Tikrit Journal of Engineering Sciences (2024); 31(1): 172-181
DOI: http://doi.org/10.25130/tjes.31.1.15

IRAQI Academic Scientific Journals

ISSN: 1813-162X (Print); 2312-7589 (Online)
Tikrit Journal of Engineering Sciences
available online at: http://www.tj-es.com

TJES Tikrit Journal of Engineering Sciences

Disaggregation Model of Tigris River Inflow into a Proposed Makhol Reservoir Using Parametric Approach

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Keywords:
Makhol Reservoir; Parametric Approach; SAMS 2010; Spatial and Temporal Methods; Streamflow Disaggregation; Stochastic Generation Techniques.

Highlights:

- *The disaggregation models are considered important for the planning and managing of large-scale water resources systems, especially those parts of management requiring shorter periods other than the based time steps in the available data.*
- *This research highlights the parametric approaches' validity in disaggregating river flow, especially those with tributaries.*
- *The study is considered temporal disaggregation (Lane model) and spatial disaggregation (Valencia and Schaake, VS model; Mejia and Rousselle, M&R model) in the sense that it explores the strengths and the weaknesses of these models based on preserving the observed data statistics.*

ARTICLE INFO

Article history:

Received	08 Aug.	2023
Received in revised form	21 Oct.	2023
Accepted	05 Nov.	2023
Final Proofreading	16 Dec.	2023
Available online	29 Feb.	2024

Citation: Yahya AM, AL-Zakar SHD, AL-Mohseen KA. **Disaggregation Model of Tigris River Inflow into a Proposed Makhol Reservoir Using Parametric Approach**. *Tikrit Journal of Engineering Sciences* 2024; **31**(1): 172-181.
http://doi.org/10.25130/tjes.31.1.15

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Abstract: Since Makhol dam is planned to be constructed on Tigris River to the north of Baiji discharge measurement station, it is essential to study the nature of inflow into this reservoir. The information concerning this inflow is of great help in operating and management of the prospective reservoir. From our point of view, it is necessary to know how these inflows are distributed and contributed to Tigris from different upstream sources. Disaggregation flow models are stochastic generation techniques, that used to divided data into lower time scales from higher time scales using parametric approaches with two main categories: spatial and temporal. In the streamflow disaggregation model, historical data statistics (mean, skewness, standard deviation, maximum, and minimum) can be preserved while distributing single-site values to several sites in space and time. In this study, the aggregated streamflows data at a key station will be disaggregated into a corresponding series of discharges at sub-stations that are statistically similar to those observed by applying Stochastic Analysis Modeling and Simulation (SAMS 2010) software. To investigate the appropriate the disaggregation method for modeling monthly flow data, we used the annual and monthly data flow of five gauging stations in the Tigres River in Iraq (Mosul Dam station on Tigris river, Asmawah on AlKhazir river, Eski Kalak on Upper Zab, Dibs Dam on Lower Zab, and Baiji station on Tigris river) for the duration 2000–2020. The application approach's statistical outcomes were contrasted with their historical counterparts and the results showed that most years and months at all stations were in good agreement with the historical data. Therefore, we argue that this method have ability to be used when making decisions about water management strategies in these regions which is essential for water resource managers and decision makers.

نموذج لتجزئة جريان نهر دجلة الداخل الى خزان سد مكحول المقترح باستخدام المفهوم المعلمي

عائشة مهند يحيى، شذى الزكر، كامل عبد المحسن

قسم هندسة السدود والموارد المائية / كلية الهندسة / جامعة الموصل / الموصل – العراق.

الخلاصة

من المعلوم ان القرار قد اتخذ فعلا لانشاء سد مكحول على نهر دجلة شمالي محطة بيجي الخاصة بقياس تصاريف نهر دجلة. لذا أمسى من المهم دراسة طبيعة وتوزيع الجريان الوارد الى هذا الخزان اذ ستساعد هذه المعلومات كثيراً في عملية تشغيل وإدارة الخزان المأمول إنشاؤه. يتضمن هذا المبحث بيان أهمية معرفة توزيع كميات المياه المضافة الى مجرى النهر والواردة من مصادر مختلفة، وبناءاً على ذلك فقد تم اقتراح هذه الدراسة. تعد نماذج تجزئة البيانات إحدى تقنيات التوليد العشوائية، حيث تتمتع بالقدرة على التغلب على مشكلة البيانات المفقودة من البيانات المرصودة، ويمكن تقسيم بيانات التصريف من مقاييس زمنية أعلى إلى مقاييس زمنية أقل في هذه النماذج والتي تعتبر مهمة ومطلوبة لحل العديد من مشاكل التصميمات الهيدروليكية في المشاريع الاروائية. يمكن استخدام النهجين المعلمي وغير المعلمي في نماذج التجزئة وبفئتين رئيسيتين، وهما الأساليب المكانية والزمانية. يتم استخدام نموذج تجزئة البيانات لتوزيع قيم موقع واحد على مواقع متعددة مع الحفاظ على التوزيعات الإحصائية (المتوسط، التباين، الانحراف، الحد الأدنى والحد الأقصى) لقيم البيانات التاريخية. ولهذا الغرض يتم استخدام النماذج المعلمية وغير المعلمية. تنقسم هذه االنماذج أساسًا إلى مجموعتين رئيسيتين: الزمانية والمكانية. يعد تطبيق النموذج المعلمي زمانيا ومكانيا لتجزئة التصريف السنوي إلى تصاريف شهرية هو الهدف الرئيسي لهذا البحث من خلال تطبيق برنامج (SAMS 2010 ،Stochastic Analysis Modeling and Simulation). تقترح هذه الطريقة أن يتم تطبيق التوزيع الطبيعي على البيانات لإثبات فعالية هذه الاستراتيجية، تم استخدام بيانات التصريف لخمس محطات قياس موجودة على نهر دجلة في العراق وهي (محطة سد الموصل، محطة اسماوة على نهر الخازر، محطة اسكي كلك، محطة سد الدبس، ومحطة بيجي) وللفترة الزمنية (٢٠٠٠-٢٠٢٠). تم مقارنة النتائج الإحصائية لنهج التطبيق مع نظيراتها التاريخية وأظهرت النتائج أن معظم السنوات والأشهر في جميع المحطات لها توافق جيد ولهذا يمكن استخدام هذه الطريقة لتوليد بيانات التصاريف الشهرية لتخطيط وإدارة هذه المنطقة من النهر.

الكلمات الدالة: المفهوم المعلمي، الطرائق الزمانية والمكانية، برنامج SAMS، تجزئة تصاريف النهر، خزان سد مكحول، طرائق التوليد التصادفية.

1.INTRODUCTION

Disaggregation streamflow models play a significant role in the stochastic generation technique. They succeeded in resolving the data asymmetry problem. These models enable the disaggregation of streamflow data at higher temporal and spatial scales into lower-level scales. Data on a short timescale are needed to address many hydrologic designs and operational concerns. The model's input data can be yearly or the sum of annual flows at some sites to break down processes into smaller timescale values [1]. All independent time series can be combined to form the main time series and then disaggregated using the disaggregation approach. Due to the necessity of maintaining the statistical distributions for all stations and the correlation coefficient and the continuity between all the stations, a detailed process for the disaggregation flow data in multiple stations and short duration must be considered. Proposed the parametric disaggregation model in 1973 Valencia and Schaake [2]. They created a seasonal flow from annual flow using a linear structure and the Autoregressive Moving Average (ARMA) approach, frequently employed by hydrologists. This method was expanded by Mejia and Rousselle [3]. They included a term to maintain the correlation of seasonal data throughout two subsequent years. The issue of parameter estimation in this model derives from its inconsistent structure. The Mejia approach's parameter estimation issues were then addressed with several modifications. For instance, Stedinger and Vogel [4] presupposed that the approach's random component was also autoregressive. Although these models did not explicitly preserve many correlation coefficients of the flow data, Lane and Lin (a, b) [5-7] proposed an additional moment equation procedure to make the set of moment equations mathematically consistent. Indeed, various disaggregation models were proposed to reduce the number of parameters and overcome the inconsistency problem of prior approaches [4, 8]. To avoid data transformation, Koutsoyiannis [9, 10] introduced sequential disaggregation methods that allow the use of non-Gaussian data directly in the disaggregation scheme. Santos and Salas [11] proposed using stepwise disaggregation to overcome the matrix sizes' and its parameters' drawbacks. To replicate monthly flows, they employed the lag one model for multiple sites and the symmetric stepwise lag one and nonsymmetric stepwise lag two models for single sites. They demonstrated that combining approaches outperforms other methods when considering the matrix size and number of parameters. Ismail et al. [12] simultaneously applied Valencia Schaake, VS, and SPIGOT models to Malaysia's streamflow and rainfall series. They concluded that the VS model was the most effective disaggregation model. In addition, the first- and second-moment statistical values were successfully retained by the two models. A periodic disaggregation approach was applied by Mondal and Saleh [13] to subdivide seasonal flows based on data generated from a periodic autoregressive (PAR) approach for orders larger than AR (1). This approach preserved the first and second moments and was used to create decadal every (10-day) flows from monthly flows on the Ganges River near Farakka in India. The findings showed that the proposed strategy operated quite effectively and offered flexible options for synthetic hydrology. Proietti [14] described the state space of time-series disaggregation approaches using regression techniques. The author discovered that logarithms were used to deal with temporal disaggregation and recommended fitting an autoregressive distribution lag model and appropriate initial conditions. Saada [15] employed ARMA and the PARMA temporal disaggregation techniques to predict and simulate rainfall in arid and semi-arid regions. The analysis was performed in only one location in the Kingdom of Saudi Arabia. The two models maintained the seasonal statistics of the observed data well. The ARMA model can maintain the correlation structure of the seasonal data; however , the PARMA model can maintain the correlation structure of the annual data. Kossieris et al. [16] used the Bartlett-Lewis process, which creates rainfall events, combined with adjusting procedures to change the lower-level variables, i.e., hourly, so that they are consistent with the higher-level ones, i.e., daily, to disaggregate rainfall at fine time scales. Amin and Lotfy [17] successfully matched using the ARMA model to produce future synthetic rainfall data. Then, the monthly-based version of the forecasted data was broken down into a daily time series. Then, 1000 realizations of the daily forecast rainfall time series for the following 100 years were available and ready to be used in hydrological models to study the performance of the upcoming flash floods. Saada et al. [18] conducted modeling and simulation experiments to test the SAMS capabilities for use in stochastic modeling and simulation in the Middle East. The hydrologic data used in this study consisted of historically observed rainfall data of different lengths at various sites in Jordan and Saudi Arabia. The models used included ARMA, PARMA, CARMA, and temporal disaggregation models. The results indicated that SAMS can be used as a tool for the stochastic modeling and simulation of hydrologic data in this region. John et al. [19] showed that the monthly hydrologic modeling results with daily disaggregation were generally better than those based on daily hydrological modeling, especially for ecologically relevant flow metrics. In addition, the disaggregation approach fared better than the daily model when extrapolating to the multi-year dry period. According to the average values of the evaluation indices for the two disaggregation and reconstructions using the water data package in R software methods [20], the RMSE index was 0.3 and 1.1, and the NSE index was 0.99 and 0.89, respectively. These data showed that the time disaggregation method performed better. By comparing real and simulated hourly time series, Bolouki and Fazeli [21] investigated the efficacy of multivariate rainfall disaggregation using the MuDRain model and the impact of hourly correlation among stations. They demonstrated that the model appropriately assessed the daily precipitation quantity, but usually, it simulated severe amounts of precipitation smaller than the real amounts. The present study used a parametric technique to investigate the streamflow spatially and temporally disaggregated from annual data to monthly data for specific stations in the Tigris River. The generated streamflow simulations were used to analyze how well these methods preserved the statistical properties of the historical data for multiple stations. Prior research has yet to explore the use of streamflow disaggregation with SAMS 2010 software in this region, nor has any study examined the effect of these models on periodic monthly data from the Iraq region.

2.METHODOLOGY

Two basic parametric models were used: one for temporal disaggregation of the annual flow data to monthly data and the other for spatial disaggregation of the annual or seasonal flow data in the key station to the flow at the sub-stations.

2.1.Temporal Disaggregation

The temporal Lane model [22, 23] is available for disaggregation of the annual flow data from N stations to seasonal flow data at the same N stations. The following is a description of the model:

$$Y_{v,\omega} = A_{\omega} \,.\, Y_{v} + B\omega_{\omega} \,.\, \varepsilon_{v,\omega} + C_{\omega} \,.\, Y_{v,\omega-1} \quad \textbf{(1)}$$

where Y_v is a vector column with (n*1) historical values in the year v at n key station, $Y_{v,\omega}$ is a consistent column vector with (n*1) historical values in the same year v monthly ω, $Y_{v,\omega-1}$ is a column vector (n*1) for prior month, $\varepsilon_{v,\omega}$ is the vector (n*1) of standard normal noise for year v and monthly ω, and A_ω, B_ω, and C_ω are the (n*n) parameter matrixes calculated using the moments (MOM) method. Multisite temporal models were created to maintain lag-1 month-to-month correlations through the matrix Cω for each month and the matrix Aω for each month between annual and monthly data in any year.

2.2.Spatial Disaggregation

The first method available for spatial disaggregation is the annual data of key stations (N) to annual data at substations (M), namely the Valencia and Schaake (VS) model [24].

$$Y_n = A\,X_n + B\,\varepsilon_n \quad \textbf{(2)}$$

Mejia and Rousselle (M&R) model, the second model, is expressed as [3]:

$$Y_n = A\,X_n + B\,\varepsilon_n + C\,X_{n-1} \quad \textbf{(3)}$$

where X_n is the column vector (M*1) of observed data in the n year at key stations, Y_n is the column vector (M*1) at substations, εn is the noise column vector (M*1), and A, B, and C are (M*N), (M*M), and (M*M) parameter matrices, respectively, were calculated using the moments (MOM) method. The fundamental premise underlying the parametric technique is that the data X_n, Y_n, and ε_n must come from a normal distribution. Therefore, before fitting the model, any transformation approach should be used to guarantee this requirement. According to the M&R model, monthly data are spatially disaggregated from N key station to M substations as follows:

$$Y_{v,\omega} = A_\omega X_{v,\omega} + B_\omega \varepsilon_{v,\omega} + C_\omega Y_{v,\omega-1} \qquad \textbf{(4)}$$

Where ω is devoted to the month, $X_{v,\omega}$ is the column vector (N*1) for observed value of year v, season ω at the N stations, $Y_{v,\omega}$ is the column vector (N*1) for substations of the equivalent monthly data for a month in the same year, $Y_{v,\omega-1}$ is (N*1) column vector of the prior month in substations, and $\varepsilon_{v,\omega}$ is the standard normal noise vector(N*1). The monthly parameter matrices A_ω, B_ω, and C_ω are the matrices that correspond to those used in the spatial disaggregation of annual data.

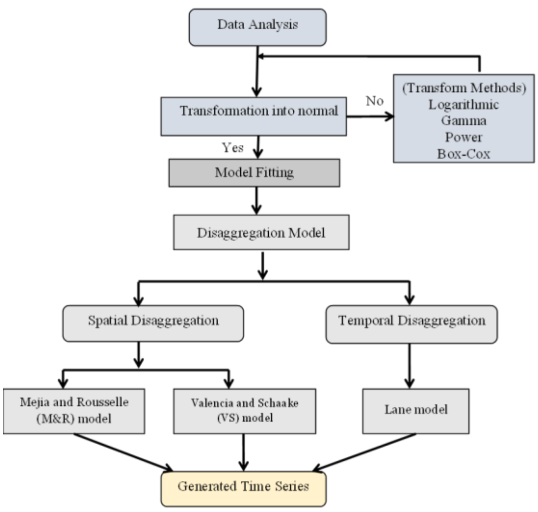

Fig. 1 A Flow Chart Represents the Stages of Disaggregation Streamflow Models.

3.STUDY AREA

The Makhol Dam is one of the most significant projects on the Tigris River in Salah al-Din Governorate, around 16 km north of Fatha Bridge and 30 km northeast of Baiji City. The Makhol dam site represents a prominent node collecting almost all the water flowing in the Tigris River after the two tributaries, i.e., the upper Zap River and the lower Zap River, join the outflow from the Mosul dam, in addition to the contributions from other sources such as rainfall and some other valleys located within its catchment area. Five discharge gauging stations on the Tigris River in the area above the dam's location were chosen for this study. The dam's axis is 3.67 kilometers long and has a storage capacity of approximately 3.3 billion cubic meters [25]. The dam is a convergence point for discharges from the study's sites. The stations chosen include the Mosul Dam station, which is situated in Mosul's northern region. The two stations on the Khazar River, Eski Kalak and Asmawah, are situated on the upper Zab tributary, followed by the Dibis Dam station on the same tributary, and finally, the Baiji station, the alleged opening situated close to Makhoul Dam. It must be noted that the current study has assumed that the observed flow at the Biji measuring discharge station represents the inflow entering the Makhool reservoir due to the lack of data at the dam site and the relatively short distance between these two points. The daily and monthly flows for the five selected stations were obtained from the National Center for Water Resources in Iraq and the Department of Water Resources in the Kurdistan Region for the 2000-2022 period. Fig. 2 shows the measurement stations' locations chosen for this study. Also, Table 1 contains information about the site, such as its latitude, longitude [26], and observation period.

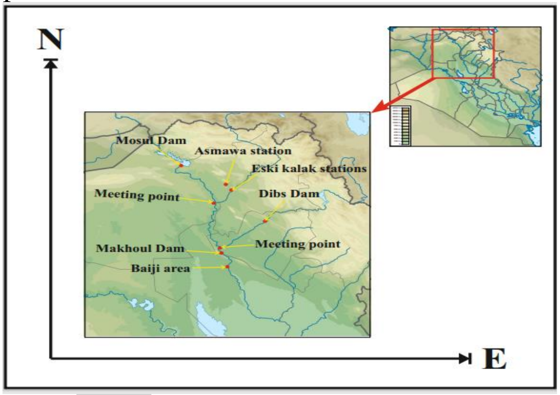

Fig. 2 The Location of Streamflow Measurement Sites.

Table 1 The List of Site Information, Including Latitude, Longitude, and Observation Period.

Station Name	Latitude	Longitude	Historical duration
Mosul Dam	42° 49' 23"	36° 37' 48"	2000-2022
Asmawah	43° 31' 49"	36° 31' 28"	2000-2022
Eski Kalak and	43° 34' 33"	36° 10' 43"	2000-2022
Dibs Dam	44° 06' 38"	35° 41' 21"	2000-2022
Baiji	43° 29' 35"	34° 55' 45"	2000-2022

4. RESULTS AND DISCUSSION

The historical data of each station must be converted into a normal distribution using SAMS 2010 software, which is the fundamental principle of the parametric method. Before implementing the model, a logarithmic converted method was used by putting the transformed data on a normal probability paper and using the skewness test to obtain the skewness coefficient (gc) [27] to determine the transformed data adequacy. The theoretical distribution was compared based on log transformation with a significance level of 10% and the skewness test (gc), which was equal to

0.7476, depending on the amount of data [28]. The test is accepted if gc is less than 0.7476, as indicated in Table 2.

Table 2 Results of Skewness Test.

Stations	Skewness test	Result
Mosul Dam	-0.0658	Accepted
Asmawah	0.1120	Accepted
Eski Kalak	-0.2649	Accepted
Dibs Dam	0.1109	Accepted
Baiji	-0.2602	Accepted

4.1.Temporal Disaggregation

Basic statistics, such as the mean, variance, skew coefficient, maximum and minimum discharge, and lag-1 autocorrelation coefficient, were calculated from 100 generated traces, each of 20 years (the same length of historical data), and then displayed as boxplots and tables. The whiskers on the hinges represent the 5th and 95th percentiles of simulated values, and the box represents the interquartile range (IQR). The triangle represents the relevant historical statistical data. The box's horizontal line denotes the median of generational data. Figs. 3-7 show the statistical findings from generated data for each station. Due to the necessary alteration of the data during the modeling stage, the resulting mean values are expected to preserve historical ones. The mean values of the key series and random terms should be zero, and even at the back-transformed stage, the model coefficients are constants, which was observed in the present study. As can be observed, the generated data for each station maintained the mean value of the original data. The mean of the historical streamflow was nearly identical to the median of the simulated data for each month and station according to tight box plots, which demonstrate the high degree of agreement between simulations and historical data, even though these agreements appear to be violated in October, November, and September, which correspond to the other months. For skewness statistics, although there were notable exceptions at the Dibs Dam station in January, June, and August, the disaggregation approach appears to have underestimated the skewness statistics in December and January for the other stations. In contrast, the other months were seen as very tightened boxes. The marginal density transform should not work in these months since the parametric approach creates a normal distribution with zero skews. The standard deviation statistics showed indisputably that the median of the simulated data in the boxplots closely resembled the historical data for most months at all stations. The minimum and maximum statistical values were successfully replicated except for March and April for the Eski Kalak station due to high flow in these months. During low flow months at all stations, the approach can produce values outside the minimum historical data or very little negative data (0.01%). Maximum flow generation performed better than minimum flow generation using parametric disaggregation. Backward Lag-1 correlations were also well captured through October-September (the first month of the year and the last month of the previous year), which were overly correlated in all stations. The Lag-1 correlation values indicated how effectively the model caught the temporal dependency.

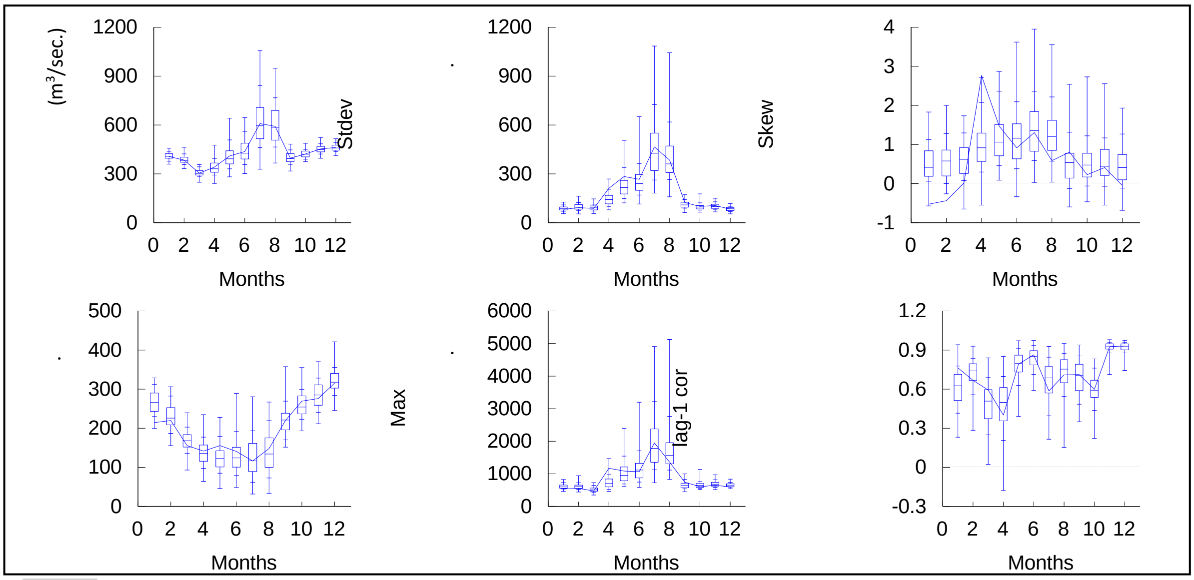

Fig. 3 Statistics of Observed and Simulated Streamflow (Mosul Dam Station), The Polygonal Line Represents the Observed Values.

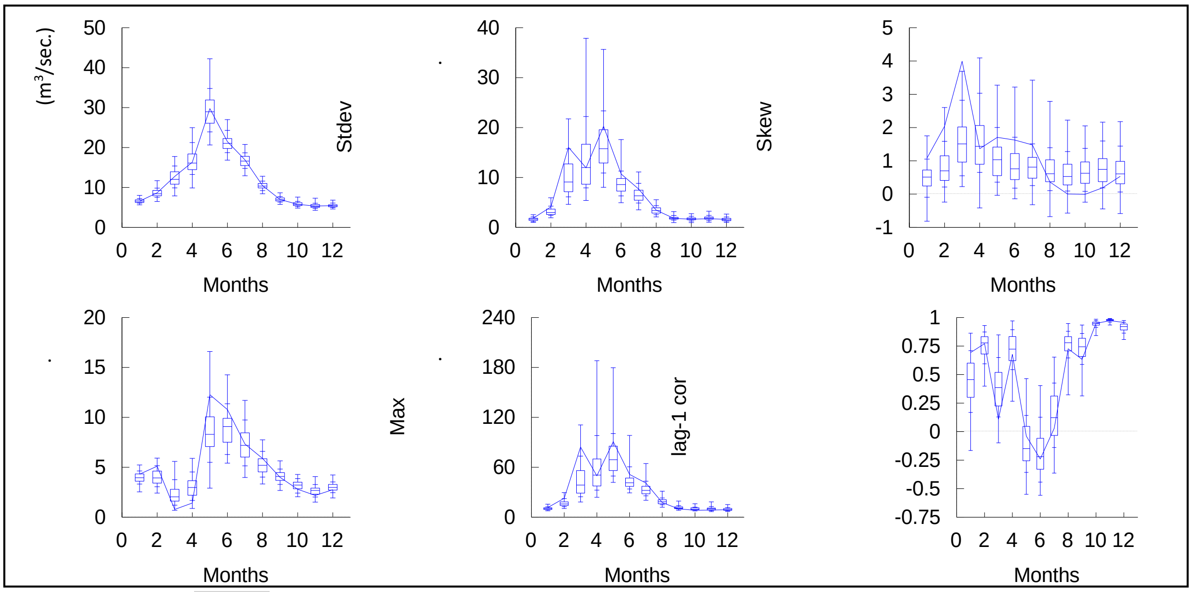

Fig. 4 Statistics of Observed and Simulated Streamflow (Asmawah Station), the Polygonal Line Represents the Observed Values.

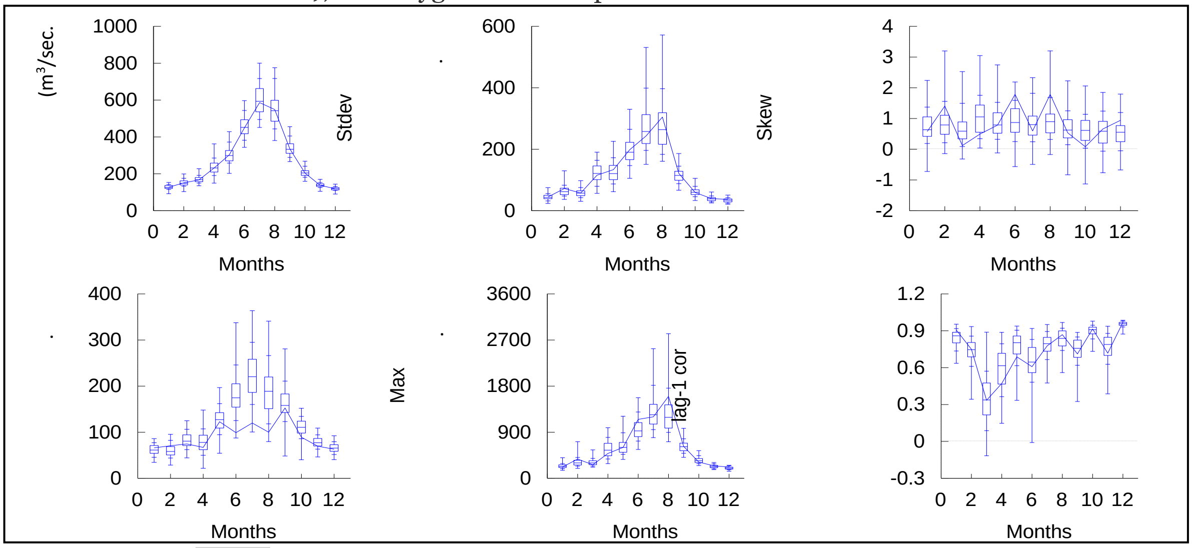

Fig. 5 Statistics of Observed and Simulated Streamflow (Eski Kalak Station), the Polygonal Line Represents the Observed Values.

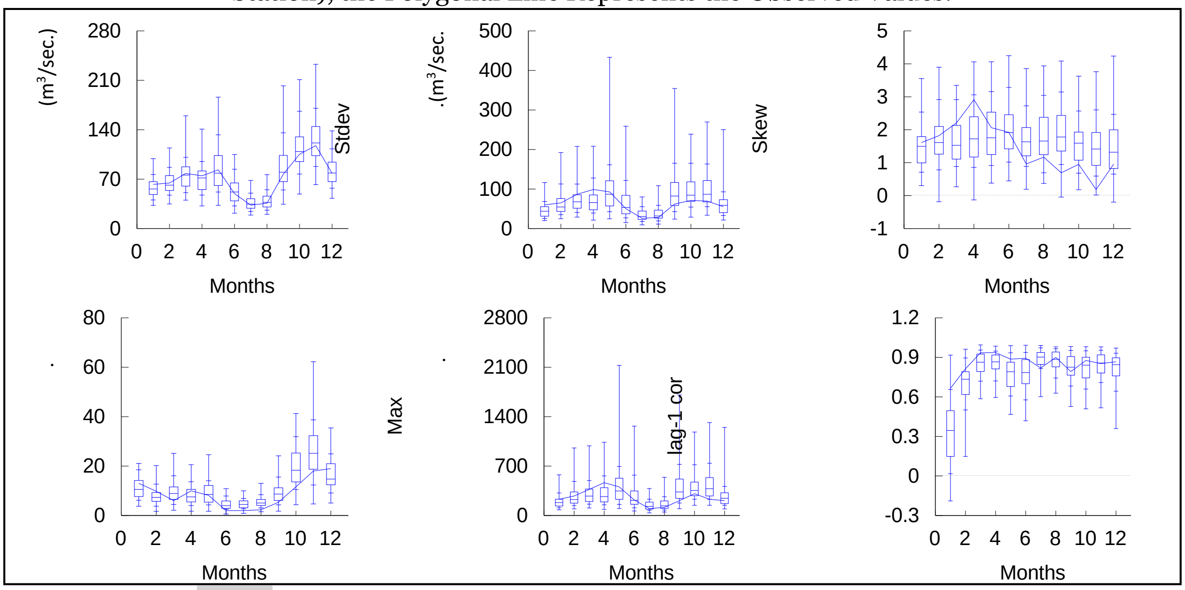

Fig. 6 Statistics of Observed and Simulated Streamflow (Dibs Dam Station), the Polygonal Line Represents the Observed Values.

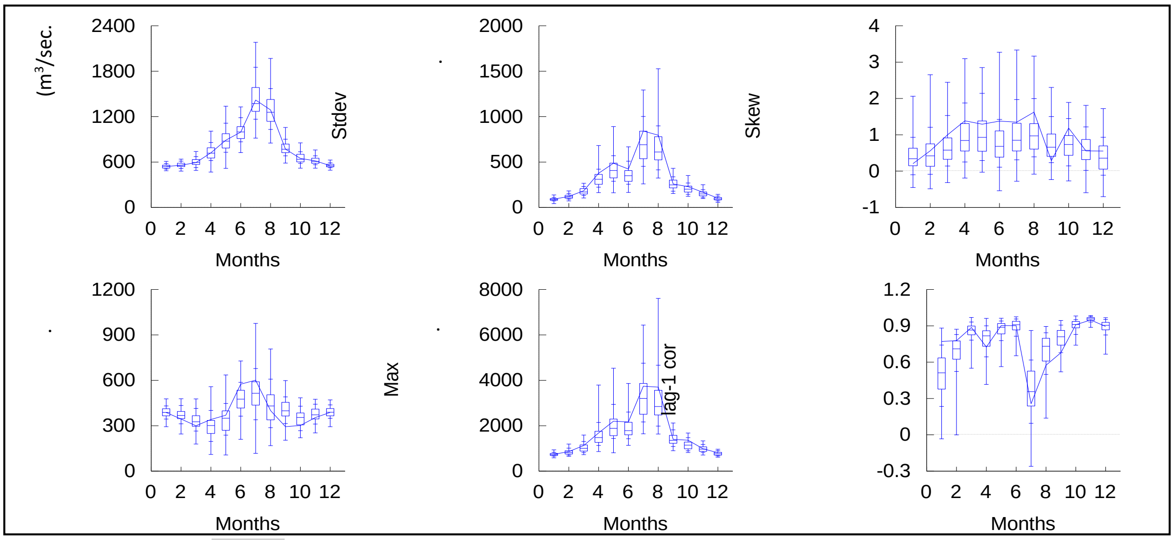

Fig. 7 Statistics of Observed and Simulated Streamflow (Baiji Station), the Polygonal Line Represents the Observed Values.

4.2.Spatial Disaggregation

Table 3 presents the annual statistics obtained from the simulated data after applying the spatial approach to disaggregate the annual flow data from the key station (Baiji station) to the annual flow at substations (Mosul Dam, Asmawah, Eski Kalak, and Dibs Dam). The annual statistics from the V.S. and M&R approaches were then compared with observed statistics for all stations. It is clear from Table 3 that the mean of the annual flow was accurately captured at each station, and St.Dev statistic values from the generated data were quite comparable to those from the observed data. Station Dibs Dam performed better than the other stations in capturing the skewness statistic. Additionally, the maximum and minimum flow statistics were approximated rather well. The minimum values, however, were underestimated in certain locations and overestimated at the Eski Kalak station. Additionally, all stations except Asmawah station overstated the data generated for maximum flows. The coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NS) are determined for the validating goal of assessing the proposed disaggregation approach effectiveness. The formulas generated by the statistics in this investigation can be seen in references [29- 31]. The VS model was the best in application, as shown by comparing the R^2 and (NS) values between the observed data and the data derived from Eqs. (2), (3), which reached the following values in Table 4.

Table 3 Comparison of Annual Values Between Historical and Disaggregated Data.

Statistics	Mosul Dam station			Asmawah station		
	Observed	Disaggregate VS Model	M&R Model	Observed	Disaggregate VS Model	M&R Model
Mean	434.9	439.6	438.7	12.21	12.24	12.22
St.Dev	116.9	111.6	119.7	3.375	3.303	3.324
Skew	0.235	-0.05	0.552	0.7601	0.0703	0.663
Min	266.0	219.4	251.3	7.523	5.901	7.156
Max	668.5	654.2	718.9	21.13	18.9	20.28
Statistics	**Eski Kalak station**			**Dibs Dam station**		
	Observed	**Disaggregate VS model**	**M&R model**	**Observed**	**Disaggregate VS model**	**M&R model**
Mean	280.0	282.4	286.2	71.70	71.27	75.43
St.Dev	90.71	88.14	97.09	54.33	51.24	59.06
Skew	0.484	-0.11	0.640	1.463	1.208	1.518
Min	124.4	133	141.7	16.96	28.43	16.86
Max	491.8	447.5	512.1	235.5	172.3	244.2

Table 4 Values of R^2 and NS Statistics Values between Historical and Annual Disaggregated Data by VS and M&R Approach.

Station Name	M&R model		VS model	
	R^2	NS	R^2	NS
Mosul Dam	0.815	0.971	0.9886	0.985
Asmawah	0.882	0.928	0.781	0.995
Eski Kalak	0.917	0.968	0.9967	0.997
Dibs Dam	0.892	0.839	0.9941	0.991
Baiji	0.813	0.881	0.8807	0.879

Using the VS and M&R models, the monthly generated data for spatial disaggregation streamflows from the key station (Baiji) to the substations (Mosul Dam, Asmawah, Eski Kalak, and Dibs Dam) were computed. The fundamental statistics set at all stations was computed for comparison with the observed data. Table 5 displays some of the statistical values obtained for October,November, and December. Table 5 indicates the used model's satisfactory performance in preserving the mean and the standard deviation values. However, the model failed to do so and underestimated those parameters in Asmawah station on Khazer River, particularly during December. Additionally, there were some deflations in the skew value of the disaggregated flows compared to the observed values, which can be attributed to the insufficient transformation process. In most months, the minimum and maximum statistics values obtained by generated data were lower than the actual results, except for Mosul Dam Station. The satisfactory outcomes for other months were found in all stations (not shown due to limited space). It can be concluded that the proposed approach produced a good level of agreement for most statistics. Despite the convergence of the two models' results, the correlation coefficient R^2 and Nash coefficient (NS) of the MR model values were the best, as shown in Table 6.

Table 5 Comparison Moment Values Between Historical and Disaggregated Data.

Statis.	October			November			December		
		Disaggregate			Disaggregate			Disaggregate	
	Obs.	VS model	M&R model	Obs.	VS model	M&R model	Obs.	VS model	M&R model
Mosul Dam station									
Mean	406.4	408.3	408	384	387.2	386.7	304.6	307.6	307.7
St.Dev	82.3	89.26	89.13	92.2	99.89	99.02	88.32	92.81	95.49
Skew	0.202	0.2156	0.5153	0.23	0.252	0.5901	0.29	0.2961	0.6376
Min	214.5	266.6	266	219.8	230	231.1	155.5	168.3	163.7
Max	537.9	615.2	611.8	554	617.8	615.6	477.2	524.7	531.4
Asmawah station									
Mean	6.574	6.618	6.628	8.66	8.616	8.611	12.77	12.39	12.56
St.Dev	1.851	1.68	1.711	4.10	3.258	3.217	16.05	10.85	11.53
Skew	1.084	0.476	0.508	2.04	0.826	0.7994	3.992	1.582	1.61
Min	4.31	3.943	3.926	5.11	4.023	4.09	0.78	2.264	2.243
Max	11.66	10.41	10.54	22.8	16.66	16.46	84.36	44.28	46.37
Eski Kalak station									
Mean	127.2	127.8	127.2	151.2	151.2	151.6	167.1	170.1	170.4
St.Dev	44.65	45.01	43.11	72.11	66.02	71.23	57.49	58.9	55.17
Skew	0.577	0.7107	0.63	1.407	0.85	0.89	0.120	0.6867	0.170
Min	66	61.56	41.35	70.6	60.49	51.37	74.61	82.91	59.76
Max	221.3	236.1	210.8	375.7	314.9	289.2	265	311.2	227.2
Dibs Dam station									
Mean	62.59	58.29	60.21	64.5	64.71	63.78	78.17	76.51	78.19
St.Dev	59.8	49.9	53.24	65.01	71.04	64.25	86.87	78.92	83.44
Skew	1.612	1.522	1.542	1.821	1.747	1.667	2.207	1.713	1.607
Min	13.0	11.25	11.15	9.8	7.886	9.005	6.00	9.638	11.09
Max	230.4	200.2	209.6	276	273.9	247	370	307	303.4

Table 6 Values of R^2 and NS Statistics Values between Historical and Monthly Disaggregated Data by VS and M&R Approach.

Station Name	M&R Model		VS Model	
	R^2	NS	R^2	NS
Mosul Dam	0.9954	0.995	0.9991	0.999
Asmawah	0.9997	0.999	0.9994	0.998
Eski Kalak	0.9869	0.985	0.8829	0.995
Dibs Dam	0.9691	0.968	0.8356	0.995
Baiji	0.9971	0.996	0.9453	0.927

It can be seen that the model can preserve historical data in the time and space domains, particularly for the two moments (mean and St.Dev); however, there is a limitation in capturing the higher moments, i.e., the skewness coefficient. One additional finding of this paper is that using the spatial approach results in acceptable outcomes for all the stations considered in the present study.

5.CONCLUSIONS

In the present study, data on streamflow at five stations along the Tigris River in Iraq were disaggregated using a parametric disaggregation model. The streamflow data were temporarily disaggregated from annual data at the key station to monthly data at the same station and to substations by spatial disaggregation. Various test statistics were calculated from the historical and generated data. A comparison of these statistics revealed each approach's performance in the disaggregation model. From the comparison, it is concluded that the temporal disaggregation by the VS approach preserved the monthly statistics spatially for the moments (mean and St.Dev), while the skewness coefficient limited the capturing of the higher moments. In addition, spatial disaggregation was the best to preserve monthly statistics by the M&R

approach and the VS approach for annually generated data. The spatial disaggregation approach has the benefit of being able to provide accurate streamflow data and realistic spatial structures at each time step, easily adaptable to different regions, and more attractive for users who need to find flow at the upstream stations from the downstream ones in the fields. In conclusion, the results showed that the parametric disaggregation model was effective and provided a flexible choice for generating synthetic streamflow series, which can assist in the future operation and management of the Makhol reservoir in the sense that the operator would be quite aware of how the different tributaries contributed to Tigris inflow to Makhol. Additionally, if the reservoirs' operation was integrated into a single system, one could control the releases from different components of the reservoir system until an optimal operating policy for this reservoir is achieved.

ACKNOWLEDGEMENTS

The authors express their gratitude to the College of Engineering at the University of Mosul for their assistance in carrying out the current study. Postgraduate Research Grant (PGRG) No.3/7/147/2023.

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