

# Using the SAMS Stochastic Program for Analysis and Modeling Climate Data in Nineveh Governorate

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## Abstract

Hydrological data is considered essential information in the design of water resource projects. Therefore, stochastic simulation of hydrological time series based on mathematical models is necessary to estimate the generated statistical properties. In this study, SAMS 2010 software was used to fit four models: ARMA, BB, ISM, and KGK, for generating statistical properties of monthly rainfall data and maximum and minimum temperatures for Mosul, Tal Afar, Rabia, and Sinjar stations in Nineveh Governorate for the time period 1985-2021. The results revealed that the nonparametric disaggregation model is capable of producing the statistical properties of hydrological time series and preserve the correlation structure between historical and generated models. The ISM model excelled in preserving the basic annual statistical properties. Meanwhile, other models showed agreement between historical and generated monthly data in representing general trends of rainfall and temperatures with slight differences not exceeding  $\pm 5\%$ . The ARMA model recorded the lowest ability to preserve the temporal correlation structure in most stations. The study concluded that nonparametric disaggregation models for hydrological time series represent an effective tool among stochastic generation methods, making them an effective choice and tool for water resources management and future planning.

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**Keywords:** Disaggregation model, Nonparametric, Nineveh, Rainfall, SAMS, Temperature.

## 1. Introduction

Rainfall and temperature are among the most important climatic elements, and predicting them is difficult. Nevertheless, they remain of great importance and are highly beneficial in the management of water resources and agricultural projects. Moreover, the impacts of global warming are increasingly evident, as extreme events such as prolonged droughts, heavy rainfall, and rising temperatures have begun to affect agriculture and socio-economic development worldwide. Therefore, a comprehensive understanding of rainfall and its past and future fluctuations has become necessary in light of current climate change in to develop effective adaptation and mitigation strategies (Dai et al., 2024). As the primary source of fresh water, rainfall plays a fundamental role in agriculture and the economy. Consequently, fluctuations in rainfall patterns directly influence water availability, agricultural production, and economic stability, making climate change a central factor in managing water resources (Vetrihangam et al., 2025; Al-Bazaz & Agha, 2023). In this context, climate change involves long-term shifts in climatic elements such as rainfall and temperature, occurring at both local and global scales (Hussain et al., 2025).

Furthermore, climate change represents one of the most serious challenges facing humanity. Alterations in rainfall and temperature disturb the environmental balance and the hydrological cycle, increasing the vulnerability of ecosystems. This situation highlights the urgent need for

accurate predictions and advanced modeling techniques to support and improve the management of natural disasters, such as droughts and floods (Al-Bazaz & Agha, 2023; Wang & Liu, 2023).

In the last decade, Nineveh Governorate has been significantly exposed to climate change (UNCCD, 2022), as there has been a change in the pattern of rainfall and a difference in temperatures, and this has affected water resources and agricultural projects, as the study area is characterized as a farming region (Al-Bazaz and Mahmood Agha, 2024).

Based on the foregoing, it has become necessary to employ simulation and analysis techniques, foremost among them hydrological software models, as these are considered vital tools for water resources management. Numerous models and techniques are available to assess and predict hydrological elements, and each differs in terms of accuracy, duration, and scope of work (Makridakis et al., 1984).

SAMS 2010 is a software package specialized in stochastic analysis, modeling, and simulation of hydrological time series, developed as a collaborative effort between Colorado State University and the U.S. Bureau of Reclamation in Denver, Colorado, to meet hydrological research needs in the analysis of climatic and water data. The SAMS program provides a set of options and tools, including three main options: first, statistical analysis of data; second, stochastic model construction; and third, generating synthetic series

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for future estimation. The program also allows application to annual, seasonal, and monthly data. In addition, the program includes parametric models, such as linear decomposition models and multivariate autoregressive models, as well as nonparametric techniques, which are essential for analyzing data that do not follow a probability distribution (Qassem, 2021). The program's capabilities include historical data analysis, parameter estimation, and data generation (Saada et al., 2019). Saada (2015) indicated that the use of stochastic models for climatic time series to generate synthetic time series by demonstrating the statistical properties (mean, variance, and skewness) of the generated data is one of the modeling problems represented in finding a model capable of preserving historical properties. Saada (2014) also confirmed the possibility of using modeling models for monthly rainfall forecasting in arid and semi-arid regions, which is the climate that characterizes the study area. Moreover, Jöckel and Pflaumer (2024) indicated that the temporal dependence on previous values in the data significantly affects risk assessment, and that using ARMA models helps make variance estimation more accurate. Consequently, by utilizing ARMA models, decision-makers can obtain a more precise assessment of risks. In this way, the ability to make such predictions is of utmost importance in improving the effective management of water resources (Hamdi et al., 2008).

Researchers (Abdullah et al., 2019) tested the capabilities of the SAMS program by applying four stochastic models to monthly and annual rainfall data and the SPI drought index for sites in Jordan and Saudi Arabia. The researchers showed that the models succeeded in preserving the statistical properties of the climatic data at each site.

In Iraq, Al-Mohseen (2010) analyzed the annual flow status using three stochastic models with the SAMS 2007 stochastic model analysis system program. He showed that there is variation in the models' ability to preserve the statistical properties of generated time series and confirmed that the SAMS program is effective for analyzing, modeling, and generating hydrological data. Moreover, Qassem (2021) used five linear models (ARMA, GAR1, BB, ISM, and KGK) to regenerate monthly data. It was found that there is strong convergence between historical and generated statistical properties, and it was confirmed that the nonparametric approach has a high ability to regenerate observed data with a preference using the ISM model based on statistical criteria. Furthermore, in their study of the flow conditions at the Kut Dam on the Tigris River, Al-Youdawi and Al-Badrane (2025) used a univariate ARMA model in the SAMS program, relying on 21 years of dam discharge data. Their findings highlighted the model's effectiveness in capturing the underlying patterns in discharge data, leading to more accurate predictions of flow. Their results demonstrated the feasibility of using the SAMS program with the ARMA model to analyze observed Tigris River discharges at the Kut Dam and predict future discharges.

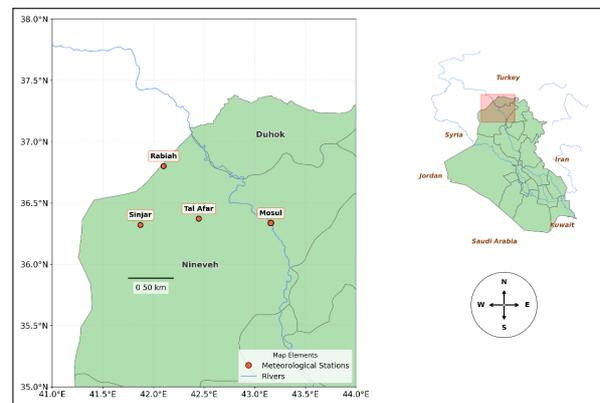
The objective of this study is to investigate the possibility of using the nonparametric disaggregation model on climatic data (rainfall, maximum and minimum temperatures) for Mosul, Rabia, Sinjar, and Tal Afar stations in Nineveh

Governorate for the period 1985-2021 and to demonstrate the extent to which the nonparametric model can succeed in preserving the generated statistical properties using SAMS 2010 software. Also, this paper is the first study to use nonparametric disaggregation of climatic data in the study area and Iraq.

**2. Materials and methods**

**2.1 Study Area and Data Used**

The historical monthly rainfall data used in this study extend for 37 years (1985-2021). Four meteorological stations were selected in Nineveh Governorate: Mosul, Rabia, Tal Afar, and Sinjar. Climatic data were obtained from the Iraqi General Authority for Meteorology and Seismology, part of the Iraqi Ministry of Transport. The selected meteorological stations cover the north and northwest of Nineveh Governorate, an area of strategic importance because it mainly comprises agricultural lands dependent on rain-fed agriculture. This area is also considered one of the areas affected by climate change. Figure 1 shows the geographical location of meteorological stations in Nineveh Governorate.



**Figure 1.** Locations of meteorological stations in the study area.

**2.2 Methods**

Four nonparametric disaggregation models were used to generate climatic data without making any assumptions, and their statistical properties, such as mean and standard deviation, were compared.

**2.2.1 Autoregressive Moving Average Model (ARMA)**

The ARMA (p,q) model was used. This model links autocorrelation parameter p to moving-average parameter q. The best model is chosen from several tests based on the Akaike Information Criterion (AICC) (Akaike, 1974) and Schwarz Information Criterion (SIC) (Hurvich and Tsai, 1989). The best model is the one with the lowest values for both criteria (Sveinsson et al., 2011).

$$Z_t = \sum_{i=1}^p \phi_i Z_{t-i} + \varepsilon_t - \sum_{j=1}^q \theta_j \varepsilon_{t-j} \dots\dots\dots (1)$$

Where:

Zt: Climatic parameter at year t, Zt-i: Climatic parameter at previous time points,  $\varepsilon_t$ : White noise term,  $\phi_j$ : Autoregressive (AR) coefficient,  $\theta_j$ : Moving average (MA) coefficient, p: Order of the autoregressive coefficient, q: Order of the moving average coefficient.

**2.2.2 Index Sequential Model (ISM)**

This model involves sequentially reordering the observed data (Ouarda et al. 1997). In this model, the observed data

are reordered from the first observed point to the end of the observed time record.

$$Y = [y_1 + y_2 + y_3 + \dots + y_n] \dots\dots\dots (2)$$

$$\dot{Y}_i = [y_i + y_{i+1} + y_{i+2} + \dots + y_{n+i-1}] \dots\dots\dots (3)$$

Where:  $\dot{Y}_i$  : Sum of the reordered data,  $i$ : Step size between years,  $n$ : Number of years (length of the time series).

**2.2.3 Block Bootstrapping (BB) Model**

It is an algorithm for nonparametric time series resampling (Vogel and Shallcross, 1996). In this model, historical data are resampled as blocks with replacement. The time series must be long enough to ensure the preservation of its correlation structure. The model steps are as follows:

1. Define the block length  $i$  The candidate overlapping blocks are:

$$Y_{B1} = [y_1, y_2, y_3, \dots, y_i] \dots\dots\dots (4)$$

$$Y_{B2} = [y_2, y_3, \dots, y_{i+1}] \dots\dots\dots (5)$$

$$Y_{B(N-i+1)} = [Y_{n-i+1}, Y_{n-i+2}, \dots, Y_n] \dots\dots\dots (6)$$

2. One of the  $(N-i+1)$  blocks is selected by generating a discrete uniform random number from 1 to  $N-i+1$ . If  $c$  is chosen from the random numbers,  $[Y_1, Y_2, \dots, Y_i] = [Y_c, Y_{c+1}, \dots, Y_{c+i-1}]$ , where  $Y_j$  is the generated number. In this case, the required block is resampled.
3. The following values to be resampled  $[Y_{i+1}, y_{i+2}, \dots, y_{2i}]$  are obtained in the same way as in Step 2.
4. These steps continue until the generated series is obtained.

**2.2.4 K-Nearest Neighbor with Gamma Kernel Estimation (KGK) Model**

It is a nonparametric method that resamples data using a Gamma distribution. Furthermore, the determination of gamma parameters leads to some bias in variance and arithmetic mean (Lee and Salas, 2008).

$$Y_{x^2/h^2, t^2/x}(\mathbf{t}) = \frac{t^{x^2/h^2 - 1} e^{-t/(h^2/x^2)}}{(h^2/x)^{x^2/h^2} \Gamma(x^2/h^2)} \dots\dots\dots (7)$$

Where:  $h$ : Smoothing parameter, It can be calculated through Least Squares Cross-Validation (LSCV) proposed by Chen (2000),  $t$ : Generated random number,  $x$ : Historical data

The four models (ARMA, BB, ISM and KGK) were applied using SAMS 2010 software, developed as a

collaborative effort between Colorado State University and the U.S. Bureau of Reclamation in Denver, Colorado (Sveinsson et al., 2011), to disaggregate monthly climatic data (rainfall and maximum and minimum temperatures), extract historical and generated statistical properties, and generate 100 time series of data for 37 years at the four selected stations.

**3. Results and Discussion**

Time series generation is an essential tool in operations research, as this data serves as the basis for decision-makers in many studies. This study examines the efficiency of nonparametric models for generating time series and preserving their statistical properties. The Stochastic Analysis, Modeling, and Simulation (SAMS, 2010) program, widely used in hydrology for time series modeling, was adopted. It is a specialized software tool for stochastic modeling and simulation of hydrological data due to its high ability to preserve the statistical properties of generated time series. This capability makes it an important tool in hydrological analysis, as it helps simulate the future behavior of hydrological systems under random climatic conditions. In this study, four models (ARMA, ISM, BB and KGK) were applied to analyze hydrological data comprising rainfall and maximum and minimum temperatures collected from four meteorological stations in areas famous for rain-fed agriculture. These are Mosul, Tal Afar, Sinjar, and Rabia stations in Nineveh Governorate. Statistical tests (arithmetic mean and standard deviation) were calculated from 100 time series over 37 years, yielding accurate results that showed convergence between historical and generated values. Its ability to preserve statistical properties when generating synthetic data makes it particularly useful for areas with limited historical records or for assessing future scenarios under different climatic conditions.

Table 1 shows the results of the ARMA test analysis for rainfall, maximum, and minimum temperatures at the four climatic stations: Mosul, Sinjar, Rabia, and Tal Afar. The optimal ARMA models were selected based on statistical criteria represented by AICC and SIC values, where the model with the lowest values is considered the best for both requirements, providing reliable measures for model selection (Sveinsson et al., 2011). These results are consistent with hydrological studies that emphasize the importance of appropriate model identification for accurate time series analysis. This approach leads to a better model that more accurately represents the data. (Al-Youdawi & Al-Badrance, 2025; Hamdi et al., 2008; Hussain et al., 2025).

**Table 1.** Results of the ARMA tests for the rain, T max, and T min in all stations

Stations		Rain		T max		T min	
Mosul	AICC	398.492	1-1	217.259	0-2	217.436	1-0
	SIC	398.986		217.753		216.694	
Sinjar	AICC	402.608	1-0	203.352	0-1	228.261	0-2
	SIC	401.886		202.61		228.756	
Rabiah	AICC	390.882	1-0	233.452	0-2	201.839	0-2
	SIC	390.140		233.946		202.333	
Tal-Afar	AICC	395.960	1-0	218.468	0-2	213.407	0-1
	SIC	395.218		218.962		212.665	

For rainfall data, three stations (Rabia, Tal Afar, and Sinjar) showed compatibility with the ARMA (1,0) model, while the Mosul station showed an ARMA (1,1) pattern. As for maximum temperatures, most stations followed the ARMA (0,2) pattern, while the Sinjar station showed an ARMA (0,1) model. ARMA models for minimum temperatures showed clear variation among climatic stations, with ARMA (1,0) in Mosul, ARMA (0,2) in both Sinjar and Rabia, and ARMA (0,1) in Tal Afar.

Through the comparison between historical data and data generated via the four stochastic models (ARMA, BB, ISM, KGK), the effectiveness of these methods in preserving the statistical properties of climatic data is evident, as shown in Figure 2. Tables (2-4) show a comprehensive comparison between observed and generated values for annual and monthly rainfall and maximum and minimum temperatures

across all stations. The close agreement between historical and generated statistical parameters (arithmetic mean and standard deviation) demonstrates the strength of the stochastic generation process. The results showed strong convergence between the means of historical and generated rainfall data for the ISM, BB, and KGK models, outperforming the ARMA model. As for maximum and minimum temperatures, the BB and ISM models outperformed the ARMA and KGK models in the time-series comparison. Also, the ISM (the improved semi-parametric model) showed superior performance across most stations and parameters, confirming Saada's (2015) earlier findings on the effectiveness of nonparametric methods in modeling hydrological data. This result aligns with Abdullah et al. (2019), who found that SAMS models successfully preserve the statistical properties of climatic data for sites in Jordan and Saudi Arabia, which share climatic characteristics similar to those of the study area.

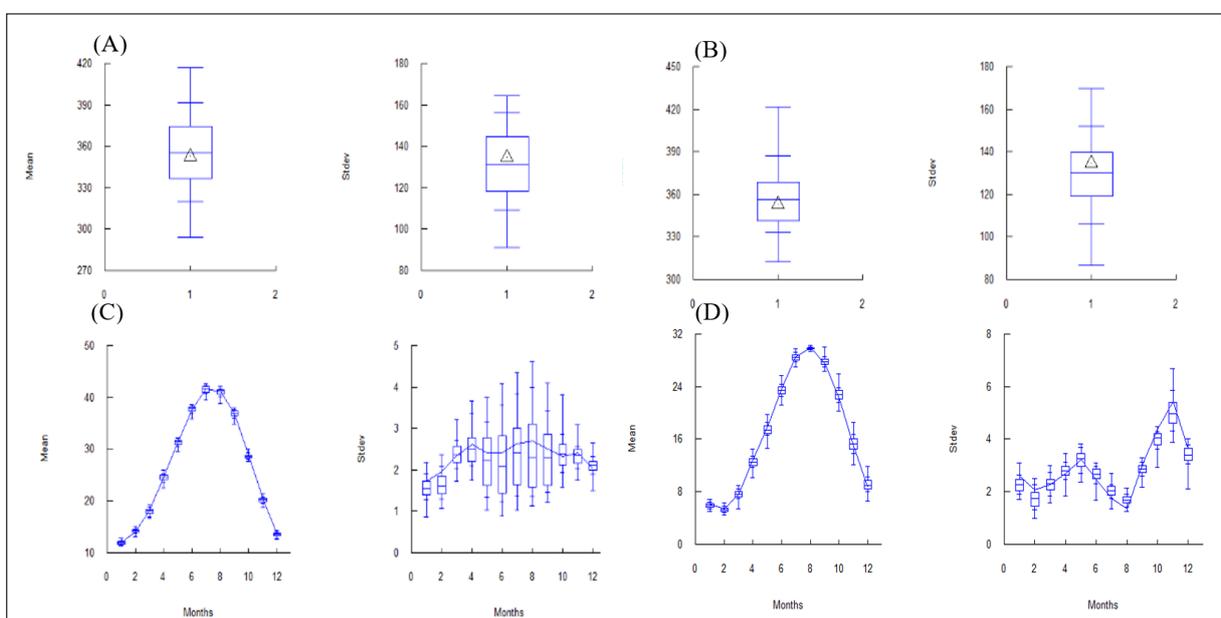


Figure 2. Statistical characteristics (A) ARMA model for rainfall at the Mosul station, (B) BB model for rainfall at the Mosul station, (C) KGK model for maximum temperatures at Rabia station, and (D) ISM model for minimum temperatures at the Sinjar station

**Table 2.** Comparison of Observed and Generated Values in Models for Annual and Monthly Rain in Stations

		Historical		ARAM		BB		ISM		KGK	
		Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev.
Mosul Station	Annual	352.7	134.5	354.4	132.3	357.9	129.5	352.7	134.5	346.5	152.6
	M 1	61.46	43.57	64.07	45.25	64.52	45.62	62.78	46.34	64.35	47.12
	M 2	55.62	32.5	56.37	36.12	58.03	35.61	56.63	35.38	58.08	36.63
	M 3	60.22	48.18	61.87	48.56	58.81	46.16	59.89	46.07	58.27	46.74
	M 4	42.4	41.49	37.6	33.01	38.52	35.55	37.89	36.26	39.48	36.31
	M 5	14.72	27.12	11.28	19.44	13.36	21.75	12.76	21.73	13.38	22.2
	M 10	13.76	19.02	14.78	20.59	14.85	20.43	15.04	20.75	14.42	19.39
	M 11	40.82	38.27	42.8	36.66	43.81	38.6	43.26	38.63	42.27	39.13
	M 12	61.76	38.38	61.5	37.08	63.16	38.96	62.45	38.34	63.29	40.65
Sinjar Station	Annual	334.6	132.3	323.5	136.1	341	125.3	334.6	132.3	327	153
	M 1	64.67	50.3	60.6	44.31	62.22	44.7	61.12	44.95	61.56	47.27
	M 2	52.79	36.75	49.93	38.16	53.17	37.89	51.92	38	51.9	39.46
	M 3	57	46.46	51.04	46.68	55.04	45.84	53.63	45.26	54.37	46.56
	M 4	29.24	26.87	30.4	28.03	29.3	26.4	29.62	27.43	29.79	26.57
	M 5	14.89	24.7	13.98	22.2	14.9	24.22	15.34	26	16	27.93
	M 10	17.62	22.47	21.07	28.94	19.36	24.97	20	24.98	19.57	25.35
	M 11	38.01	37.99	39.35	37.21	42.05	39.7	39.55	39.13	38.25	39.5
	M 12	58.56	46.8	58.19	47.99	63.29	48.04	61.53	47.91	62.36	48.99
Rabiah Station	Annual	341.4	113.4	340.4	111.8	348.3	107.6	341.4	113.4	358.4	130.3
	M 1	63.27	46.49	60.29	41.02	60.51	41.93	59.33	40.05	67.05	45.4
	M 2	51.35	29.7	51.3	31.7	53.34	31.37	52.72	32.13	55.58	33.31
	M 3	56.8	42.06	55.47	43.79	56.08	43.92	54.48	41.24	57.3	44.57
	M 4	36.44	33.17	37.84	35.1	36.78	33.14	35.52	31.69	38.16	33.47
	M 5	20.51	22.31	21.24	22.78	21.68	22.99	21.79	23.74	24.22	25.82
	M 10	21.23	27.13	22.084	29.39	22.96	29.38	22.22	28.8	24.78	31.5
	M 11	31.15	25.93	31.53	25.38	33.61	26.44	33	26.76	34.67	27.39
	M 12	57.3	42.23	57.99	43.15	60.1	42.39	59.68	42.25	62.6	44.46
Tal-Afar Station	Annual	305.9	123.3	304.2	120.9	311.7	118.2	305.9	123.3	295.4	136.8
	M 1	59.66	49.82	56.15	42.8	60.51	46.14	58.86	44.79	59.62	47.09
	M 2	42.91	26.29	42.41	27.52	42.87	27.44	41.77	27.38	42.68	27.99
	M 3	55.57	47.67	56.24	54.44	55.4	47.46	53.21	47.76	52.39	47.17
	M 4	32.36	31.74	29.7	27.82	29.88	28.18	29.91	29.54	29.68	28.84
	M 5	15.46	26.54	15.24	23.45	15.27	25.06	16.31	26.18	16.28	27.11
	M 10	12.17	15.35	13.65	17.93	13.29	17.69	13.11	16.85	12.74	16.8
	M 11	35.67	36.25	40.83	38.63	39.77	37.7	39.59	37.54	37.91	38.22
	M 12	49.96	35.72	48.94	33.47	51.89	35.4	50.59	34.72	49.57	35.71

**Table 3.** Comparison of Observed and Generated Values in Models for Annual and Monthly T max in Stations

		Historical		ARAM		BB		ISM		KGK	
		Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev.
Mosul Station	Annual	341.3	13.64	341.40	13.03	341.0	13.04	341.3	13.64	331.00	52.20
	M 1	13.09	1.67	13.11	1.46	12.99	1.45	13.03	1.54	13.04	1.62
	M 2	15.48	1.93	15.60	1.58	15.51	1.60	15.57	1.67	15.49	1.81
	M 3	19.8	2.25	19.70	2.17	19.71	2.13	19.74	2.21	19.48	2.26
	M 4	26.01	2.23	26.07	2.20	26.02	2.20	26.04	2.29	25.92	2.26
	M 5	33.51	1.77	33.63	1.66	33.56	1.57	33.58	1.66	33.44	1.88
	M 6	39.82	1.15	39.87	1.33	39.85	1.37	39.84	1.37	39.67	1.47
	M 7	43.37	1.90	43.51	1.90	43.54	1.88	43.51	2.01	43.29	2.13
	M 8	43.34	1.19	43.30	1.55	43.30	1.57	43.30	1.48	43.13	1.60
	M 9	38.64	1.50	38.71	1.62	38.60	1.63	38.63	1.64	38.54	1.64
	M 10	31.78	3.61	31.35	2.67	31.29	2.54	31.43	2.85	31.30	2.95
	M 11	31.78	3.61	21.64	2.23	21.68	2.29	21.70	2.28	21.43	2.31
M 12	14.92	2.08	14.94	2.16	14.90	2.20	14.91	2.13	14.66	2.16	
Sinjar Station	Annual	257.1	10.9	257.1	10.5	257	10.61	257.1	7.537	253.4	39.16
	M 1	7.53	1.39	7.57	1.24	7.55	1.25	10.9	1.28	7.60	1.29
	M 2	9.29	1.66	9.43	1.35	9.38	1.37	257.1	7.53	9.55	1.31
	M 3	13.52	2.10	13.5	2.0	13.56	1.94	10.9	1.28	13.81	1.90
	M 4	19.24	1.98	19.28	1.95	19.34	1.99	257.1	7.53	19.6	1.91
	M 5	25.88	1.49	25.88	1.42	25.92	1.39	10.9	1.28	26.11	1.32
	M 6	31.85	1.09	31.79	1.19	31.85	1.20	257.1	7.53	32.07	1.15
	M 7	35.53	1.19	35.63	1.27	35.61	1.32	10.9	1.28	35.88	1.29
	M 8	35.05	1.07	34.92	1.24	34.94	1.3	257.1	7.53	35.17	1.23
	M 9	30.71	1.26	30.77	1.38	30.68	1.4	10.9	1.28	30.89	1.41
	M 10	23.53	1.95	23.44	1.86	23.41	1.86	257.1	7.53	23.7	1.78
	M 11	15.24	1.91	15.19	1.79	15.21	1.77	10.9	1.28	15.44	1.76
M 12	9.68	1.7	9.64	1.73	9.611	1.79	257.1	7.53	9.82	1.75	
Rabiah Station	Annual	320.1	17.45	320.20	20.90	319.9	17.26	320.10	17.45	311.30	51.48
	M 1	11.91	1.723	11.89	1.93	11.94	1.51	0.25	1.57	11.87	1.54
	M 2	14.06	1.943	14.15	2.01	14.23	1.66	14.22	1.66	14.19	1.68
	M 3	18.15	2.33	18.08	2.47	18.10	2.31	18.09	2.33	17.98	2.37
	M 4	24.51	2.614	24.45	2.52	24.54	2.47	24.59	2.50	24.41	2.53
	M 5	31.3	2.4	31.32	2.32	31.38	2.17	31.38	2.18	31.32	2.24
	M 6	37.71	2.402	37.84	2.19	37.80	2.17	37.79	2.17	37.75	2.26
	M 7	41.55	2.639	41.60	2.38	41.65	2.37	41.72	2.40	41.61	2.49
	M 8	41.12	2.697	41.25	2.53	41.13	2.41	41.15	2.39	41.04	2.53
	M 9	36.89	2.514	36.96	2.35	36.91	2.32	36.98	2.32	36.89	2.41
	M 10	28.92	2.328	28.84	2.89	28.65	2.49	28.65	2.39	28.68	2.46
	M 11	20.3	2.404	20.12	2.71	20.04	2.30	20.06	2.28	20.13	2.26
M 12	13.64	2.041	13.60	2.29	13.48	2.10	13.52	2.09	13.46	2.04	
Tal-Afar Station	Annual	331.5	14.64	331.70	13.87	331.2	14.09	331.5	14.64	325.3	51.42
	M 1	12.11	1.70	12.16	1.67	12.09	1.47	12.08	1.55	12.20	1.63
	M 2	14.19	2.01	14.27	1.66	14.34	1.60	14.29	1.63	14.42	1.67
	M 3	18.77	2.60	18.89	2.75	18.77	2.72	18.75	2.73	18.95	2.71
	M 4	25.45	2.42	25.53	2.45	25.47	2.39	25.46	2.41	25.66	2.45
	M 5	32.67	1.85	32.69	1.78	32.66	1.62	32.72	1.71	32.85	1.75
	M 6	38.86	1.16	38.87	1.41	38.87	1.37	38.88	1.41	39.03	1.41
	M 7	42.62	1.41	42.64	1.56	42.65	1.56	42.69	1.62	42.81	1.62
	M 8	42.26	1.21	42.17	1.48	42.17	1.56	42.17	1.51	42.33	1.54
	M 9	37.64	1.59	37.65	1.75	37.55	1.75	37.65	1.84	37.80	1.80
	M 10	32.04	4.74	31.58	3.58	31.69	4.13	31.85	4.06	32.09	4.31
	M 11	20.76	2.37	20.92	2.43	20.75	2.35	20.80	2.36	20.99	2.39
M 12	14.13	2.17	14.34	2.17	14.14	2.22	14.20	2.22	14.35	2.21	

**Table 4.** Comparison of Observed and Generated Values in Models for Annual and Monthly T min in Stations

		Historical		ARAM		BB		ISM		KGK	
		Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev.
Mosul Station	Annual	161	12.64	161.70	12.23	160.7	11.93	161.00	12.64	159.10	24.53
	M 1	2.661	1.76	2.62	1.75	2.59	1.71	2.65	1.71	2.62	1.71
	M 2	3.93	1.76	4.04	1.75	3.93	1.75	3.98	1.76	4.05	1.73
	M 3	7.392	1.92	7.61	1.65	7.47	1.67	7.53	1.74	7.66	1.68
	M 4	11.55	1.50	11.61	1.47	11.60	1.52	11.59	1.49	11.72	1.49
	M 5	16.68	1.58	16.67	1.58	16.62	1.57	16.64	1.62	16.81	1.60
	M 6	21.79	1.51	21.77	1.60	21.76	1.59	21.76	1.61	21.93	1.61
	M 7	25.53	1.40	25.54	1.49	25.52	1.52	25.51	1.54	25.70	1.56
	M 8	24.87	1.39	24.78	1.64	24.78	1.64	24.81	1.61	24.95	1.64
	M 9	20.02	1.61	20.06	1.65	20.00	1.65	20.03	1.66	20.23	1.64
	M 10	14.6	1.70	14.68	1.59	14.58	1.59	14.61	1.64	14.78	1.61
	M 11	7.89	1.69	7.90	1.68	7.87	1.67	7.89	1.74	8.00	1.68
	M 12	4.12	2.07	4.10	2.12	4.06	2.12	4.07	2.15	4.14	2.10
Sinjar Station	Annual	205.1	14.25	205.2	13.79	205	14.06	205.10	14.25	201.20	31.35
	M 1	5.957	2.602	5.998	2.359	5.883	2.139	5.83	2.26	5.92	2.26
	M 2	5.335	2.063	5.145	1.981	5.354	1.976	5.31	1.88	5.27	1.91
	M 3	7.638	2.27	7.456	2.296	7.493	2.353	7.59	2.34	7.51	2.30
	M 4	12.76	2.699	12.39	2.77	12.39	2.83	12.51	2.82	12.42	2.80
	M 5	17.86	3.209	17.2	3.232	17.2	3.275	17.39	3.23	17.36	3.24
	M 6	23.72	2.461	23.39	2.753	23.4	2.714	23.47	2.67	23.40	2.59
	M 7	28.61	1.732	28.38	2.072	28.41	2.011	28.46	2.06	28.43	2.00
	M 8	29.88	1.334	29.92	1.734	29.81	1.674	29.88	1.69	29.92	1.69
	M 9	27.53	2.984	27.86	2.773	27.84	2.74	27.76	2.87	27.97	2.80
	M 10	22.38	4.357	23	3.781	22.82	3.807	22.78	4.02	23.05	3.81
	M 11	14.8	5.438	15.49	4.958	15.36	4.877	15.23	5.01	15.50	4.92
	M 12	8.638	3.659	9.138	3.308	8.969	3.435	8.98	3.50	9.14	3.34
Rabiah Station	Annual	129.4	10.5	129.50	10.17	129.5	10.55	129.40	10.53	126.20	21.80
	M 1	0.956	1.58	0.73	1.53	0.78	1.47	0.81	1.47	0.78	1.51
	M 2	1.73	1.45	1.60	1.38	1.60	1.40	1.68	1.39	1.67	1.40
	M 3	4.84	1.74	4.92	1.42	4.91	1.46	4.93	1.44	4.97	1.43
	M 4	9.34	1.41	9.50	1.29	9.48	1.35	9.45	1.36	9.50	1.31
	M 5	13.8	1.06	13.86	1.23	13.82	1.23	13.82	1.25	13.79	1.25
	M 6	18.5	1.32	18.61	1.58	18.55	1.54	18.51	1.55	18.53	1.52
	M 7	21.84	1.31	22.01	1.45	22.03	1.51	21.98	1.48	21.98	1.51
	M 8	21.08	1.16	21.08	1.27	21.10	1.29	21.10	1.32	21.10	1.33
	M 9	16.54	1.45	16.54	1.38	16.55	1.40	16.56	1.45	16.54	1.44
	M 10	12.07	1.41	12.05	1.26	12.04	1.25	12.06	1.32	12.08	1.33
	M 11	6.25	1.55	6.26	1.54	6.24	1.54	6.20	1.54	6.23	1.53
	M 12	2.41	1.65	2.38	1.52	2.38	1.51	2.31	1.54	2.27	1.58
Tal-Afar Station	Annual	186.8	12.52	186.80	12.06	186.5	11.90	186.80	12.52	181.20	28.34
	M 1	3.81	2.41	3.85	2.28	3.88	2.42	3.92	2.31	3.65	2.48
	M 2	4.93	2.10	5.03	1.90	4.97	1.98	5.08	1.94	4.88	2.05
	M 3	8.11	1.92	8.22	1.73	8.23	1.65	8.27	1.69	8.13	1.72
	M 4	12.69	2.35	12.72	2.35	12.64	2.43	12.66	2.39	12.56	2.34
	M 5	18.64	1.64	18.57	1.72	18.58	1.67	18.55	1.70	18.43	1.70
	M 6	24.54	1.39	24.47	1.56	24.47	1.47	24.45	1.54	24.35	1.52
	M 7	28.24	1.48	28.30	1.55	28.28	1.56	28.29	1.59	28.19	1.61
	M 8	27.97	1.33	27.85	1.62	27.80	1.55	27.82	1.60	27.71	1.61
	M 9	23.90	1.58	23.90	1.58	23.90	1.58	23.90	1.58	23.90	1.58
	M 10	17.86	1.60	23.87	1.60	23.83	1.63	23.87	1.64	23.77	1.70
	M 11	10.40	1.73	17.89	1.57	17.86	1.54	17.88	1.58	17.82	1.57
	M 12	5.68	1.66	10.35	1.69	10.30	1.65	10.37	1.65	10.37	1.65

Finally, when evaluating the performance of the four models (ARMA, ISM, BB, and KGK), it was found that they were effective at generating hydrological time series. Using nonparametric simulation, synthetic time series were generated from these four models, resulting in 100 time series spanning 37 years. Statistical analyses of historical data (mean and standard deviation) revealed a strong correlation with the generated data, indicating that the models preserve the correlation structure. A test of different (which relies on taking two random samples from two normal populations) was conducted on the historical and generated data for all stations. The results of this test showed that the p-value was greater than 0.05, indicating no significant difference between the arithmetic mean and standard deviation, and thus the generated models simulated the original data well.

#### 4. Conclusion

This study represents the first application of nonparametric disaggregation of climatic data in Iraq. The study showed that, when applied to parametric models (ARMA, BB, ISM, and KGK), the ISM model performed well at preserving the statistical properties of both historical and generated climatic data across the four meteorological stations. This finding was confirmed by the difference test ( $p\text{-value} > 0.05$ ), indicating that the generated models accurately simulate the historical data, with no significant differences in means, effectively replicating the original data and enhancing the reliability of the results. Researchers in the field can use the most effective ARMA models identified. Finally, the importance of this study lies in the demonstrated potential to apply nonparametric models to climatic data for hydrological modeling, with the possibility of extending this application to other areas, especially those with limited historical data or that require assessment of future scenarios and decision-making to address climate change.

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#### Conflicts of Interest

The authors declare no conflict of interest.

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