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Spatiotemporal Analysis of Long-Term Rainfall in Semi-Arid Area Using Artificial Intelligence Models (Case Study: Ilam Province, Iran)

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Abstract: Ilam province is located in the southwest of Iran, and the primary motivation for this research is to study different dimensions of rainfall fluctuations in the Ilam province. This study is of great importance for the management of the environment in terms of the application of rainfall distribution in different areas. After collecting the data, first, the average number of rainfall months for each of the studied stations for a period was obtained. Then the data were arranged numerically in the order of Gregorian months. Ultra-innovative artificial intelligence methods were used to perform spatial–temporal analysis. The results show that in autumn and winter all three factors were influential on rainfall in the region. The equation method of regression line trend was used to express the changes in rainfall in the study period, and it was concluded that during this period the rainfall trend in March, June, and December in all stations was decreasing. In May, all stations had an upward trend except for Harsin station. In other months, there are decreasing and increasing trends among the stations. The general trend for rainfall during the study period is also one of decreasing. Regarding the results, the standard deviation for the simulation is equal to 10.22 for autumn and 12.35% for winter. This value is about 17.97% and 7.19%, respectively, for the observed rainfall. The results show there are no significant differences between the model and measured data, so the artificial network is applicable for the simulated monthly precipitation.

Keywords: spatiotemporal analysis; long-term rainfall; Ilam city; meta innovative artificial intelligence

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1. Introduction

Determining the pattern of the temporal distribution of rainfall to estimate flood and determining the flood potential of showers, as well as the configuration of drainage system, is of special importance. Further design of engineering facilities requires a comprehensive understanding of the amount of rainfall plus the temporal distribution. One of the main factors necessary in model preparation and hydrological development of catchments is to know the temporal distribution of rainfall [1,2]. Because Iran is located in an arid region, the temporal variation of rainfall in it is considerable. Although the average annual rainfall of Iran is about 250 mm and is less than 1.3 of the global average rainfall, in the rainy years it receives up to 380 mm, and, in contrast, in the years of low rainfall the country receives less than 155 mm [3]. These changes are seen not only over long periods, but also at short intervals. According to the results of many climatic classifications, this land has an arid and semi-arid climate. Low rainfall, high variability, and severe fluctuations in rainfall from year to year are the prominent features of Iran's climate, in addition to the salient features of the Iranian environment [4,5]. In addition to the above features, the spatial distribution of rainfall in this land is also homogeneous and decreases from west to east and from north to south [6]. In addition to the uneven temporal distribution of rainfall, its spatial differences in Iran are very large. On the one hand, these differences go back to the nature of the spatial behavior of rainfall, which is essentially a rebellious variable and shows severe spatial variations. On the other hand, the diversity of rainfall in different parts of Iran has caused the amount of rainfall and rainfall time to differ in each region, especially in the years when the country has less rainfall. These location differences become more pronounced. Also, in rainy years, spatial differences in rainfall in different parts of Iran decrease [7]. Parmer et al. used statistical regression and several intelligent climate models to simulate daily evaporation from the pan in semi-arid climates in Delhi, India, and the artificial neural network model was reported as the most accurate model [8]. Nuri et al. simulated the monthly flow of the Sufi Chai River in Urmia, which is the main entrance to the Alaviyan Dam using the support vector machine model based on principal component analysis. According to the obtained results, the pre-processing of the input variable to the support vector machine model has improved the performance of this model [9]. Tezel and Boyukildiz simulated the monthly evaporation of the unpopular meteorological station using an artificial neural network and a support vector machine. In this research, data on temperature, relative humidity, wind speed, and rainfall in the statistical period 1972 to 2005 were used; they used a support vector machine model with a radial base function core and a multilayer perceptron neural network. The results showed the proper performance of the multilayer perceptron neural network model with a small conjugate gradient training algorithm [10]. Soltani et al.] used the ANN model to estimate the evaporation of the Amirkabir dam reservoir. They achieved accurate and desirable results due to the high accuracy of the artificial neural network model [11].

Rawat et al. tried to identify the essential criteria and develop a methodology to select potential RWH sites in Rajasthan (India). They combined GIS modeling (multicriteria decision analysis) with applied remote sensing techniques, as these have the potential to assess land suitability for RWH [12]. Overall, their study shows the applicability of the GIS-based MCDA approach for up-scaling the traditional RWH systems and its suitability in other regions with similar field conditions, where RWH offers the potential to increase water resource availability and reliability to support rural communities and livelihoods. Salehi et al. used a 10-stage optimization method and two genetic algorithm methods for gate operations [13]. The GA methods were reported to be more effective. Although more accurate results may be obtained using more stages for the operations, more gate operations are not desirable as this increases the complexity of the gate operations. Chauhan investigated the impact of climate change and climate variability on rainfall dynamics in Haryana. Their obtained results may further guide the policymakers and beneficiaries in optimizing the use of hydrological resources [14].

In understanding the weather conditions and how the indicator parameters work, meteorological factors, such as temperature and rainfall in a place, are among the factors that determine the climate in that area in the long run. These important climatic parameters are atmospheric factors whose changes do not follow a specific trend. Many factors, such as synoptic conditions, topographic status, distance and proximity to water sources, latitude, etc., are involved in the changes. The study of the temporal and spatial distribution of rainfall in Ilam province will lead to knowledge of how rainwater is distributed in specific periods in order to use it optimally in the fields of agriculture, industry, and architecture in human societies. Also, in order to reduce the effects of urban floods, prevent flooding of roads and houses in the city, and reduce the human and financial damages caused by rainfall in Ilam province, it is necessary to know its temporal and spatial distribution. It goes without saying that to estimate floods, the possibility of optimal use of the natural environment, the design of runoff disposal systems, the management of watersheds, and the design of drainage systems require an understanding of the pattern of the temporal distribution of rainfall in the basin [15–17]. Mosaffa, et al. (2020) carried out research into spatiotemporal variations of precipitation over Iran using the high-resolution and nearly four-decade-old satellite-based PERSIANN-CDR dataset, and they found, for instance, that a remarkable decrease in precipitation amounts is detectable during dry years over the eastern, northeastern, and southwestern regions of Iran during March, April, and

December, respectively. The results of this study show that PERSIANN-CDR is a valuable source of information in low-density gauge-network areas, capturing the spatiotemporal variation in precipitation [18].

The study of different dimensions of rainfall mismatch and the identification of the impact of geographical factors on rainfall in the province, as well as spatial analysis of rain using GIS and the Kriging zoning method, is the primary motivation for this research. This study is of great importance for the management of the environment in terms of the application of rainfall dispersion in different areas. In accordance with the practical results of using monthly rainfall, some of which are mentioned in this study, we use the mentioned statistical methods as the models and techniques used, which are the term artificial neural network, decision tree, and MLP. Temporal and spatial patterns of monthly rainfall in Ilam province will be analyzed. Therefore, the questions of the present study are as follows:

Is the spatial distribution of monthly rainfall in different regions of the province, which uses the same innovative meta artificial intelligence model (decision tree and MLP), the same?

During the study periods, what was the rainfall trend in the study areas using the innovative meta artificial intelligence model (decision tree and MLP)?

2. Theoretical

Quantitative and qualitative criteria for evaluating rainfall and drought:

Intensity, persistence, extent, and frequency are the characteristics of deficiency that are determined using drought assessment indicators. Quantitative criteria for assessing drought are mainly based on the processing of large volumes of information on rainfall, snow, surface currents, etc., and lead to an overview of the dynamic water process in soil areas. This information is usually presented discretely and numerically on different scales. In addition to this, the subject of each of these indexes covers a specific range of information and the water cycle. In the following, some of the most essential parameters in this field are briefly introduced.

The Palmer Drought Intensity Index (PDSI): This indicator was invented by Palmer in 1965. The basic concept of this index is based on temperature changes and rainfall, as well as soil moisture. This indicator is used on a monthly time scale, and the fundamental factors need to be calculated. This indicator includes temperature, rainfall, soil moisture, and evapotranspiration. This index is used chiefly today by agencies related to agricultural management in different countries to assess the severity of drought. The main use of this index is also in the estimation of agrarian emergency aid. Recently, the assessment of this index at the national level in Iran has also been on the agenda of the Meteorological Organization. It should be noted that the application of this index in the country has been minimal, due to a lack of soil moisture information, and has been mainly in the form of research projects.

The Percent of Normal Index (PN): This index was presented in 1994 by Wiley et al.; its basic concept is the division of observed rainfall into normal rainfall, and is the only factor needed to calculate that rainfall. This index is used on a monthly time scale.

Decile Index: This index was introduced in 1967 by Gibbs and Maher. For this index, basically, the distribution of the probability of occurrence of recorded long-term rainfall statistics is obtained from a part of each ten percent of the distribution. The only effective factor in calculating this index is rainfall, and the time scale used in calculating and applying this index is also the monthly scale.

Standardized Precipitation Index (SPI): This indicator was introduced in 1995 by McKee et al. This indicator is based on the difference between rainfall and the mean using a particular time scale. This Indicator can be calculated in time scales of 3, 6, 12, 24, and 48 months. This index is one of the most widely used meteorological drought assessment indices because it has a dimensionless form and does not require extensive information for calculation.

Crop Moisture Index (CMI): This Indicator was invented in 1968 by Palmer. The concept of this index is based on the average temperature and total rainfall for each week in a climatic division compared to the CMI values of the previous week, and has weight coefficients according to time and place. The main factors used in this index are temperature and rainfall, and it is used on a weekly time scale.

Revival Drought Index (RDI): This indicator was introduced in 1996 by Weihurst. This indicator is similar to an indicator of surface-water storage, and is calculated based on climatic and meteorological factors, river water level, snowfall, surface currents, and water reserves, as well as temperature, and is used on a monthly time scale.

Effective Rainfall Index (ERI): This index was introduced in 1999 by Wildhite and Bion as the newest index for drought in recent years. This indicator is based on quantitative analysis of effective daily rainfall. Therefore, this is the only effective factor for analyzing the rainfall, and it is used on a daily time scale.

In accordance with the researchers' acceptance of the SPI indicator and the exact statistical content of this indicator in quantitative estimates of rainfall and the shortages based on it, this method is the basis for studying and computing drought in the target areas (five catchments, Taleghan, Karaj, Mamlu, Latian and Lar), and the presented plan to simulate rainfall has been used. The basics of this method will be detailed below.

3. Method and Materials

Ilam province, with an area of 20,150 km^2 (7780 sq mi), is the 22nd largest province in Iran. It is located in the southwest of the country, in Central Zagros, and is bordered by Iraq to the west, Khuzestan province to the south, Lorestan province to the east, and Kermanshah province to the north. Ilam province is situated at the southwestern edge of the Zagros mountains and right at the transition between the Arabian and the Iranian plateaus. Because of this, it is divided into two distinct natural areas; the northern and eastern parts are mountainous, whereas the southwest is covered with low plains that extend to the Iraqi and Khuzestan borders. Figure 1 shows the location of Ilam province. Ilam's climate is dry and semi-dry, with an annual rainfall of about 300 mm.

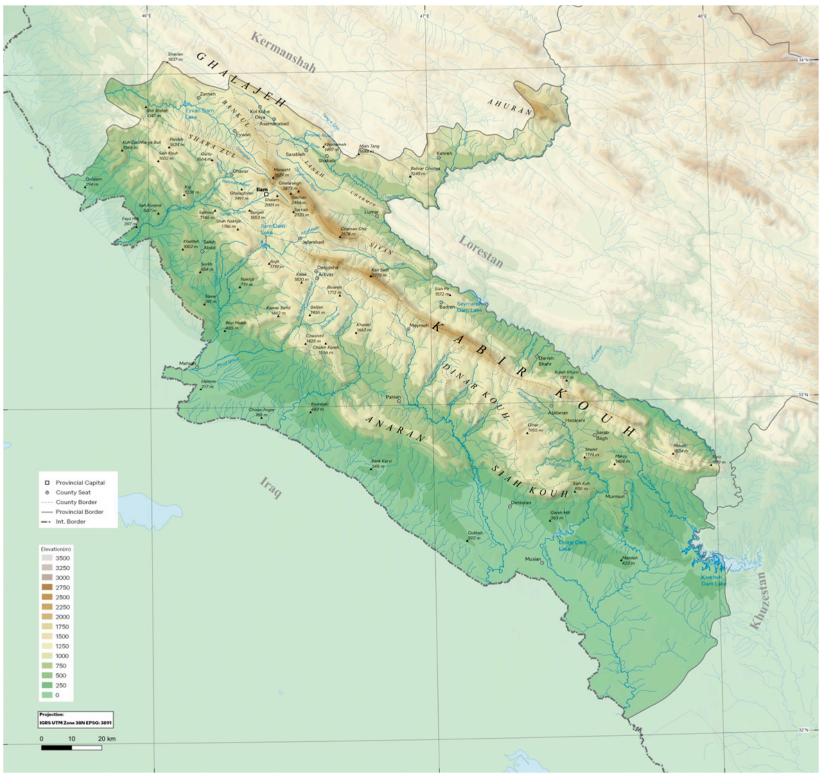


Figure 1. Location of study area (google map).

In this research, the ASCE model (2008) was used to solve the artificial neural network and also, for calibration, we used the 70 present observed data, which were obtained from the Ilam climatology station The statistical index correlation coefficient (R) and root-mean-square error (RMSE) used Equations (1) and (2).

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(y_i - \overline{Y}\right)\right)^2}{\left(\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2\left(y_i - \overline{Y}\right)\right)^2} \tag{1}$$

$$RSME = \sqrt{\frac{\left(\sum(X_i - y_i)\right)^2}{n-1}} \tag{2}$$

The present research method is analytical and applied. The following methods have been used to collect information:

1. Collecting the required data of the study area, including rainfall data from the existing stations, physical characteristics of Ilam city, information and specifications, and the amount of rainfall.
2. Investigating rainfall-runoff simulation models to determine the flood hydrograph and to select the appropriate model.
3. Studying the hydrological and hydraulic simulation models of long-term rainfall to determine the processed flood hydrograph in the downstream position of the river and to select the appropriate model.
4. Examining forecasting models (such as innovative meta artificial neural networks) that can simulate long-term rainfall hydrographs based on previous rainfall hydrographs as model input.

This section examines how artificial neural networks are designed and used to simulate rainfall at monthly and fractional time scales. It should be noted that the neural network used in this study was created through coding using Article 7 Mike 11software version 2.1.

Selection of inputs: this was carried out after collecting various station data, as well as remote impact parameters, including the monthly average of the remote impact parameters for the indicator: southern fluctuations (SOI and NINO 3,4), as well as station parameters of dew-point temperature, relative humidity, annual rainfall, and monthly rainfall (from 2003 to 2010). The files were prepared for this project. Each file was intended to simulate one month (October to March) and one section (autumn and winter). It should be noted that partial rainfall includes only the autumn part (average rainfall in October, November, and December) and the winter part (average rainfall in January, February, and March). This is also to reduce the complexity of the network structure (which may be complex, due to the large number of inputs to the network). After collecting the desired parameters through correlation operations, the parameters were more dependent on monthly rainfall (October to March) and seasons (autumn). The winter was selected as the point of entry for each section. The following are the parameters for which the correlation coefficient with monthly and partial rainfall is examined:

The average dew-point temperature is three months before the lunar or rainy season;
Average relative humidity three months before the month or section;
Rainfall of the studied month, during the last one-to-three years;
Annual rainfall of the last one or two years;
Indicator SOI: three months before the rainy months and seasons under review;
Index: NINO 3,4: three months before the rainy months and seasons under study.

Among the above parameters, for the monthly and partial rainfall forecasting model of the whole country, eight inputs including the SOI index three months before the rainy months and seasons, the mean relative humidity of the previous three months, and annual rainfall of the previous one and two years were selected. To simulate monthly and partial rainfall in arid and desert climates, index SOI three months ago was considered as the three inputs for the model. The five inputs of the monthly rainfall observed by the model and which were part of the semi-arid climate include the SOI indicator for three months before and the annual rainfall for one and two years before. In forecasting the monthly and partial rainfall of individual cities, the SOI and NINO 3,4 indices three months before the rainy months and seasons were used as six model inputs.

Data processing:

Three types of neural networks have been designed to simulate the country's rainfall for the desired time scales.

(1) Neural network to simulate monthly and partial rainfall of the whole country;
(2) Neural network for simulating regional rainfall (climatically);
(3) Neural network to simulate local rainfall.

First, the rainfall data related to the stations will be validated and, if necessary, the data reconstruction will be considered. To simulate the status of long-term rainfall in this study, artificial nervous systems, which are a subset of artificial intelligence, are of great importance.

Complex nonlinear equations and numerical calculations and dynamic analyses can be used to derive the dynamics on which the system operates, thereby obtaining the outputs needed to simulate and the estimates needed to analyze the system. In this study, MATLAB software for the innovative meta artificial nervous system and R software for statistical analysis will be used.

For all the files from October to March and the autumn and winter seasons, the eight parameters that make up the same number of input neurons in the first layer are fixed. Also, the monthly and seasonal rainfall is fixed as the only neuron (in fact, as the desired output that is supposed to be simulated) in the output layer. The optimal number of neurons in the middle (hidden) layers should be selected in such a way as to lead to the least number of errors in the training data. The number of middle layer neurons was considered as five neurons, after much trial and error. Therefore, with model 1-5-8 during the training process in the neural network, a structure of the network was selected in which the value of the sum of squares of error (SSE) of the training events reaches its lowest possible value, which was considered as the optimal value of the weights. In the training process, the output value calculated by the network is compared with the target output value defined in the training data set. Then the sum of the squares of error (SSE) on the total training patterns for neurons in the output layer of the network is calculated. Equation (3) is used to calculate the sum of the error squares.

$$SSE = \sum_{P=1}^{N} \left(t_p - Z_p^2 \right) \tag{3}$$

where t_p and z_p are the desired output and the actual calculated output (simulated) for the p pattern, respectively. After obtaining the outputs of the network and returning them from values between 1 and -1 to the observed values, in order to evaluate the performance of the neural network, the following three indices were used. These indices have been used for all parts of the rainfall forecasting.

4. Results and Discussion:

Values improved:

In this paper, we first estimated the regression coefficients using multivariate regression and, as before, we consider the data collected from 1995 to 2022 as independent variables. Then we simulate the next 6 years using the obtained equation for this model. Table 1 shows the regression coefficients. We simulated seven years using the available data, which is an indication of an inappropriate fit. Because the obtained information consists of negative values, our data become inappropriate, and they contradict the rainfall values. Table 2 displays fitted rainfall values for seven years, from 2016 to 2022.

Table 1. Table of regression coefficients.

B1	B2	B3	B4
−31,558.0	−054.0	−94,331.0	−71,041.0
422,623.0	505,038.0	383,514.0	−3739.0
−37,819.0	−70,144.0	−74,118.0	117,652.0
−703.0	361,226.0	−85,264.0	32,537.0
0	−1352.0	419.10	308,962.0
−24,496.0	−1372.0	−57,508.0	−10,597.0
−17,474.0	0	0	−7073.0
35,212.0	−17,881.0	512,987.0	731,307.0
0	315,068.0	26,606.0	0

Table 2. Fitted rainfall values for seven years from 2016 to 2022 in mm.

Year Month	2016	2017	2018	2019	2020	2021	2022
April	11.67	−66.73	40.92	72.64	38.80	47.59	28.69
May	14.04	9.88	−6.42	42.18	27.99	6.16	21.87
June	−6.24	−21.65	26.30	20.71	13.45	−19.27	−18.06
July	4.88	−11.62	1.24	7.32	−1.66	12.20	2.70
August	−5.69	0.60	2.13	1.40	2.02	−9.98	−9.26
September	0.36	1.44	−5.62	−8.57	−1.33	11.97	5.31
October	0.81	6.21	28.05	0.21	1.84	−21.83	−10.63
November	8.83	25.4	−2.54	8.44	12.51	9.50	14.90
December	2.76	5.44	56.41	43.07	456	−6.50	4.99
January	11.78	0.85	2.47	16.90	7.15	−0.72	20.87
February	32.3	67.22	−33.72	−6.78	7.06	7.73	38.27
March	30.61	3.06	24.89	41.95	29.27	−13.8	22.80

The equation and regression coefficients for this fit are as follows:

$$Y = X * B; \tag{4}$$

- All data obtained from Ilam Climatology Station

Monthly and partial rainfall in Ilam:

To simulate monthly and partial rainfall in this part of the project, station information was prepared to simulate monthly rainfall and to forecast partial rainfall. Each file contains 417 patterns. Among 14 of the first 475 patterns, each of the 14 patterns belongs to a station; and from pattern number 417 to 575 every 10 templates belong to a station. All 14 patterns simulate monthly or partial rainfall of stations during the years 1960 to 2000, and all 10 patterns simulate monthly or partial rainfall of stations during the years 2001 to 2010. Of the total 417 patterns, 80 percent of those include 475 patterns that simulate monthly or partial rainfall during the years 1960 to 2000 as training patterns. The remaining 20 percentages, i.e., the last 40 patterns that simulate monthly or partial rainfall during the years 2001 to 2010 were considered as test patterns. To assign the initial values of the weight of the connections and the bias of the neurons, the random weight function is used. In this case, it selects the random values of the weights between ±1 and the initial values of the neurons as zero. Among the methods that converge faster and have higher accuracy, the Levenberg–Marquardt algorithm was chosen to carry out the work. This algorithm determines the weights by reducing the error gradient.

The limited functions, such as the logistic function or the hyperbolic tangent one, which prevent the weights from taking on very large values, are preferable to choosing the excitation function or the transfer function, or the activity function, because in the post-propagation method these functions must be differentiable. On the other hand, the network outputs are limited to between 0 and 1 or −1 and 1. Therefore, for the transition function between the input layer and the middle layer, the hyperbolic tangent function (transit), and for the middle layer and the output layer, the linear function (purlin), are the most appropriate functions, according to the pre-processing of the events for entering the network (See Equation (1)). It should be mentioned that all components of the project are taken to have the same type of network training technique and type of activity functions. Also, the best structure that can lead to appropriate solutions for any complex and nonlinear function is considered in all parts of this project. It can lead to appropriate solutions for any complex and nonlinear function, and makes a good model for the desired phenomenon. This model consists of a three-layer perceptron network with an input layer, a hidden layer, and a single layer.

In order to investigate the effect of the studied parameters on the monthly rainfall and for partial measurements, their X-parameter coefficient diagrams are presented below. In all the diagrams in the figures in this section, DEW is used for the dew-point temperature, and numbers 1 and 2 are used for the annual rainfall of one or two years before. In diagrams A to F in Figures 2 and 3, the effect of the studied parameters on the monthly rainfall can be seen.

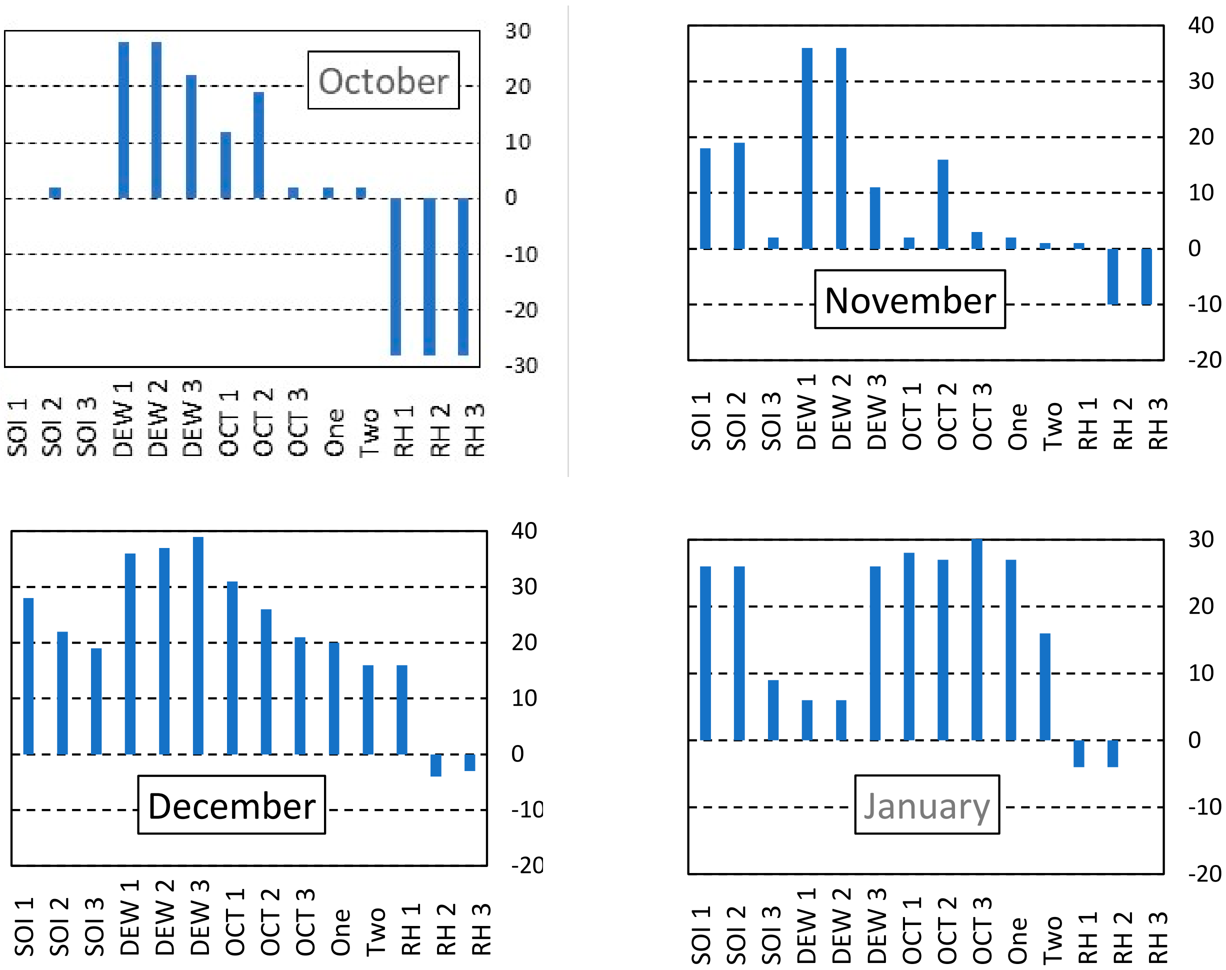


Figure 2. X Parameter coefficients of parameters with monthly rainfall in Ilam.

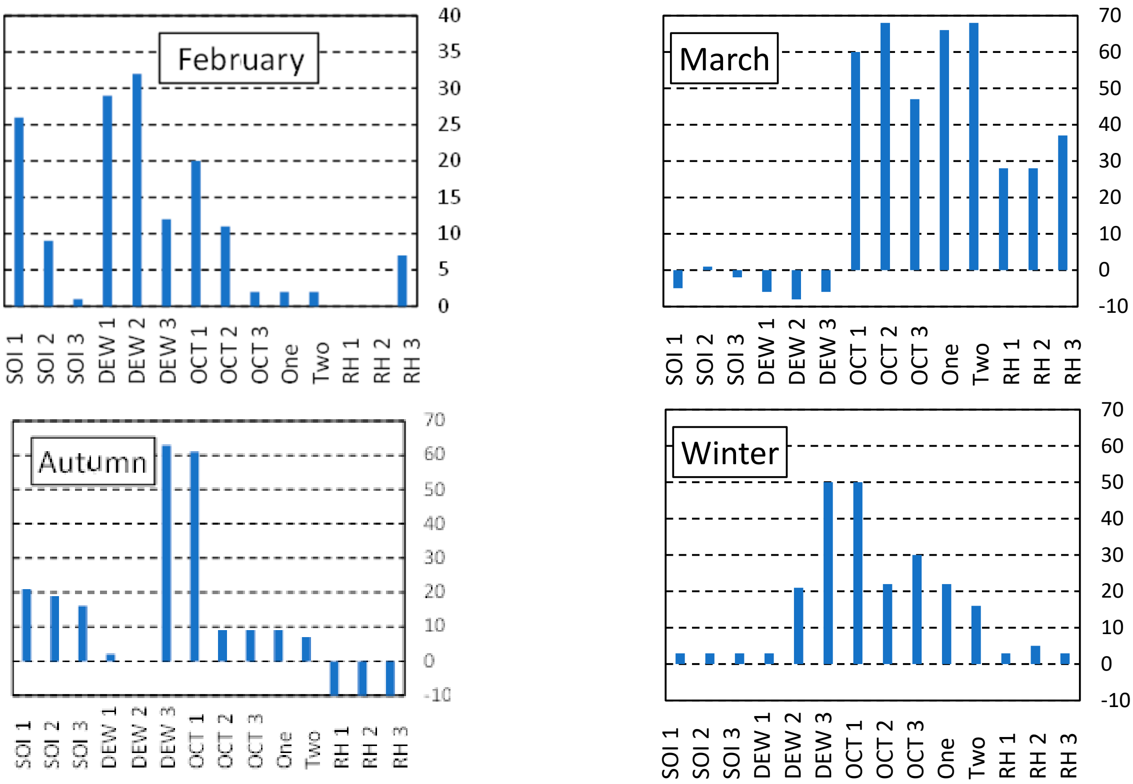


Figure 3. X Parameter n coefficients of parameters with monthly and seasonal rainfall in Ilam.

Regarding Figure 3, the SOI index three months before, from October to March, was gradually associated with a decrease in the X-Parameter coefficient, and had the greatest effect on the rainfall of October and November. The effect of dew-point temperature three months before on monthly rainfall during October and November was very small, and it had a relatively good effect on December, January, and March rainfall, but not for February. With the exception of October and November, the rainfall of the analyzed months during a period of one-to-three years had a significant impact on the rainfall of subsequent months, particularly in March. Other months' rainfall, especially March's, were significantly influenced by annual rainfall, except for January and October, to some extent. The last parameter, i.e., the mean relative humidity, had the greatest effect for March and had little effect for October and November, with a very low coefficient.

According to diagrams G and H in Figure 3, the effect of the parameters on the partial rainfall can be studied. Among the parameters, annual rainfall has the greatest effect, especially on winter rainfall. In terms of influence, the SOI index three months before, for autumn rainfall, and the NINO index 3 and 4 three months before for winter rainfall are placed next. Among the other two parameters, the mean dew-point temperature and the mean relative humidity of three months before the onset of rainfall had a relatively good effect on winter rainfall. However, these two parameters have a very low X-Parameter coefficient for autumn rainfall. In all parts of this project, to simulate the monthly and partial rainfall, we tried to select the parameters that have higher correlation coefficients on average in all files, in order to study better the results obtained from the output of the models. Therefore, this is the reason why in the X-Parameter coefficient diagrams other parameters rather than the selected inputs are observed, and are not selected as inputs, despite the higher coefficients.

Rainfall observed:

Due to the fact that Ilam stations are located in a semi-arid climate, the data from these stations, along with SOI and NINO 3,4 indices were used to simulate monthly rainfall and to simulate autumn and winter seasons.

Results obtained from the models:

After running the model for all files related to Ilam, the best results for six months and for the two sections are given in Table 3.

Table 3. The results obtained from the model for monthly and partial rainfall in Ilam.

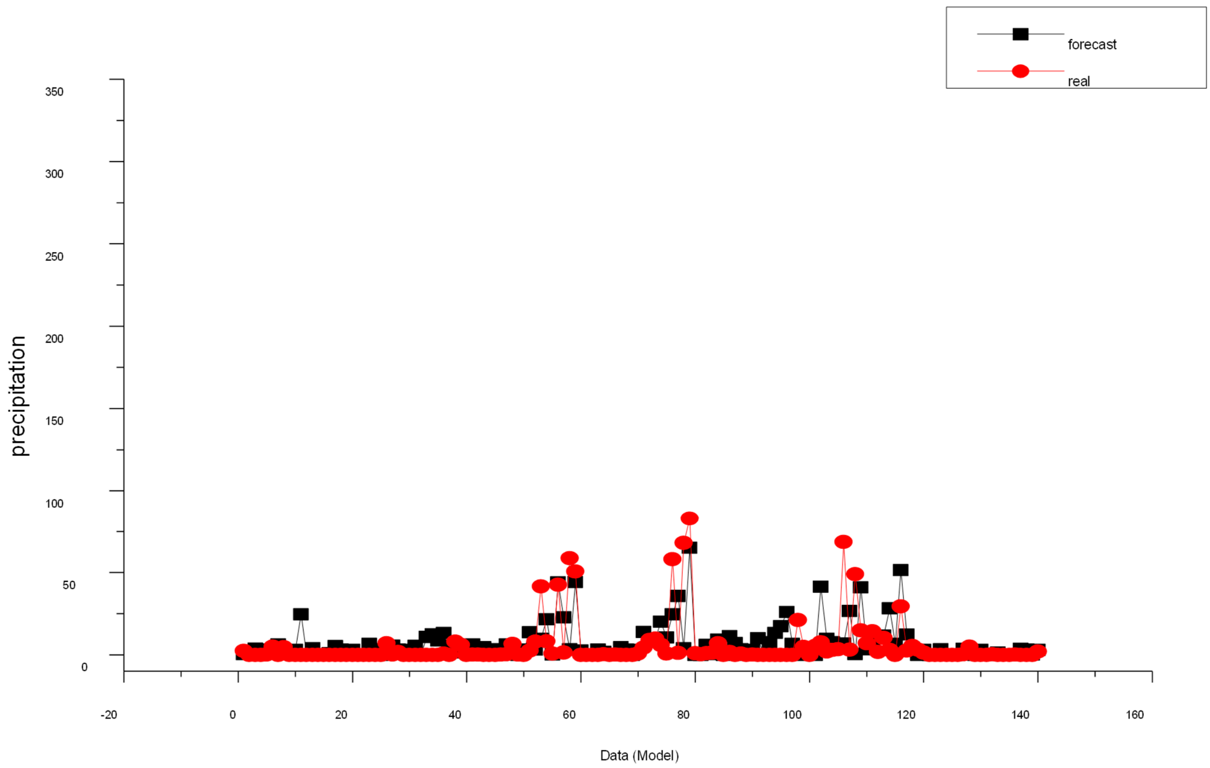
Test	Train	CORR Test	CORR Train	RMSE Test	RMSE Train	SSE Test	SSE Train	Model	Month
−1.12	−1.52	0.71	0.71	13.5	13.79	0.76	5.01	1-5-8	October
−1.14	−1.63	0.7	0.7	21.8	25.18	1.2	4.18	1-5-8	November
−1.29	−2.46	0.7	0.76	22	27.7	2.05	4.64	1-5-8	December
−1.88	−2.01	0.71	0.79	18	20.5	3.05	5.72	1-5-8	January
−1.27	−2.64	0.71	0.7	22.6	25.2	1.98	6.4	1-5-8	February
−4.61	−4.81	0.7	0.81	18	21	1.9	5.5	1-5-8	March
0	−1.02	0.7	0.76	10	12.83	1.33	4.71	1-5-8	Autumn
−1.92	−2.37	0.7	0.71	16	17.03	1.68	6.25	1-5-8	Winter

In Tables 3 and 4, the sum of squares of error (SSE), the root-mean-square of errors (RMSE), the correlation coefficients (CORR), and bias, for the training and test stages, as well as the mean and standard deviation for the actual and simulated values in the training and test are given. According to the results listed in Table 4, it can be seen that the lowest SSE and RMSE for the test phase belong to October and the autumn. Also, the highest correlation coefficient between the observed data simulated by the network in the test stage and the best bias is related to October and autumn seasons. Regarding Table 4, the standard deviation simulation is equal to 10.22 in autumn and 12.35% in winter. The real value is about 17.97% and 7.19%, respectively. The results show that there are no significant differences between the model and the measured data, so the artificial network is applicable for the monthly precipitation simulation.

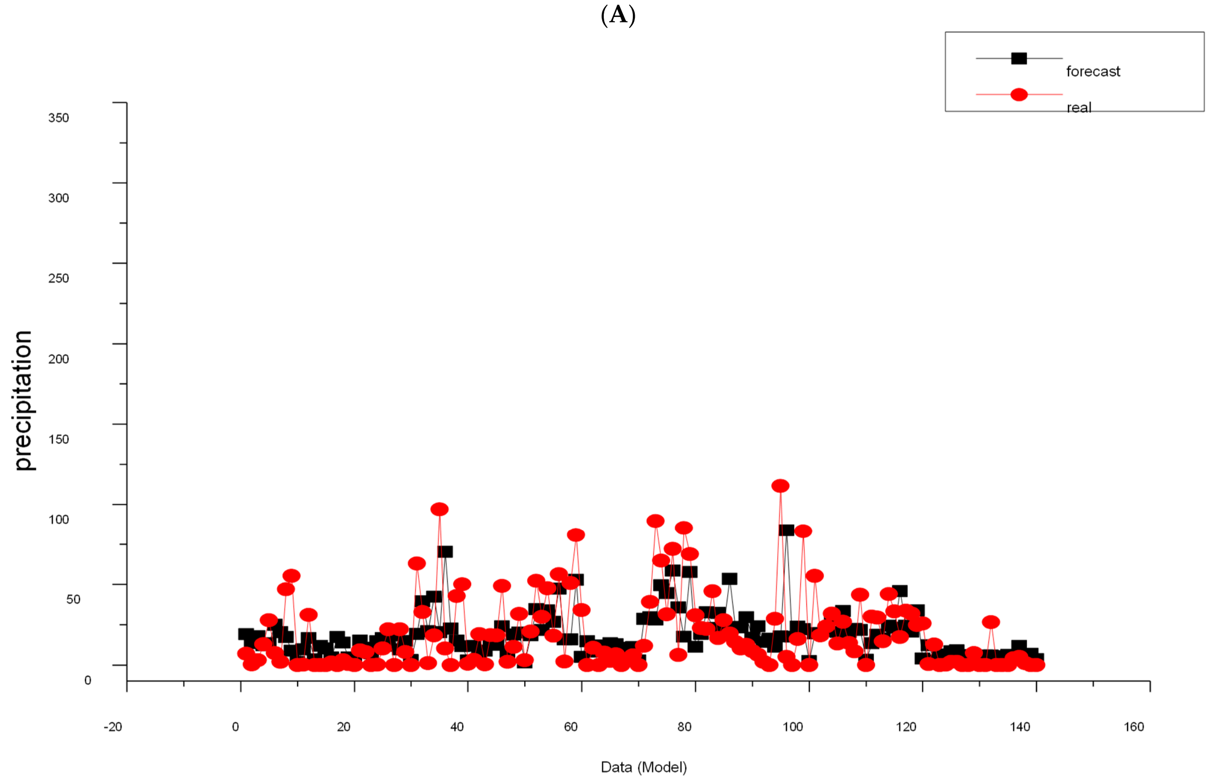
Table 4. Results obtained from the model for monthly and partial rainfall in Ilam.

Standard Deviation Simulation (Training)	Standard Deviation Observed (Training)	Standard Deviation Simulation (Training)	Standard Deviation Real (Training)	Median Simulation (Test)	True Mean (Test)	Mean Simulation (Training)	True Mean (Training)	Month
11.04	14.69	21.14	19.55	2.3	1	5.05	40	October
15.14	22.47	7.17	3.1	3.39	10.45	14	7	November
22.4	39.43	28.23	2.36	8.28	7.18	28	3.2	December
31.96	24.34	37.26	33.15	1.23	9.22	4.02	1.17	January
18.55	22.48	21	32	25.85	21.8	21.05	22.65	February
19.89	18.28	30.94	36.02	2.1	13.3	22.95	25.95	March
10.22	17.97	10.16	19.97	19.45	8.15	16.75	9.14	Autumn
12.35	7.19	17.03	24.26	7.28	3.25	9.3	2.32	Winter

In Figures 4 and 5 of the time series, the actual and simulated monthly and partial rainfall values for the Ilam test data are plotted.



(A)



(B)

Figure 4. *Cont.*

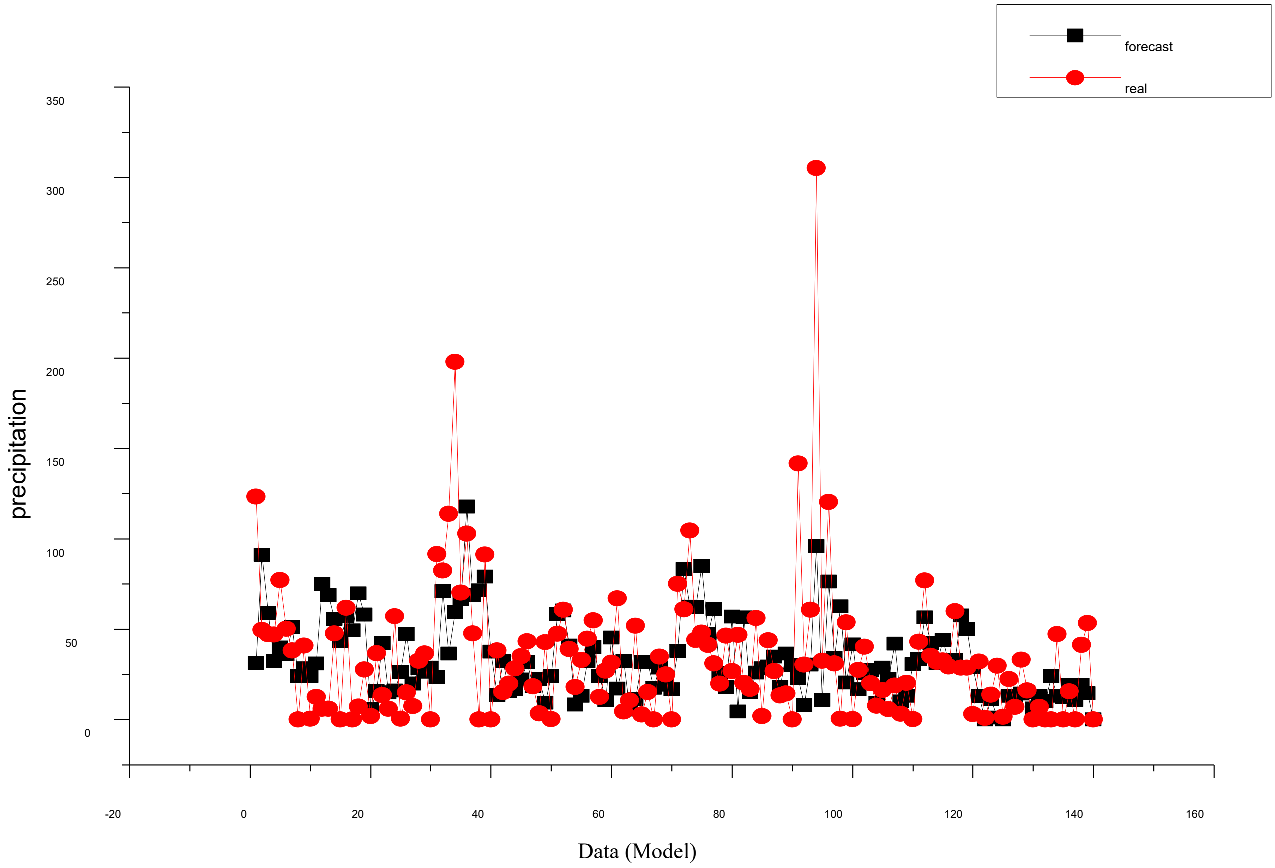
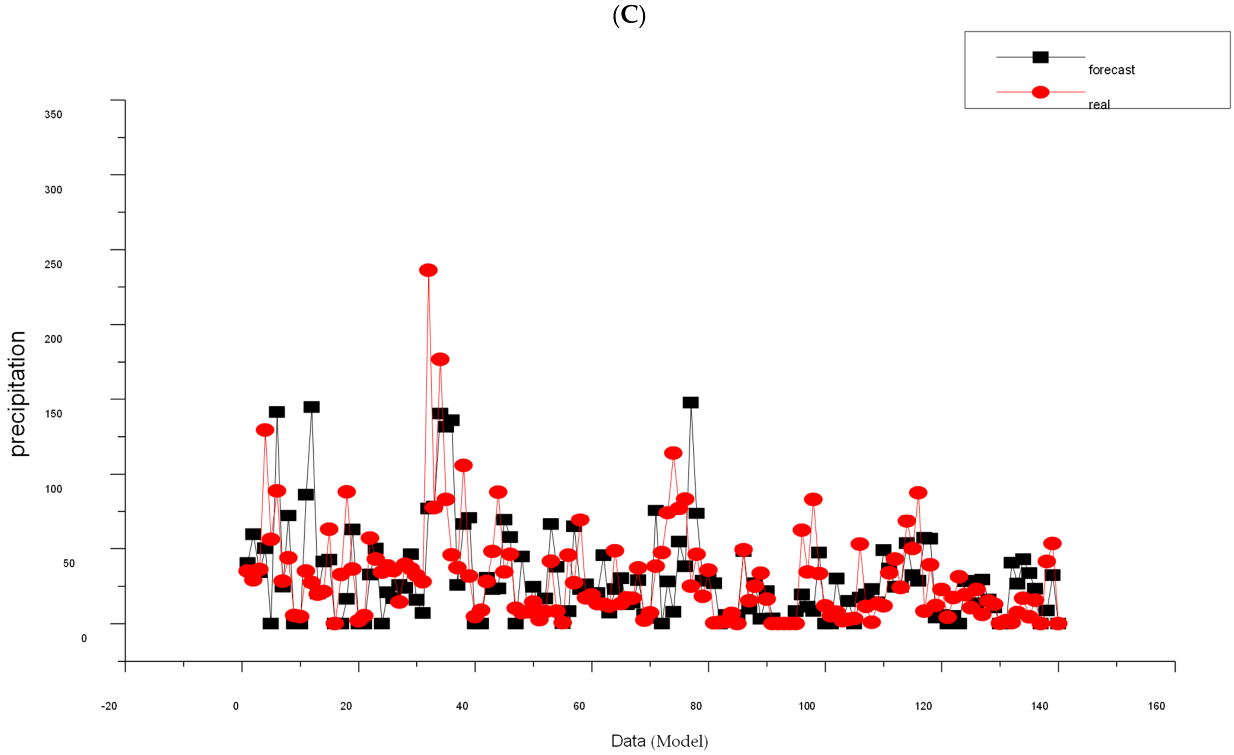


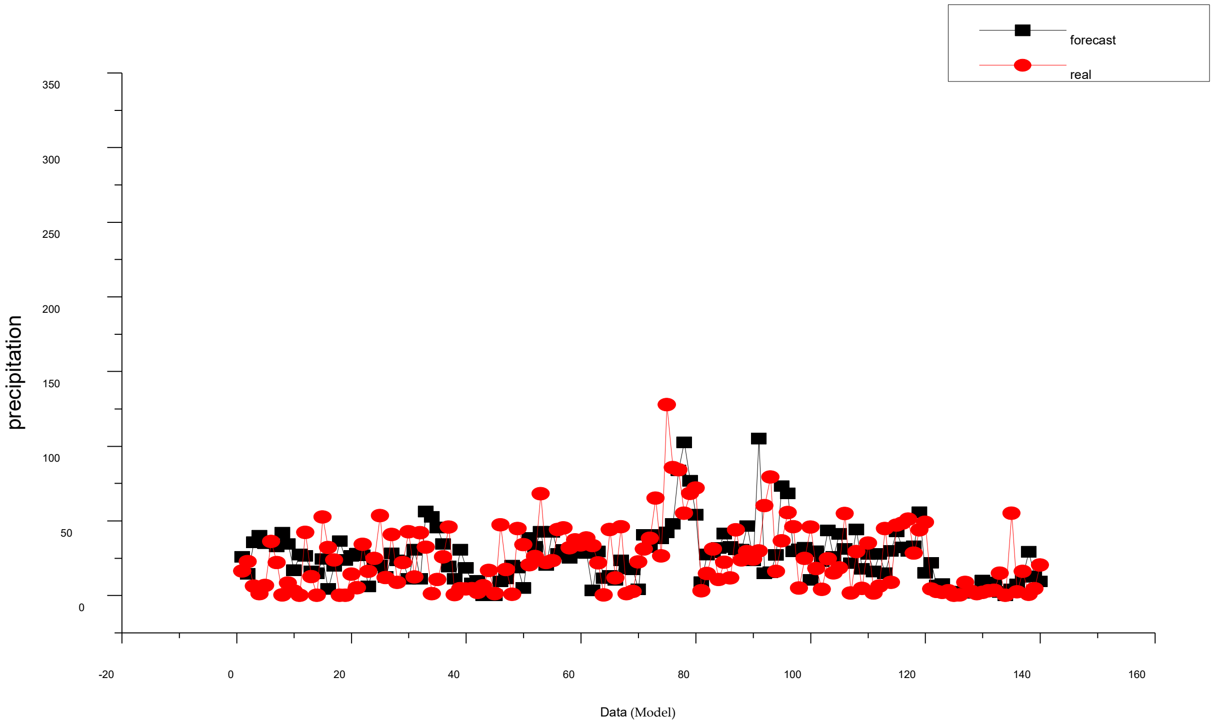
Chart C: December

(C)



(D)

Figure 4. *Cont.*



(**E**)

Figure 4. Chart (**A**): October time series of real and simulated monthly and partial rainfall values (simulated using the model). Chart (**B**): November time series of real and simulated monthly and partial rainfall values (simulated using model). Chart (**C**) Time series of real and simulated monthly and partial rainfall values. (simulated using the model). Chart (**D**): January. Chart (**E**): February.

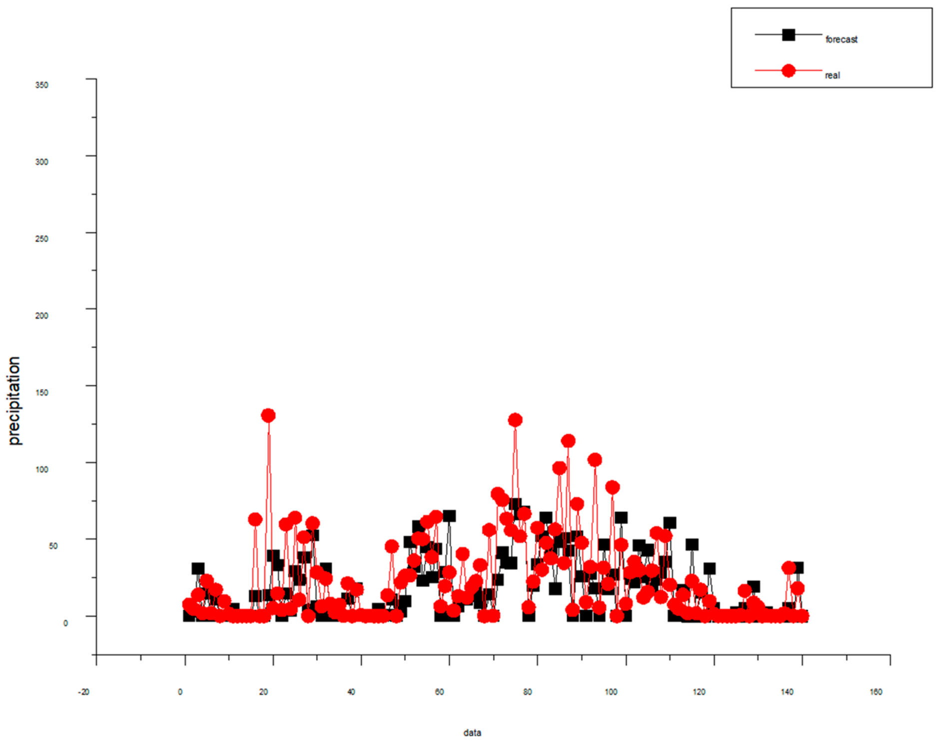


Chart F: March

Figure 5. Time series of observed and simulated values of monthly and partial rainfall.

Figure 4 Chart A shows the October time series of observed (black color) and simulated monthly partial rainfall values using the artificial neural network (red color); Charts B, C, D and E are shown for November, December, January and February, respectively. Figure 5 shows a comparison of the time series monthly precipitation observed data and simulated data using the artificial neural network for March. According to the above diagram (Figures 4 and 5), it can be seen that the time series of real values and values simulated by the network in the test phase are more consistent with each other in the autumn between October and November and between the seasons. They are closer and indicate better network performance in these months and the autumn. After several attempts, model 1-4-6 was found to be the one that produced the least amount of SSE over the months and seasons of Ilam's semi-arid environment. The results obtained from the models were returned to real values from 1 to -1, and CORR, RMSE, and bias, as well as median and standard deviation, were used to determine the validity of the obtained results.

5. Conclusions

The results of this paper after testing the lattice with hidden layers and different learning coefficients showed that the use of an artificial neural network with a multilayer perceptron provides a relatively better model, so that the simulated monthly rainfall data from the network with such a structure is more consistent with reality. According to the rainfall values observed by the network using real data, it can be said that rainfall values in Ilam city have a nonlinear trend and the values of this trend do not show an increase or decrease during the study period. In general, it can be said that climatic phenomena such as rainfall, temperature, evapotranspiration, pressure, and other variables have a nonlinear trend, and, in other words, they change over time. Therefore, to simulate and estimate them, artificial neural networks seem to work better than other models. The nonlinearity of the model, which is appropriate for simulating these phenomena, explains why this strategy outperforms other models. In this study, using multi-year monthly rainfall data and time-series models, the monthly rainfall for the following year has been simulated. First, in accordance with the autocorrelation and partial autocorrelation functions, as well as the presence or absence of trends in the data, attempts were made to fit appropriate time-series models to the data. According to the studies, it can be seen that the rainfall series in this city has partial and non-partial changes. Therefore, the SARIMA model is a suitable model for analyzing the monthly rainfall data for this city.

According to the obtained results and data review of sources, time-series models can be proposed as a suitable method for modeling climatic parameters. The observed differences between the actual and simulated values can be related to the impact of the station's rainfall on various local and dynamic factors in the region and the independence of the station's rainfall data from the station's past data. To better simulate this phenomenon, in addition to statistical models, attention should be drawn to general atmospheric circulation models under different climatic scenarios. Due to the importance of simulating rainfall in each region with different climatic conditions, researchers have used different methods and materials to obtain better results. These methods include regression methods, time series, and artificial neural networks.

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