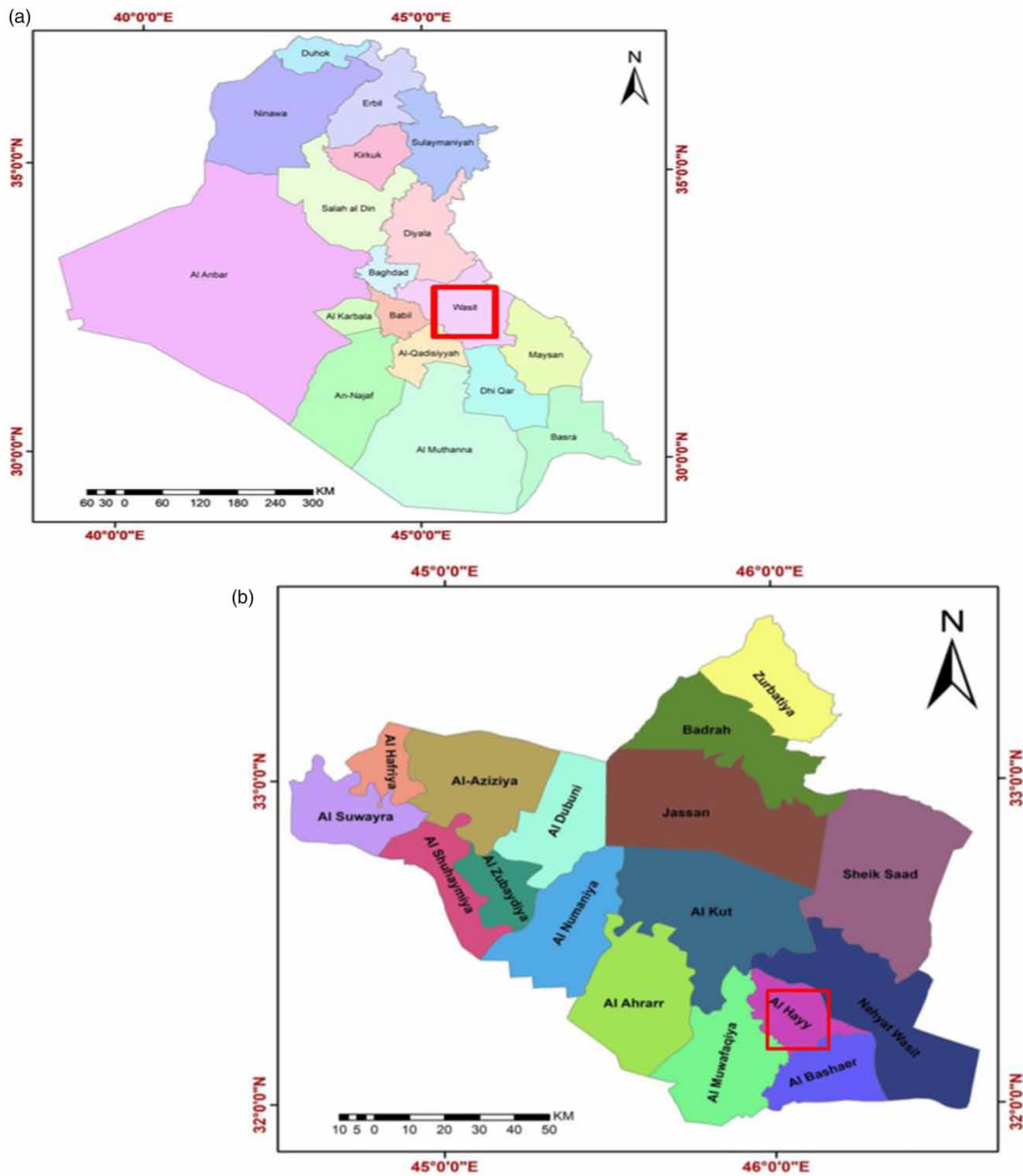
The SPI's temporal versatility is helpful in determining the beginning and finish of drought events and it permits research of the effects of dryness at various time scales by comparing them with different indicators ([Gherissi \*et al.\* 2021](#), [Rahman \*et al.\* 2021](#), and [Bi \*et al.\* 2020](#)).

## 2. STUDY REGION AND SOURCE OF DATA

The study area is located at the mid-Mesopotamian plane, Al-Hai town, Wasit province, Iraq, which is situated to the south of Wasit Governorate ([Figure 1\(a\)](#) and [1\(b\)](#)) and bounded between latitudes (32.1742°) north and longitudes (46.0433°) east. There is extremely less rainfall in the summer and winter seasons and a fairly dry, hot temperature overall. The Tigris River is the primary water source in the region. Agriculture is the main source of income for the locals in this region. The climate data for 30 years were obtained from the Metrological Directorate of Hai Town-Station (1989–2018).

## 3. METHODOLOGY OF WORK

The Excel program was used to calculate the rain indicators, and to find out the cases of drought and the time variation of rainfall annually, seasonally, and monthly. Many parameters and indicators were used to analyze the characteristics and rainfall analyses. Steps involved in Excel program: first, open the program and the



**Figure 1** | (a) and (b) Study sites.

worksheet, after that enter the data into the cells, then choose the empty cell to write all Equations (1)–(8). Next, press on the fill handle option to copy the equation to the rest of the cells.

### 3.1. Standardized Rainfall Index

The Standardized Rainfall Index (SRI) is based on the availability of a lengthy dataset of rainfall data spanning which is at least of 30 years. In this index (Table 1), the data series are statistically transformed from the gamma distribution principle to the normal distribution. According to McKee *et al.* (1993), Table 1 describes the SRI categorization system's definition of drought intensity. The SRI values vary between (–2 and 2) and greater than zero signifies a wet situation. Also, a number below zero indicates a state of drought. After the SRI (Formula (1)) computation, the circumstances of both humid as well as dry were separated. This formula may be applied for confirmation whether a dryness event lasts for a little period of time or for a long duration (Wang *et al.* 2015). Moreover, long-term SRI is necessary for the study of water availability, including supply of groundwater, the

**Table 1** | SRI classification system (McKee *et al.* 1993)

SRI value	Category
$\geq 2$	Extreme wet situation
1.5–1.99	Severe wet situation
1.0–1.49	Moderate wet situation
–0.99 to 0.99	Near normal situation
–1.0 to (–1.49)	Moderate dryness situation
–1.5 to (–1.99)	Severe dryness situation
Less or equal –2.0	Extreme drought condition

surface water supply, and reservoir level, whereas short-term SRI is essential for agricultural uses.

$$\text{SRI} = \frac{X - \bar{X}}{\sigma} \quad (1)$$

where  $X$ ,  $\bar{X}$ ,  $\sigma$ , is the monthly, seasonal, or yearly rainfall data, the average monthly, seasonal, or annual rainfall and the standard deviation, respectively. In this research, the SRI was calculated for monthly, seasonal, and yearly rainfall information.

### 3.2. Rainwater concentration indicators

The Rainwater Concentration Index (RCI) is defined as the uniformity and non-uniformity of rainfall across time (year, season, month). *Asfaw et al.* (2018), *Saha* (2020), and *Zhang et al.* (2019) took into account elements for water resource planning, risk assessment due to flooding or droughts, as well as the control of natural resources (Table 2). Formula (2) shows the limits and computing of the RCI.

$$\text{RCI} = \frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2} * 100 \quad (2)$$

where  $P_i$  is the rainfall value (monthly, seasonally, annually). In this study, the RCI was calculated for annual, seasonal, and 6 months

**Table 2** | RCI limit

RCI value	Category
$\text{RCI} \leq 10$	Uniform distribution of precipitation (low concentration of precipitation)
$\text{RCI} > 10 \leq 15$	Moderate rainfall distribution
$\text{RCI} > 15 \leq 20$	Unequal distribution of rainwater
$\text{RCI} > 20$	Distribution of rain that is extremely irregular

### 3.3. Normal annual rainfall

The mean of a 30-year consecutive rainwater series was used to compute the normal yearly rainfall. In the current research, time series of the month, season, and year of rainfall were taken into consideration. Normal annual rainfall was estimated, using the following formula (Subramanya 2008).

$$N = \frac{\sum_{i=1}^{30} P_i}{30} \quad (3)$$

where  $N$  is the normal annual rainfall.

### 3.4. Index of wetness

For determining the amount of rainfall or its deviation for a specific year, the index of wetness (IW) was used on the basis of IW (Formula (4)). The rainfall is classified as normal ( $\text{IW} = 100$ ), good ( $\text{IW} > 100$ ), and bad

(IW < 100). The levels of rainfall deficiency were classified on the basis of Formula (5): large (30–45)%, serious (45–60)%, and devastating (beyond 60%). Subramanya (2008)

$$\text{Index of wetness} = \frac{\text{Rainfall in a particular year at a place}}{\text{Normal annual rainfall}} * 100 \tag{4}$$

$$\text{Rainfall deficiency} = 100 - \text{index of wetness} \tag{5}$$

### 3.5. Coefficient of variation

The CV is calculated to evaluate the variation of the rainwater using Formula (6). A larger CV value indicates greater variability and the opposite is also correct. The CV value is calculated as:

$$\text{CV} = \left( \frac{\sigma}{\mu} \right) * 100 \tag{6}$$

where CV is the variance coefficient,  $\sigma$  is the standard deviation, and  $\mu$  is the average amount for rain water. Also, in accordance with Asfaw *et al.* (2018), CV is used to categorize rainfall events' amount of variation as low when CV is less 20, moderate when CV between (20 and 30) and high (CV greater 30).

### 3.6. Statistical analysis and variability indices

Using the DataFit 9.1 (2014) program, statistical models were constructed to forecast (IW) based on RCI, SRI, CV, and N. There were four math models constructed that were non-linear (Tables 3–5) to evaluate the accuracy

**Table 3** | Constructed models for IW prediction

Models	
IW models	1 $IW = a_0 * SRI + a_1 * RCI + a_2 * N + a_3 * CV + a_4$ 2 $IW = a_0 + a_1 * SRI + a_2 * \ln(RCI) + a_3 * (SRI)^2 + a_4 * \ln(RCI)^2 + a_5 * SRI * \ln(RCI) + a_6 * (SRI)^3 + a_7 * \ln(RCI)^3 + a_8 * SRI * \ln(RCI)^2 + a_9 * (SRI)^2 * \ln(RCI)$ 3 $IW = \text{EXP}(a_0 * SRI + a_1 * RCI + a_2 * CV + a_3)$ 4 $IW = \text{EXP}(a_0 * SRI + a_1 * CV + a_2 * N + a_3)$

**Table 4** | IW model coefficients

Coefficient	Model			
	1	2	3	4
$a_0$	0.008	-5244.322	0.123	0.056
$a_1$	-0.040	83.956	-0.035	0.0004
$a_2$	100.077	4621.977	0.010	0.496
$a_3$	0.013	-2.426	4.178	4.168
$a_4$	-0.852	-1330.699	-	-
$a_5$	-	-52.724	-	-
$a_6$	-	0.104	-	-
$a_7$	-	127.518	-	-
$a_8$	-	9.529	-	-
$a_9$	-	1.328	-	-
$R^2$	99.99	99.77	96.98	99.43
SEE	0.28	2.55	8.23	3.55
RMSE	0.253	2.084	7.670	3.308
MAE	0.221	1.574	5.979	2.388
RE	0.221	1.574	6.019	2.385



**Table 5** | Measured and predicted (IW) for the best model

Years	Measured	Predicted	Residual	%Error
1989	107.28	107.10	0.18	0.17
1990	59.33	59.10	0.23	0.38
1991	152.37	152.21	0.16	0.11
1992	116.89	117.11	-0.22	-0.19
1993	152.20	152.19	0.01	0.01
1994	151.29	151.20	0.09	0.06
1995	59.91	59.94	-0.03	-0.04
1996	195.30	195.23	0.07	0.03
1997	133.38	133.18	0.20	0.15
1998	81.83	82.140	-0.31	-0.38
1999	109.45	109.11	0.34	0.31
2000	74.72	75.11	-0.39	-0.52
2001	55.64	55.95	-0.31	-0.55
2002	114.63	115.16	-0.53	-0.46
2003	45.66	46.09	-0.43	-0.95
2004	35.15	35.01	0.14	0.39
2005	88.86	89.10	-0.24	-0.27
2006	149.86	150.11	-0.25	-0.16
2007	53.97	53.96	0.01	0.01
2008	73.30	73.13	0.17	0.23
2009	71.38	71.07	0.31	0.43
2010	67.19	66.99	0.12	0.30
2011	104.43	104.12	0.31	0.30
2012	67.94	68.12	-0.18	-0.26
2013	157.48	157.17	0.31	0.20
2014	165.93	166.05	-0.12	-0.07
2015	162.83	163.19	-0.36	-0.22
2016	103.34	103.10	0.24	0.23
2017	39.08	39.01	0.07	0.18
2018	49.34	49.04	0.30	0.61

and effectiveness of the model. Equations (7)–(9) of the standard statistical measures ( $R^2$ , SEE, RMSE, MAE, and RE) were employed, following the methodology of earlier researchers (Al-humairi *et al.* (2020, 2023); Pandey *et al.* (2020), Zakwan & Niazkar (2021), Rahal & Al-humairi (2019), Al-humairi & Rahal (2023)). Following are the building steps of the program:

Start of program → Worksheet → Data Entry → solve → Regression → non-linear → Model selection → fit information

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (X_p - X_o)^2}{n}} \quad (7)$$

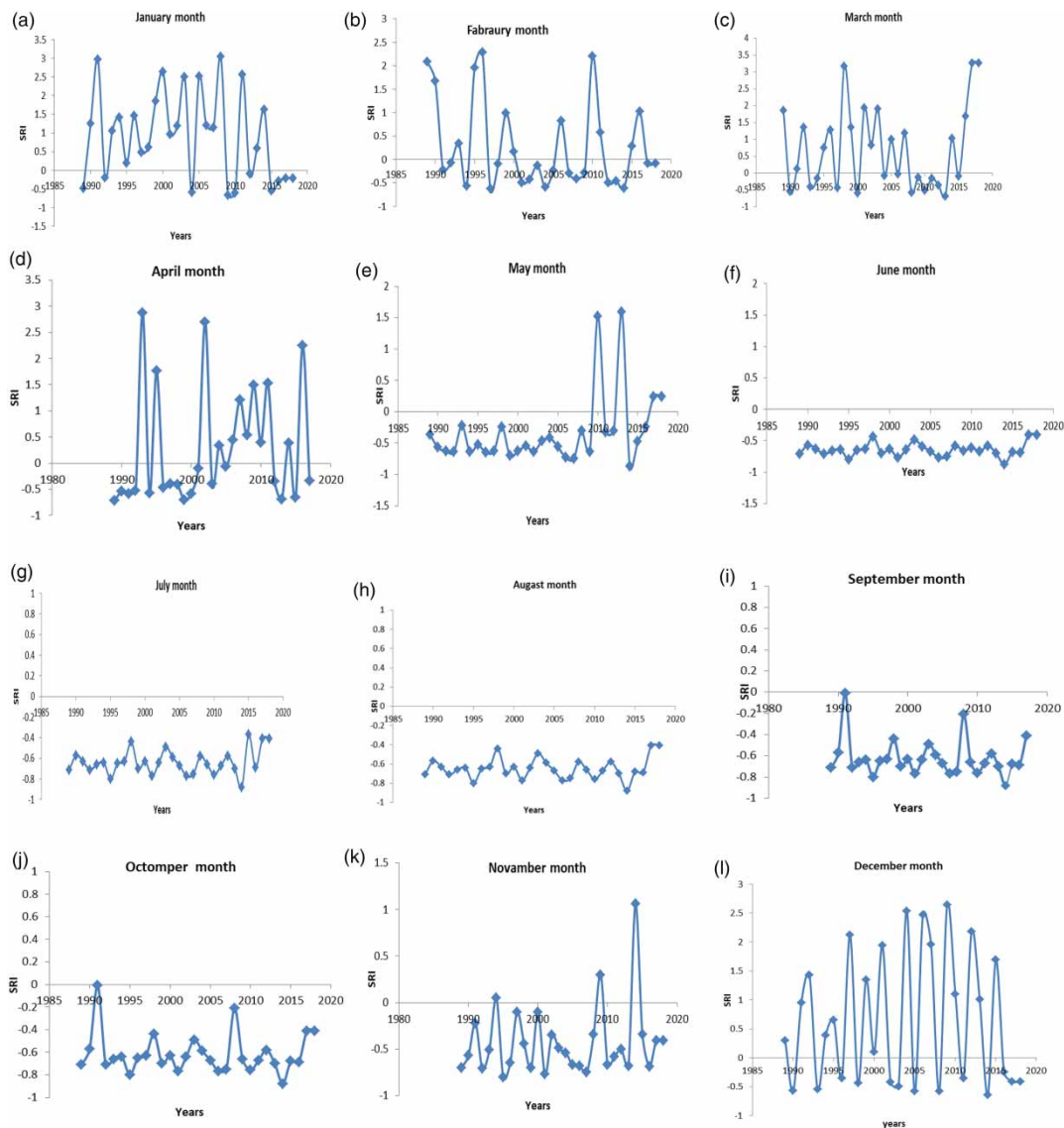
$$\text{MAE} = \frac{\sum_{i=1}^n (X_p - X_o)}{n} \quad (8)$$

$$\text{RE} = \left( \frac{\text{MAE}}{\text{ave}} \right) * 100 \quad (9)$$

The predicted and observed values are denoted by  $(X_p)$  and  $(X_o)$ , respectively. The number of samples and the average of the predicted values are also included as  $(n)$  and  $(ave)$ .

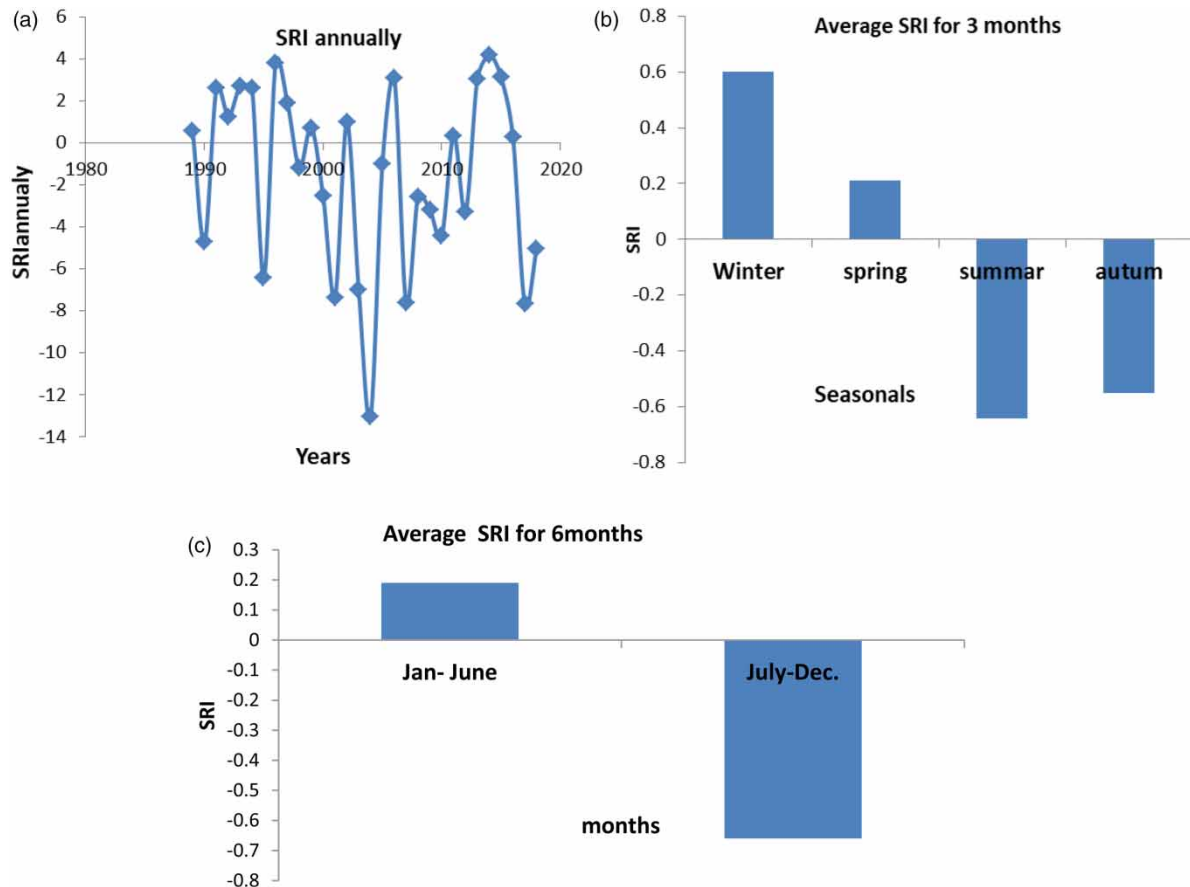
#### 4. RESULTS AND DISCUSSION

The Excel software was used to calculate the indicators and distribution of rainfall. Results show that for the monthly standard rainfall index, the high value is 3.26 mm (Figure 2) in March month for 2017 and 2018 years. This indicates that the Hai city was of extreme wet conditions in March month, lower value is  $-0.88$  mm in June, July, August, September, October months in 2014. This means that Hai town was near normal drought condition in these months (Figure 2). Also, the town has a high SRI annually which was equal to 3.81 and 4.19 mm in 1996 and 2014, respectively. Accordingly, the city was in extreme wet condition in 1996 and 2014. It has low SRI annually in 2004 which was equal to  $-13.04$ . This clearly indicates an extreme drought condition during 2004 (Figure 3(a)). In addition, the standard rainfall distribution index was calculated for the periods of 3 months and 6 months. However, December, January, and February were characterized by a greater rainfall rate when rainfall data were used every 3 months compared to the average of the other months of the year. These differences for the SRI with the four seasons are shown in Figure 3(b). Furthermore, clear differences were noticed in calculating the SRI due to high temperatures when using the total from July to December as a result of very low intensity of rainfall rates in those months compared to other months (Figure 3(c)).



**Figure 2** | SRI for all months (a-l) during the period 1989–2018.





**Figure 3** | SRI annually, for 3 months, and for 6 months during the period 1989–2018.

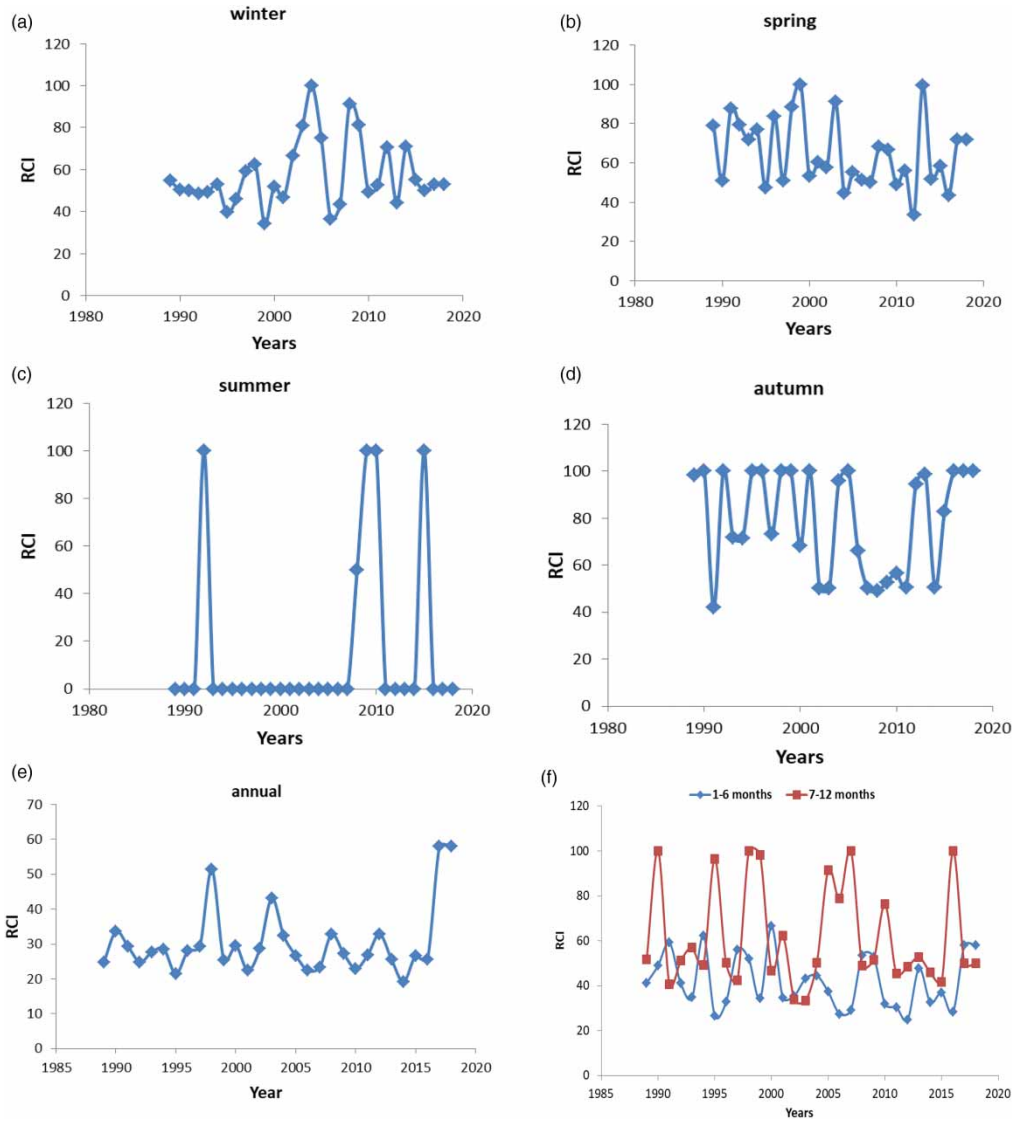
RCI values ranged from 19.12 representing irregular rainfall distribution to 57.95 representing strong irregularity rainfall distribution, in winter, spring, summer, autumn season, and during 6 months of the years (Figure 4).

Average normal monthly rainfall ranged between 25.19 and 0.00 mm in January and August, respectively. The average annual rainfall range was 19.45–3.50 mm in 1996 and 2004, respectively, Figure 5 shows the variation in rainfall in all months and all years.

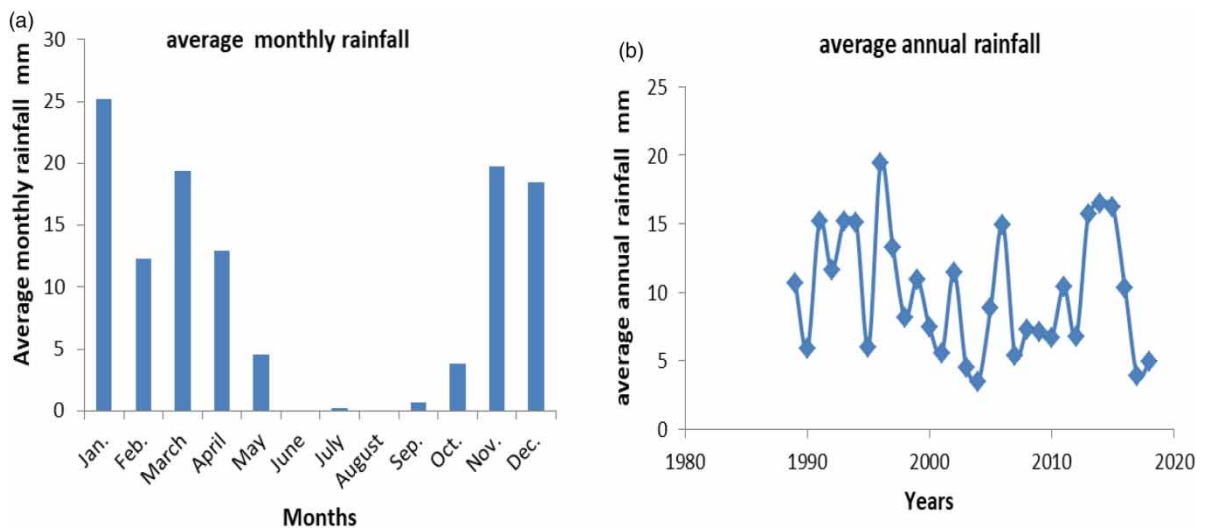
Figure 6 illustrates a high IW equal to 195.3 and 165.93 during 1996 and 2014, respectively. This indicates no deficiency in rainfall and the lowest IW was in 2004 and equal to 35.15 which is considered as bad and indicates a large deficiency in rainfall.

The coefficient of variation (CV%) ranged between 113.78 and 244.01 with standard deviation values of 18.80 and 11.99, for the periods 2014 and 2018, respectively. This variation of rainfall is classified as high variability. The high average degree of variance value indicates significant internal oscillations in the rainwater (Asfaw *et al.* 2018; Figure 7).

Tables 3–5 and Figure 8 explain the resulting statistical models that were applied to develop indicator of wetness estimates. Using DataFit program, mathematical models have been constructed linking IW and other indicators (RCI, SRI, CV,  $N$ ). The models with the greatest  $R^2$  value and smallest SEE, MAE, RE, and RMSE values were selected. In order to forecast the IW, four models were constructed. In terms of forecasting IW values, Model 1 fared the best.  $R^2$ , SEE, RMSE, and RE for Model 1 are 99.99%, 0.28, 0.253, and 0.221, respectively. Ratios of positive errors were between 0.01 and 0.61%. Additionally, the range of variations between the actual results and the expected models for the years 1993, 2007, and 2018 falls between 0.01 and 0.3, respectively. The range of negative percent errors was between (–0.04 and 0.95%). Additionally, during 1995 and 2003, there were variations between the outcomes of theoretical models and measurements taken in reality ranging from –0.03 to –43, respectively. The developed models can be used to determine the intensity of rainfall in steady areas. Also, it can use them to determine the irrigation time and its duration.



**Figure 4** | SRI annually, seasonally, and for 6 months during the period 1989–2018.



**Figure 5** | Average rainfall (monthly and annual) for the period 1989–2018.

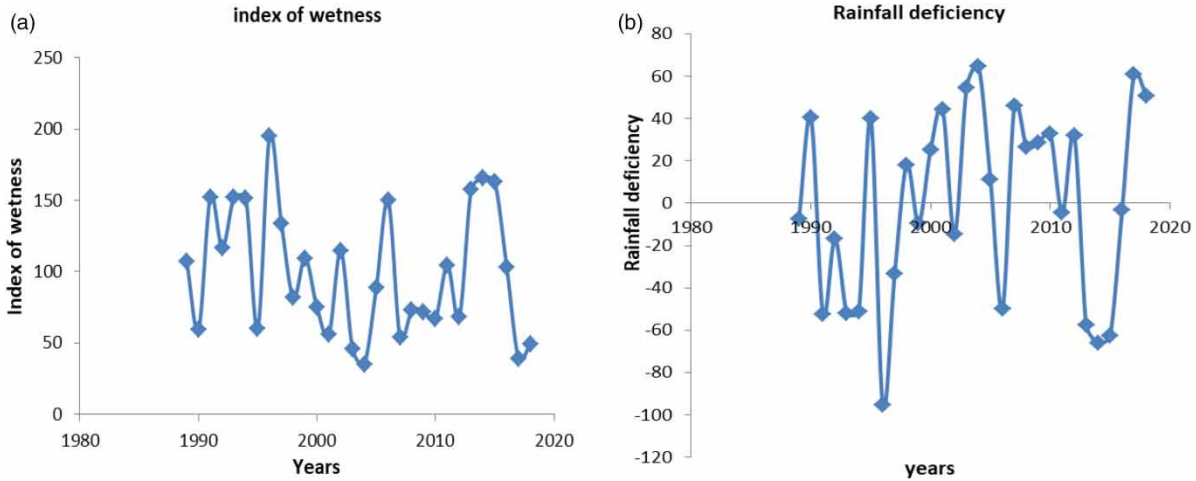


Figure 6 | Index of wetness and rainfall deficiency for the period 1989–2018.

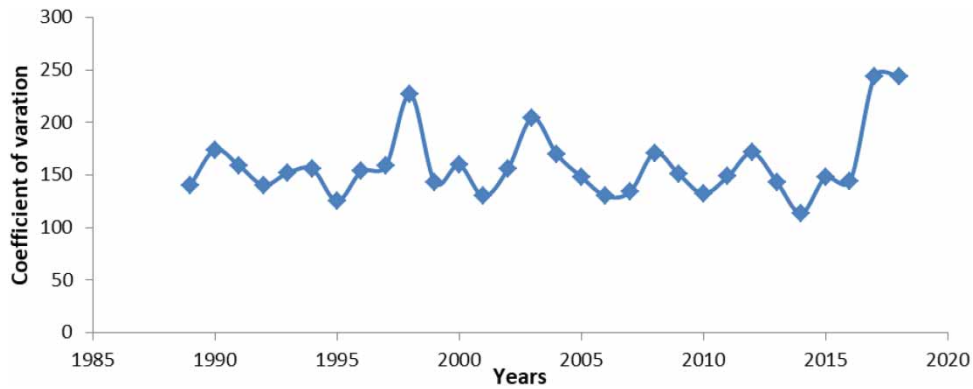


Figure 7 | Coefficient of variation for the period 1989–2018.

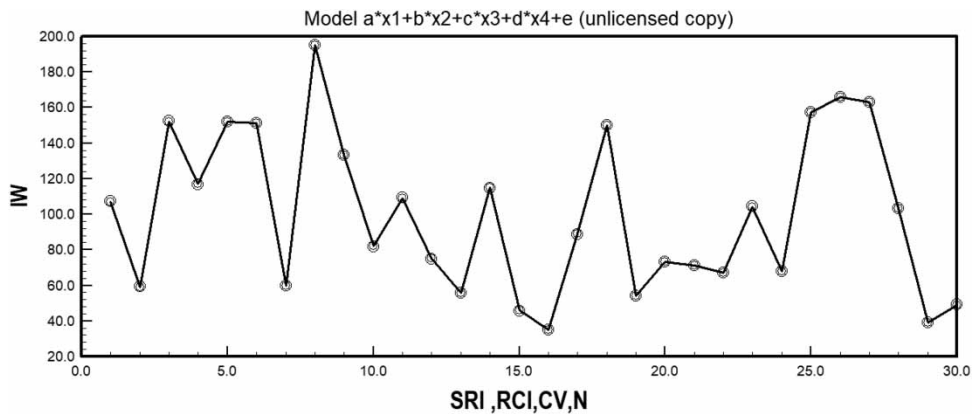


Figure 8 | Plot for model 1.

### 5. CONCLUSIONS

The amount of rainfall in a location has a significant impact on a number of aspects of managing water resources including monitoring water quality, distributing water, planning, and using water. The objective of this study was to evaluate the variation of rainwater and drought monitoring in Hai town by using Excel and DataFit software . The determination of rainfall variation was done based on the yearly, seasonal, and monthly rainfall series of data

as well as the SRI, rainfall concentration index (RCI), IW (IW), and coefficient of variation (CV). The results showed that the years 2014 and 1996 had a high SRI yearly values and wetness indices of 165.93 and 195.3, respectively. Also, were regarded to be under very wet conditions. In contrast, the year 2004 had a low SRI value, which indicated an extreme drought condition with a wetness index of 35.15. Except for the RCI in the year 2014, which was an irregularity in rainfall distribution. The RCI value for yearly, seasonal, and for 6 months is characterized by strong irregularity in rainfall distribution. The CV showed that Hai town's rainfall was extremely variable. The mathematical models were constructed using DataFit software to forecast IW, and the results indicated that model 1 ( $IW = a_0 * SRI + a_1 * RCI + a_2 * N + a_3 * CV + a_4$ ) is the more appropriate model. Its values include RE = 0.221, SEE = 0.28, RMSE = 0.253. The better model for forecasting IW had positive proportions of errors between 0.01 and 0.61% and a negative error value between -0.04 and 0.95%. These models are crucial for managing irrigation water systems and water resources. The results show that rain indicators has important difference and alteration from time to time throughout the study period. It is suggested to establish water reservoirs to store surplus rainwater in wet times and to use the stored water in the dry season. Also, it is recommended to use a modern irrigation system such as sprinkler or drip irrigation during dry periods.

#### DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

#### CONFLICT OF INTEREST

The authors declare there is no conflict.

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