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Inflow generation using Thomas- Fiering model for Thaphanseik Reservoir in Myanmar

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Abtract: Thomas-Fiering (T-F) model was applied for generating synthetic streamflow for the Thaphanseik reservoir. The Thomas-Fiering model accommodated the non-stationarity of seasonal data. Time series of streamflow are crucial for the planning, design, and management of various water resource systems. In this study, the model was tested using historical data spanning 39 years (from 1985 to 2023). The model's performance was evaluated by using statistical measurements such as Coefficient of Determination (R2) and Nash-Sutcliffe Efficiency (NSE). Additionally, this model was utilized to generate synthetic streamflow data for the years 2024 to 2100. The logarithmic transformation method was used in order to avoid the negative flows in the synthetic data. In this study, synthesis flow data were generated using different random sequences. The mean, standard deviation and correlation coefficient of different synthetic series were calculated. The calibration process was performed for the periods 1985 to 2016 and validation process was performed for the years 2017 to 2023. Based on R2 value, most suitable synthetic series were chosen. The generated data showed a high goodness of fit, with R and NSE values. An analysis of the historical and synthetic discharge statistics revealed that the model successfully captured the features of the historical data and integrated them into the generated sequences.

Keywords: Streamflow; Thomas-Fiering model; Synthetic; Thaphanseik reservoir

1. Introduction

Stochastic simulation of hydrologic time series has been extensively employed to address various issues in water resource planning and management over several decades [1]. Common applications include determining reservoir capacities, assessing the adequacy and reliability of reservoirs, evaluating water resource management strategies under different hydrologic scenarios, and analyzing irrigation system performance amid uncertain water distributions. These simulations rely on mathematical models, with various models having been proposed. Time series data on streamflow are essential for

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both hydrological research and water management practices. Assessing surface water flow is a crucial element in hydrological projects, including water quality monitoring, flood analysis and prediction, geomorphological studies, and the support of aquatic ecosystems, among other areas [2].

Water is an essential and valuable resource for humanity. It is crucial for agriculture, industry, transportation, and energy production. A significant issue arises when water is unavailable or lacks sufficient quality at the times and places it is required. Therefore, forecasting inflows into storage reservoirs is necessary for effective reservoir management, ensuring optimal use of limited water supplies [3]. Managing water resources, as well as addressing floods and droughts in hydrology, involves forecasting future conditions in a probabilistic manner. Temperature and streamflow data can be helpful for predicting precipitation, while climate data may assist in forecasting streamflow. This level of coherence can be assessed using wavelet techniques [4]. The planning and design of water resources projects largely rely on hydrologic and economic data, with streamflow records being a key component of hydrologic information. Surface streamflow data serve two main purposes. Firstly, they offer valuable regional insights, representing "natural" conditions. This information can be combined with similar data from other locations to develop a comprehensive understanding of streamflow patterns in a given area.

Streamflow time series are crucial for the planning, design, and management of various water resource systems. However, in many cases, there is a lack of comprehensive flow records at the sites of interest. Consequently, relying solely on existing historical streamflow data may not yield reliable estimates of flow statistics [5]. Since the future cannot be directly observed and remains uncertain, predictions must be made, often through various hydrological models. These models are typically driven, calibrated, and assessed using historical data to form hypotheses about catchment behavior.

Although the modeling process itself has been widely covered in literature, this discussion will focus specifically on the variables used to project future discharge, including catchment discharge, precipitation, and evapotranspiration estimates [6]. The creation of forcing variables is inherently linked to the observable data used for calibration and validation. However, this process will involve stochastic elements due to the inherent variability in the observables themselves and the uncertainty of future values. It is important to note that the historical time series of these observables can be uncertain, especially when applied to a catchment area. Consequently, historical data should be treated as virtual variables [7]. The model was originally developed to generate long sequences of feasible streamflow time series in Thaphanseik reservoir to simulate, analyze, and optimize water management policies [8].

Time-series analysis is a simple method for examining a sequence of data points arranged in chronological order. This technique involves gathering data at consistent time intervals rather than in a random or haphazard manner. It goes beyond merely organizing the data by investigating how these values change over time. Additionally, it provides insights into the relationships between different data points. Techniques used in time-series analysis can also predict future values based on past data trends. However, it necessitates that the data values confirm regularity and dependability. The application of time-series forecasting includes estimating the probable change in data values, like seasonality or cyclic behavior, which deliver an improved understanding of data variables.

Most water resource projects necessitate a historical streamflow data record, with longer records leading to more informed decisions during design and operation. Unfortunately, a lengthy streamflow data record is often unavailable, making it crucial to synthetically generate streamflow sequences that statistically resemble the observed data. There are models for generating these sequences for both single rivers (single-site) and for rivers along with their tributaries (multi-site). However, before applying these models to real systems, it is important to conduct comparative studies [9].

The Thomas-Fiering model to maintain the normal distributions of annual flow, the log-normal distributions of monthly flows, and the autocorrelation for both annual and monthly flows [10]. In the past ten years, the TF model has been employed for various applications, including streamflow forecasting [11], reservoir operations [12] and rainfall predictions [13]. This study assessed the effectiveness of stochastic streamflow models in generating synthetic streamflow data. The Thaphanseik Dam experienced its lowest water levels in 2019, with reservoir storage dropping to 518,000 acre-feet by August 30 of that year. This issue of low water levels was also noted in 2004 [14]. Therefore, The Thomas-Fiering (T-F) model was employed to simulate the Thaphanseik reservoir in the Mu River basin, using historical monthly streamflow data from 1985 through 2023. The statistical evaluation metrics were computed to assess the performance of the Thomas-Fiering model by comparing observed and simulated inflow during the calibration period. Synthesis flow data were created by utilizing different random variables and selected the optimal result.

The mean, standard deviation, and correlation coefficients were computed for both the gauged data and the synthetic series from the first through fifth runs. Calibration was conducted for the period from 2001 to 2016, while validation took place from 2017 to 2020. The synthetic series deemed most suitable were selected based on the R values. The Thomas-Fiering T-F model has demonstrated its effectiveness as a valuable tool for simulating the Thaphanseik Reservoir. It can reverse key historical statistical parameters, making it useful for predicting future values, especially when applied in its transformed format. Furthermore, these sequences allow for the development of a probabilistic framework to predict overall system performance, extending beyond specific events and the timing of recorded droughts. The results of this study provide important insights for decision-making regarding the management of the Thaphanseik reservoir. Additionally, the model created in this research was utilized to generate synthetic streamflow, which is crucial for effective planning and management of water resource.

2. Material and methods

This research involves choosing the study area and location, gathering data, evaluating the model's performance, determining the correlation coefficient between observed data and synthetic series, and inflow generation for the years 2024 to 2100.

2.1 Study area

The Mu River, situated in the upper central region of Myanmar, serves as a tributary to the Ayeyarwady River, the primary river of the country. It drains the Kabaw Valley and part of the dry zone located between the Ayeyarwady River to the east and its major tributary, the Chindwin River, to the west. The river flows approximately 275 kilometers from north to south before joining the Ayeyarwady River to the west of Sagaing, near Myinmu. It is predominantly utilized for irrigation, with the Mu River basin covering an area of 6,000 square miles.

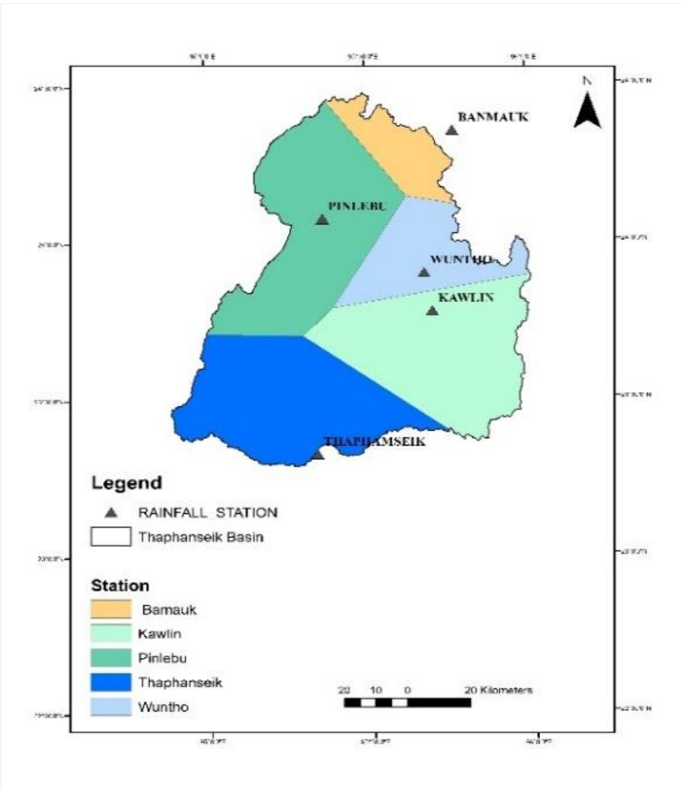

Figure 1: Location map of Mu River basin at Thaphanseik dam site

The Thaphanseik Dam, situated on the Mu River in Sagaing Region, was completed in 2001 and spans 6 kilometers, making it one of Southeast Asia's largest dams. This multi-purpose structure supports both irrigation and power generation for national development. The dam is designed to retain and regulate water flow in the Mu River. It is positioned between latitudes 23° 17' N and 24° 28' N and longitudes 94° 30' E and 96° 00' E, within Kyunhla Township in the upper Sagaing Region [15]. The region experiences an average annual rainfall of approximately 962 mm. Figure 1 illustrates the location of the Mu River basin at the Thaphanseik Dam site. The inflow datasets for the Thaphanseik Reservoir were collected from the Irrigation and Water Utilization Management Department (IWUMD).

2.2 Stochastic data generation

Stochastic simulations of streamflow sequences are essential for water resource planning and management [16]. Many hydrologists view streamflow and rainfall sequences as instances of a stochastic process during their analysis [17]. The data derived from these sequences, especially monthly time series like streamflow or rainfall, play a crucial role in water resources planning and management by helping to assess the variability in future system performance. Stochastic simulations of streamflow provide a viable alternative for representing streamflow patterns that closely match the observed data from a river basin. These simulations generate time series across multiple locations, capturing both short- and long-range temporal dependencies, as well as non-stationarities and spatial correlations in extreme events [18].

However, since these observed data are usually limited in temporal scope, the variability captured in stochastic streamflow simulations especially regarding extreme events can be restricted. The purpose of stochastic data generation is to create synthetic data that statistically mirrors the observed data. Consequently, this generated data is vital for developing more precise solutions to complex challenges in water resources planning, design, and operations.

2.3 Thomas-fiering model

Thomas and Fiering were the first to create a mathematical model for the sequential generation of streamflows [19]. The Thomas-Fiering model utilizes a regression equation that relies on discharge data collected over successive time intervals [20]. The earliest model introduced in hydrology for generating synthetic monthly flow sequences was developed by Thomas and Fiering in 1962 [21]. Thomas and Fiering pioneered a mathematical framework for the sequential generation of stream flows. Their approach models the flow for any given period as a linear function of the previous period's flow. This model is versatile, applicable to various time scales including weekly, monthly, seasonal, and annual flows.

The Thomas-Fiering (TF) model is a traditional technique used to generate synthetic flow time series through linear regression [22]. It predicts the flow for the next month based on the previous month's flow. For instance, the flow in February depends on the flow in

January, and this relationship continues for subsequent months. The equation for the Thomas-Fiering (TF) model is presented as follows.

$$q_{i+1} = \bar{q}_{j+1} + b_j \left(q_i - \bar{q}_j\right) + z_i \ \sigma_{j+1} \sqrt{1 - r_j^2} \tag{1}$$

$$b_j = \frac{r_j \ \sigma_{j+1}}{\sigma_j} \tag{2}$$

By applying a log transformation to historical monthly streamflow data, it is possible to generate synthetic monthly streamflow using the Thomas-Fiering model, since the transformed data exhibit a normal distribution. The Thomas-Fiering model was enhanced by specifying the model parameters in advance to reduce forecast errors [23].

2.4 Data

Inflow data of the Thaphanseik reservoir covering the period from January 1985 to December 2023, was analyzed in the study. The inflow datasets for the Thaphanseik Reservoir were sourced from the Irrigation and Water Utilization Management Department (IWUMD). Figures 2 and 3 display the monthly and annual inflow data series utilized in this research.

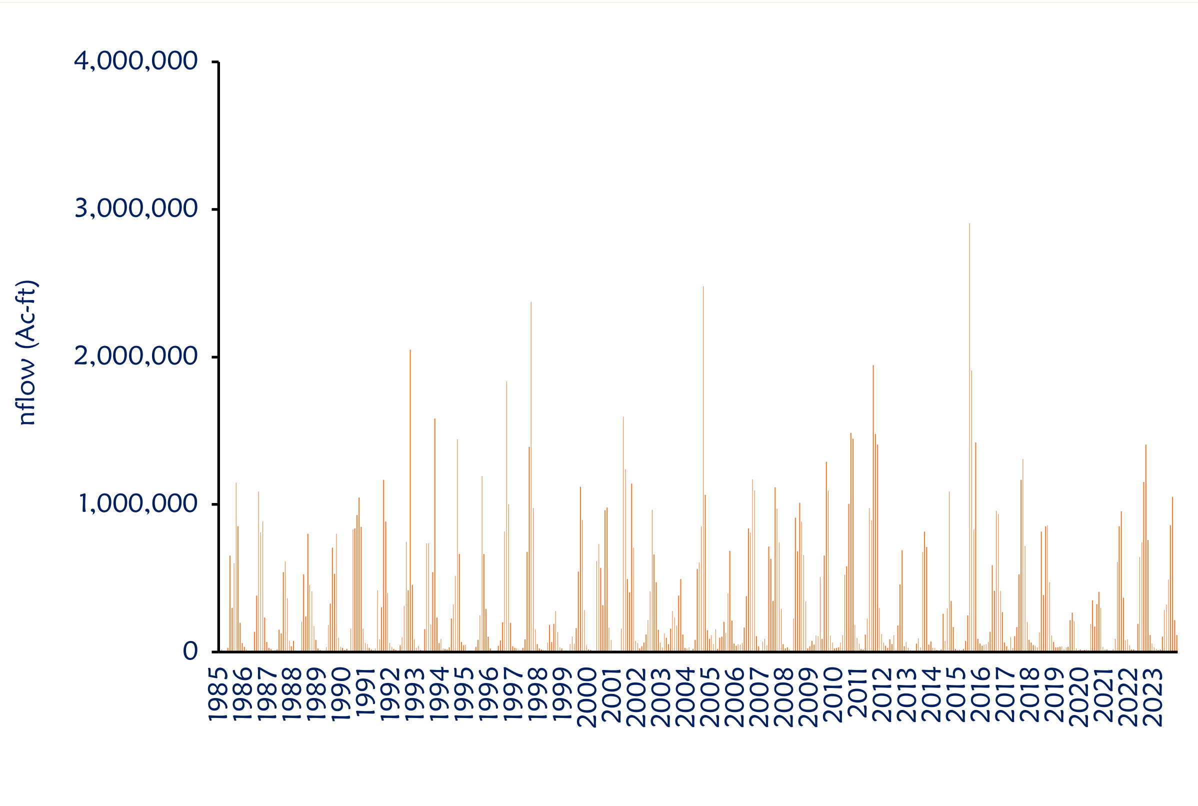

Figure 2: Monthly inflow of Thaphanseik dam

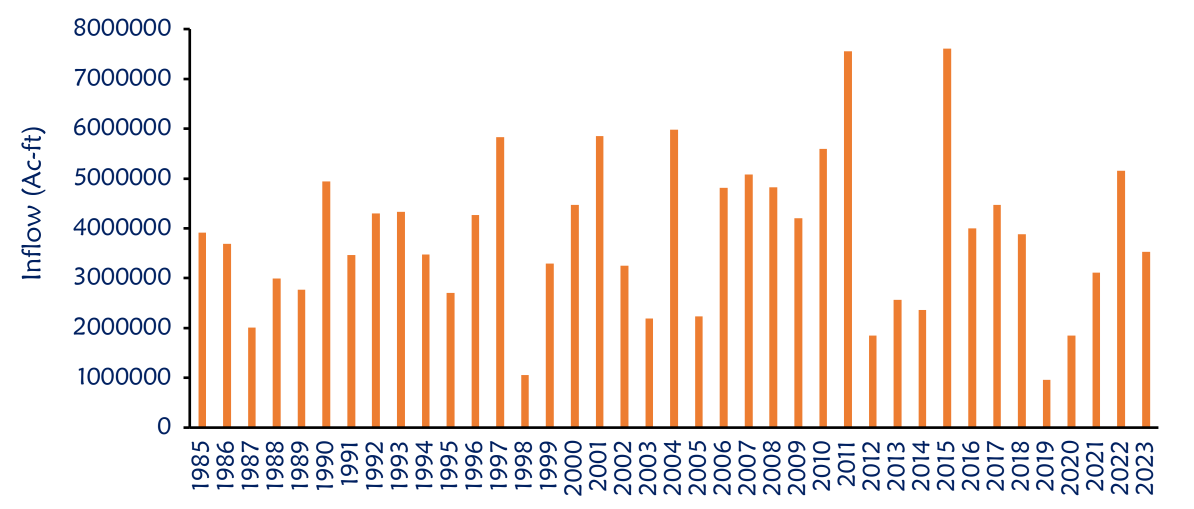

Figure 3: Annual inflow of Thaphanseik dam

3. Results and discussion

3.1 Random number component

In stochastic models, randomness is inherent to the process. Generating rainfall data relies heavily on random numbers, which are crucial for accurate simulations. Computers use a sub-function to produce these numbers with a uniform distribution. Each number in a series with a uniform distribution is generated independently, creating a random sequence throughout the time series. The dataset includes 12 variables, one for each month from January through December. In the models, the incidental random numbers used are typically distributed according to a normal distribution [24]

Random numbers are characterized by a sequence where each number is equally likely, making it impossible to predict future values from the current sequence. These numbers are produced using mathematical algorithms that ensure a uniform distribution across the entire range of possible values [25]. Normally distributed random numbers with a mean of zero and a standard deviation of one were then generated. A set of 12 regression equations was established. In this research, logarithmic transformations of the flows were employed to address the issue of negative values in synthetic data. Subsequently, statistical metrics such as the mean, standard deviation, and serial correlation coefficient for each month were determined.

3.2 Thomas-fiering model calibration and validation

According to the Thomas-Fiering model, extending existing streamflow data necessitates at least 12 years of inflow data. The Thaphanseik reservoir provides inflow records from 1985 to 2023, yielding approximately 39 years of monthly streamflow data. Calibration was carried out for the period from 1985 to 2016, while validation was conducted for the years 2017 to 2023. The most appropriate synthetic series were selected based on their R values. Ultimately, the synthetic inflow data were converted back from their logarithmic form to obtain the actual flow values. Basic statistical measures, including the mean and standard deviation, were calculated and compared between historical and generated streamflow data. The synthetic flow data were created using various random sequences in this study. The mean, standard deviation, and correlation coefficients for both the observed data and the synthetic series of multiple runs were computed. Table 1 shows the correlation coefficient between observed data and synthetic series for five runs. The analysis revealed that synthetic result 3 provided the most favorable results and was therefore selected for the final outcomes.

Table 1: Correlation coefficient between observed data and synthetic series

Year	Synthetic Result 1		Synthetic Result 2		Synthetic Result 3		Synthetic Result 4		Synthetic Result 5	
	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Calibration (1985-2016)	0.35	0.34	0.48	0.47	0.63	0.6	0.23	0.23	0.36	0.35
Validation (2017-2023)	0.35	0.32	0.44	0.42	0.56	0.53	0.23	0.22	0.35	0.33

The results demonstrate a consistency in the statistical characteristics of both observed and generated mean and standard deviation, as shown in table 2. The synthesized monthly flow data align closely with the observed flows, with coefficients of determination (R) of 0.99 for the mean and 0.89 for the standard deviation. Comparison of observed and synthetic mean and standard deviation were shown in Figures 4 and Figure 5 respectively. It is noted that mean values are close in most months.

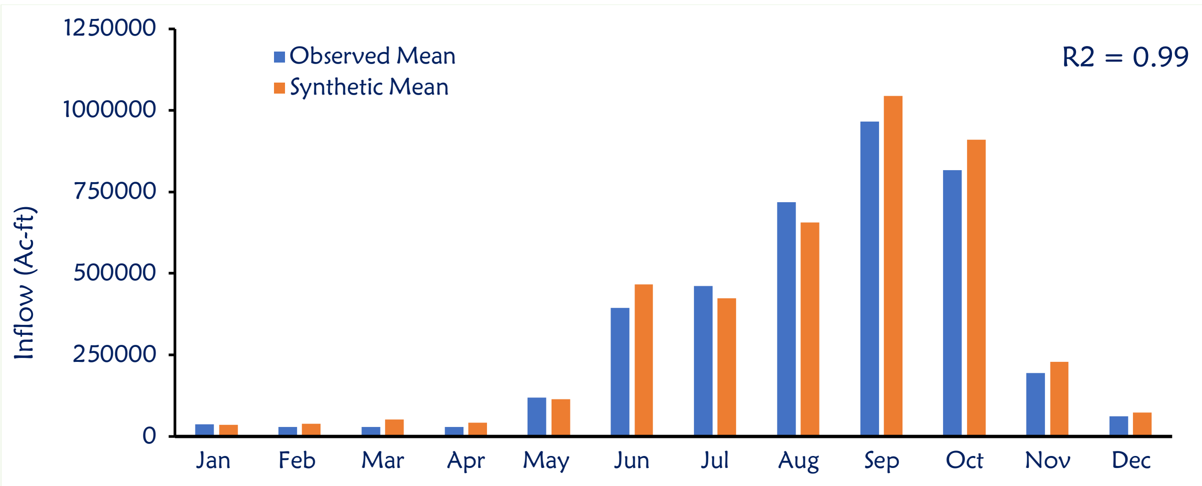

Figure 4: Comparison of observed and synthetic means

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Table 2: Comparison of observed and synthetic mean and standard deviation

Month	Observed Mean (Ac-ft)	Synthetic Mean (Ac-ft)	Observed Standard Deviation (Ac-ft)	Synthetic Standard Deviation (Ac-ft)
Jan	37002	36139	22627	24905
Feb	29124	38901	23136	45883
Mar	28452	51713	32102	91853
Apr	28577	42823	30270	76620
May	119981	114246	144139	109052
Jun	393807	466692	339528	524807
Jul	461133	423517	493276	442410
Aug	718760	656227	443035	403608
Sep	965226	1043880	519900	643089
Oct	817068	909898	401332	567372
Nov	194103	229733	132309	192807
Dec	61726	72678	25599	57361

Figure 6 displays the overall simulation flows, achieving an R value of 0.63 and the Nash-Sutcliffe efficiency (NSE) was 0.6 for the calibration process. Figure 7 presents the comparison of observed and synthetic flows during the validation period from 2017 to 2023. The coefficient of determination R was 0.56, and the Nash-Sutcliffe efficiency (NSE) was 0.53. This indicates a similarity between the observed and synthetic results.

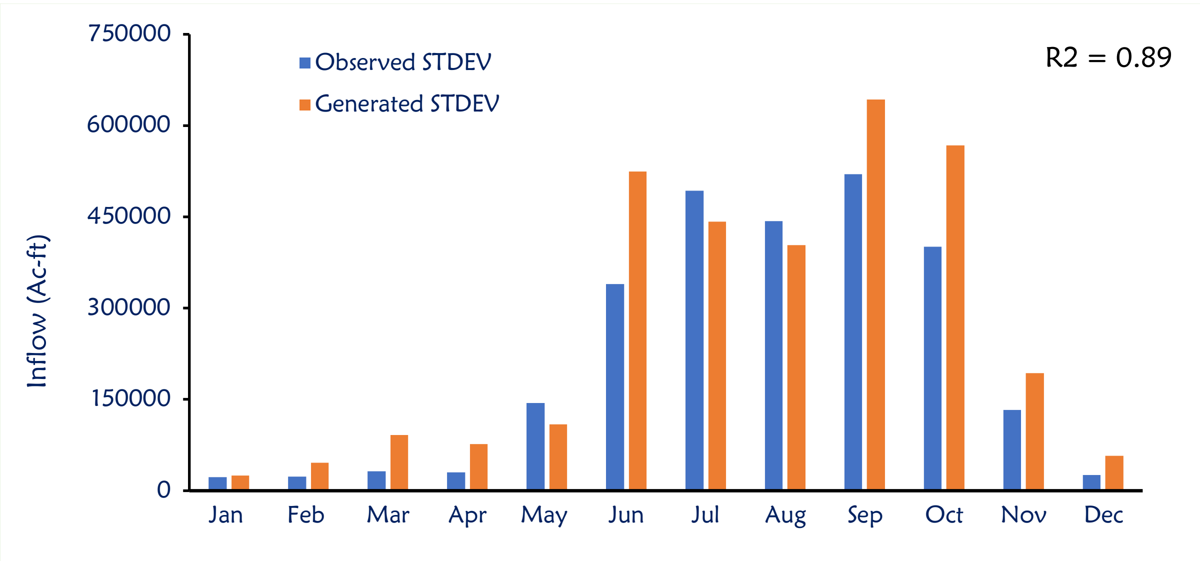

Figure 5: Comparison of observed and synthetic standard deviations

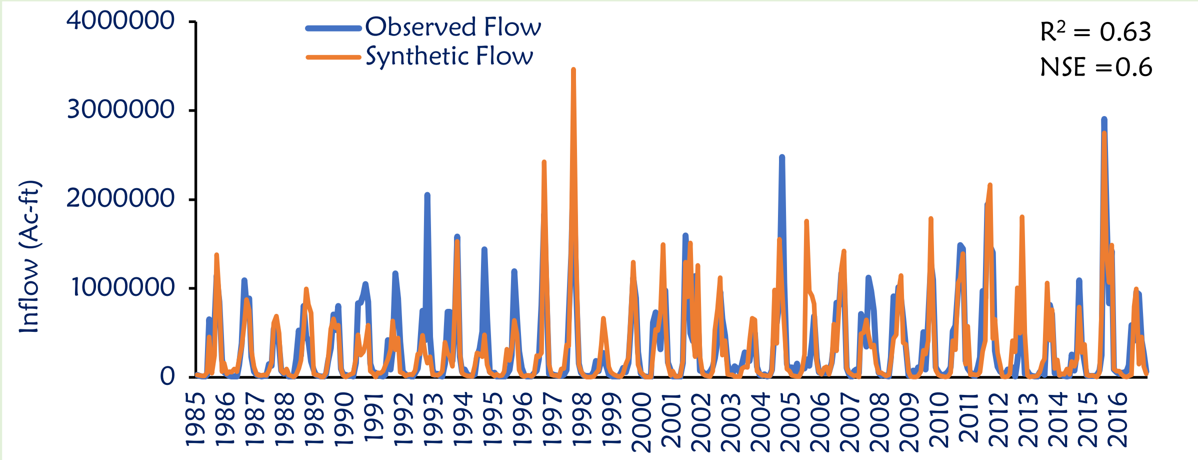

Figure 6: Comparison of observed and synthetic flows for calibration process (1985 to 2016)

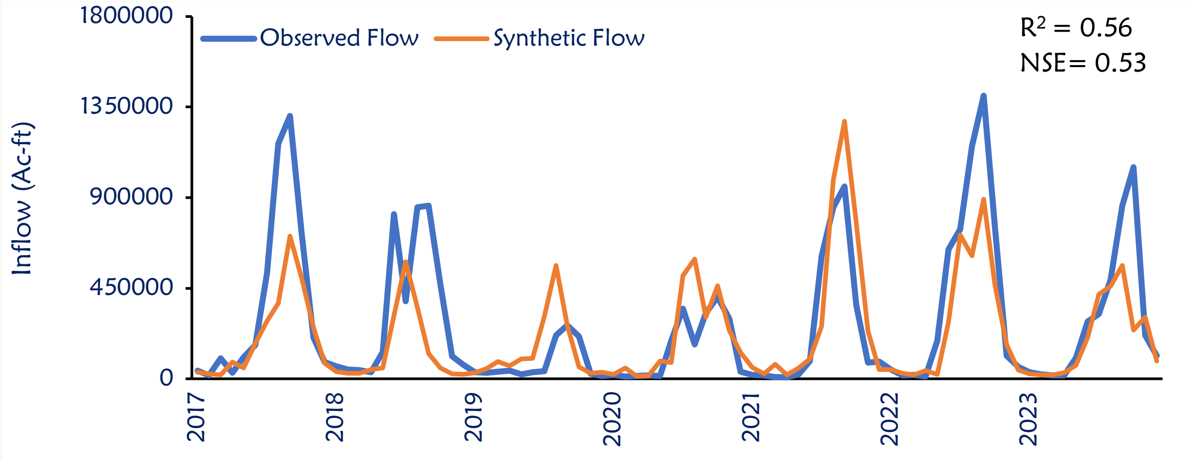

Figure 7: Comparison of observed and synthetic flows for validation process (2017 to 2023)

3.3 Inflow generation by thomas-fiering model

Additionally, synthetic monthly data spanning from 2024 to 2100 were produced using the chosen model. It is important to note that if any generated streamflow values were negative, they were substituted with the minimum observed streamflow for that month. Alternatively, negative values could be addressed by applying the log transformation. The comparison of statistics between historical and synthetic discharges demonstrated that the model successfully preserved the characteristics of the historical series and effectively incorporated them into the generated data. Figures 8 and 9 show the generated series of synthetic flows based on 39 years length record. Future possible predicted inflow using Thomas-Fiering model can be used for managing the operation of Thaphanseik dam.

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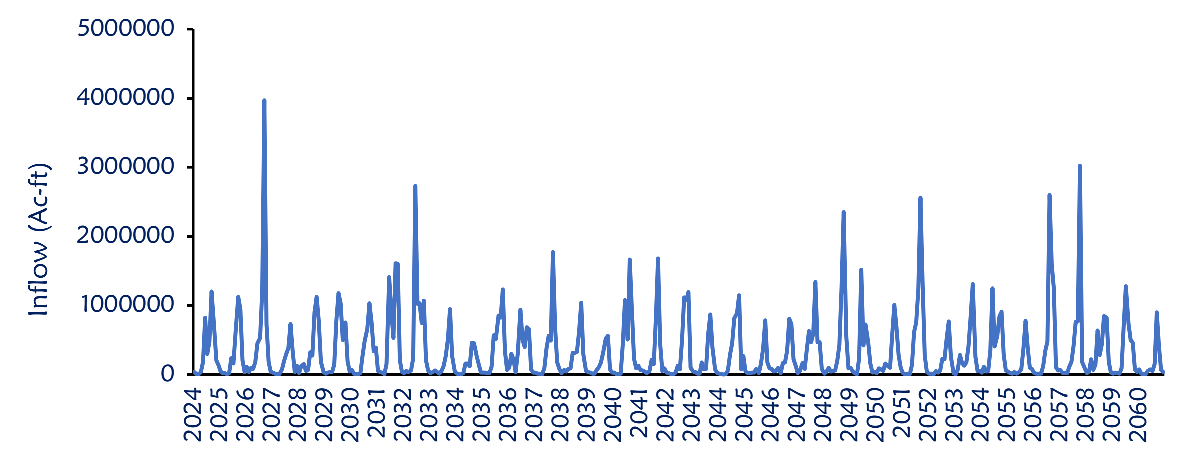

Figure 8: Generated flows for the periods (2024 to 2060)

After the calibration and validation process, same Thomas-Fiering model structure was used to forecast the inflow timeseries for the period of 2024–2100. It is clear from Figure 8 and 9, that the maximum flows are predicted in the years 2026 and 2097. Whereas the lowest flows are expected in the year 2035. This forecasted inflows timeseries was used in the reservoir operation. After this, the forecasted rule curve of reservoir was determined, and water shortage was also determined. These predictions may help the reservoir operators and managers to fulfil the water demands. The Thomas-Fiering stochastic streamflow generation model was employed to synthetically create monthly inflow scenarios for the Thaphanseik Reservoir. These scenarios will be utilized in an optimization model based on stochastic programming that is currently being developed for the management of Thaphanseik Dam. Analysis of a 39-year historical dataset used for parameter estimation indicated that the statistics of the generated data closely matched those of the historical records. This suggests that the Thomas-Fiering model effectively captures the statistical characteristics of the historical data in the generated values. Therefore, it can be concluded that the model is well-suited for generating the inflow scenarios required for the stochastic optimization model.

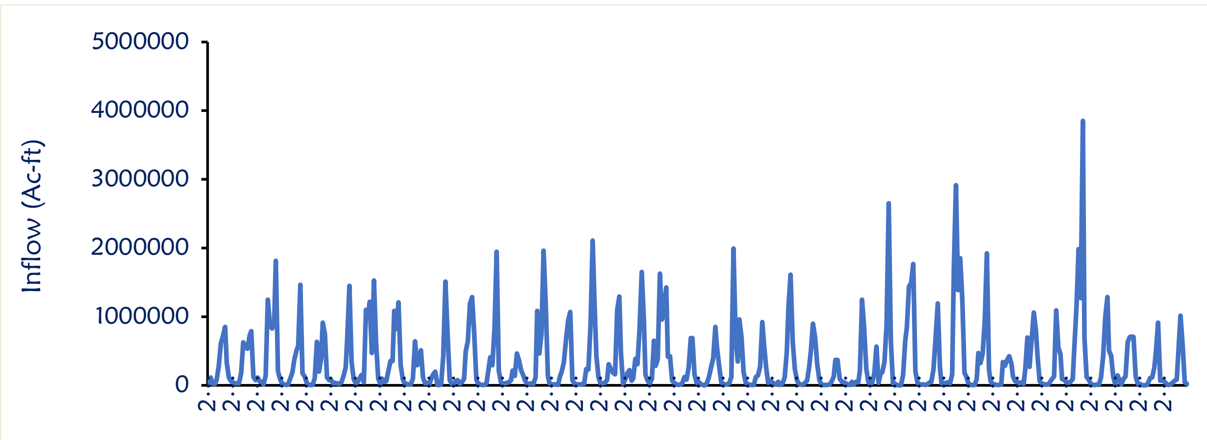

Figure 9: Generated flows for the periods (2061 to 2100)

The Thomas-Fiering model has been widely utilized by researchers to generate streamflow for the effective operation of reservoir systems [5], [26]. Comparable research has also been performed on various reservoirs and river systems in India [27], [28], [29]. Overall, the synthetic data sequences produced are statistically similar to the observed data, making them essential for developing more accurate solutions to complex challenges in water resources planning, design, and management. The investigators reported that Thomas-Fiering model effectively preserves all specified statistics and is therefore recommended for generating monthly streamflow.

4. Conclusion

In this research, the Thomas-Fiering stochastic streamflow generation model was utilized to create synthetic monthly inflow scenarios for the Thaphanseik reservoir in Mu River basin. A key feature of this model is its ability to account for non-stationary monthly inflow data. Analysis using a 39-year historical dataset to calibrate the model revealed that the generated data closely matched the historical statistics, including mean, standard deviation, and coefficient of determination (R2). This analysis revealed that the performance of stochastics model in generating synthetic streamflow time series. By using log-transformed historical monthly streamflow data, the Thomas-Fiering model was able to produce synthetic monthly streamflow effectively.

The mean, standard deviation, and correlation coefficients were calculated for both the observed data and the synthetic series across the multiple runs. The calibration period with optimum series yielded an overall R   value of 0.63, which aligns well with historical records and demonstrates a satisfactory performance in predicting inflows. According to result, the histogram of the synthetic inflow series was similar to that of the observed series. This indicates that the Thomas-Fiering model effectively incorporates the statistical characteristics of historical inflows into the generated data, demonstrating its suitability for producing inflow scenarios required for the optimization model.

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Declarations

Author contribution

Win Win Zin: Conceptualization, Methodology, Project management, Supervision, Reviewing and Editing. Zin Mar lar Tin San: Conceptualization, Methodology, Formal analysis, Reviewing and Editing. Yin Nwe Latt: Conceptualization, Methodology Investigation, Validation, Visualization, Manuscript Writing, Reviewing and Editing.

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Conflict of interest

The authors declare no conflict of interest in this research and publication.

Ethical Clearance

This research does not involve human subjects.

References

[1] B. S. Kim, H. S. Kim, and B. H. Seoh, "Streamflow simulation and skewness preservation based on the bootstrapped stochastic models," *Stochastic Environmental Research and Risk Assessment*, vol. 18, no. 6, pp. 386–400, Dec. 2004, https://doi.org/10.1007/s00477-004-0212-6

[2] M. I. Alfa, M. A. Ajibike, and D. B. Adie, "Reliability assessment of Thomas Fiering ' s method of stream flow prediction," *Nigerian Journal of Technology*, vol. 37, no. 3, p. 818, Jul. 2018, https://doi.org/10.4314/njt.v37i3.35

[3] R. Chetansinh, V. Vaghela, and R. V. Ajaysinh, "Synthetic Flow Generation," *Int. Journal of Engineering Research and Applications*, vol. 7, no. 6, pp. 66–71, 2014. https://www.ijera.com/papers/Vol4_issue7/Version%206/I047066671.pdf

[4] E. Ghaderpour and T. Vujadinovic, "The Potential of the Least-Squares Spectral and Cross-Wavelet Analyses for Near-Real-Time Disturbance Detection within Unequally Spaced Satellite Image Time Series," *Remote Sens (Basel)*, vol. 12, no. 15, p. 2446, Jul. 2020, https://doi.org/10.3390/rs12152446

[5] J. A. Ahmed and A. K. Sarma, "Artificial neural network model for synthetic streamflow generation," *Water Resources Management*, vol. 21, no. 6, pp. 1015–1029, Jun. 2007, https://doi.org/10.1007/s11269-006-9070-y

[6] K. Beven, "Issues in generating stochastic observables for hydrological models," *Hydrol Process*, vol. 35, no. 6, Jun. 2021, https://doi.org/10.1002/hyp.14203

[7] J. E. Kiang *et al.*, "A Comparison of Methods for Streamflow Uncertainty Estimation," *Water Resour Res*, vol. 54, no. 10, pp. 7149–7176, Oct. 2018, https://doi.org/10.1029/2018WR022708

[8] J. H. Stagge and G. E. Moglen, "A nonparametric stochastic method for generating daily climate-adjusted streamflows," *Water Resour Res*, vol. 49, no. 10, pp. 6179–6193, Oct. 2013, https://doi.org/10.1002/wrcr.20448

[9] S. Medda and K. K. Bhar, "Comparison of single-site and multi-site stochastic models for streamflow generation," *Appl Water Sci*, vol. 9, no. 3, p. 67, Apr. 2019, https://doi.org/10.1007/s13201-019-0947-3

[10] A. A. Harms and T. H. Campbell, "An extension to the Thomas-Fiering Model for the sequential generation of streamflow," *Water Resour Res*, vol. 3, no. 3, pp. 653–661, Sep. 1967, https://doi.org/10.1029/WR003i003p00653

[11] A. Kurunç, K. Yürekli, and O. Çevik, "Performance of two stochastic approaches for forecasting water quality and streamflow data from Yeşil ι rmak River, Turkey, " *Environmental Modelling & Software*, vol. 20, no. 9, pp. 1195–1200, Sep. 2005, https://doi.org/10.1016/j.envsoft.2004.11.001

[12] G. S. Joshi and K. Gupta, "A simulation model for the operation of multipurpose multireservoir system for River Narmada, India," *Journal of Hydro-environment Research*, vol. 3, no. 2, pp. 96–108, Oct. 2009, https://doi.org/10.1016/j.jher.2009.07.002

[13] A. A. Yousif and F. K. Aswad, "Performance of ARIMA model and Modified ThomasFiering Model for Predicting the Monthly Rainfall Data for Tallafar Station," *Journal of Polytechnic*, vol. 6, no. 1, pp. 293–309, 2016, Accessed: Sep. 26, 2024. [Online]. Available: https://www.researchgate.net/publication/310023832_Performance_of_ARIMA_model_and_Modified_Thomas-_Fiering_Model_for_Predicting_the_Monthly_Rainfall_Data_for_Tallafar_Station

[14] "Thaphanseik Dam receives record inflows against last year - Global New Light Of Myanmar." Accessed: Sep. 26, 2024. [Online]. Available: https://www.gnlm.com.mm/thaphanseik-dam-receives-record-inflows-against-last-year/

[15] "Mu River - Wikipedia." Accessed: Sep. 26, 2024. [Online]. Available: https://en.wikipedia.org/wiki/Mu_River

[16] B. Jia, J. Zhou, Z. Tang, Z. Xu, X. Chen, and W. Fang, "Effective stochastic streamflow simulation method based on Gaussian mixture model," *J Hydrol (Amst)*, vol. 605, p. 127366, Feb. 2022, https://doi.org/10.1016/j.jhydrol.2021.127366

[17] N. A. Ismail, S. Harun, and Z. Yusop, "Synthetic simulation of streamflow and rainfall data using disaggregation models," *Malaysian Journal of Civil Engineering*, vol. 16, no. 2, Mar. 2018, https://doi.org/10.11113/mjce.v16.15666

[18] R. Baum, G. W. Characklis, and M. L. Serre, "Effects of Geographic Diversification on Risk Pooling to Mitigate Drought-Related Financial Losses for Water Utilities, " *Water Resour Res*, vol. 54, no. 4, pp. 2561–2579, Apr. 2018, https://doi.org/10.1002/2017WR021468

[19] T. Davie and N. W. Quinn, *Fundamentals of Hydrology*. Third Edition. | New York : Routledge, 2019. | Series: Routledge Fundamentals of Physical Geography

series | Previous edition: 2008.: Routledge, 2019. https://doi.org/10.4324/9780203798942

[20] P. Kabbilawsh, D. S. Kumar, and N. R. Chithra, "Performance evaluation of univariate time-series techniques for forecasting monthly rainfall data," *Journal of Water and Climate Change*, vol. 13, no. 12, pp. 4151–4176, Dec. 2022, https://doi.org/10.2166/wcc.2022.107

[21] Z. ŞEN, "A mathematical model of monthly flow sequences / Un modèle mathématique des séquences débits mensuels," *Hydrological Sciences Bulletin*, vol. 23, no. 2, pp. 223–229, Jun. 1978, https://doi.org/10.1080/02626667809491791

[22] Dr. Cheleng A. Arselan, "Stream flow Simulation and Synthetic Flow Calculation by Modified Thomas Fiering Model," *AL-Rafdain Engineering Journal (AREJ)*, vol. 20, no. 4, 2012, https://doi.org/10.33899/rengj.2012.54160

[23] Q. Cui, X. Wang, C. Li, Y. Cai, and P. Liang, "Improved Thomas–Fiering and wavelet neural network models for cumulative errors reduction in reservoir inflow forecast," *Journal of Hydro-environment Research*, vol. 13, pp. 134–143, Dec. 2016, https://doi.org/10.1016/j.jher.2015.05.003

[24] F. Kh. Aswad, A. A. Yousif, and S. A. Ibrahim, "Evaluation the Best Random Component in Modified Thomas-Fiering Model in Generating Rainfall Data for Akre station," *Polytechnic Journal*, vol. 9, no. 2, pp. 186–192, Dec. 2019, https://doi.org/10.25156/ptj.v9n2y2019.pp186-192

[25] A. Bikos, P. E. Nastou, G. Petroudis, and Y. C. Stamatiou, "Random Number Generators: Principles and Applications," *Cryptography*, vol. 7, no. 4, p. 54, Oct. 2023, https://doi.org/10.3390/cryptography7040054

[26] M. I. Brunner and E. Gilleland, "Stochastic simulation of streamflow and spatial extremes: a continuous, wavelet-based approach," *Hydrol Earth Syst Sci*, vol. 24, no. 8, pp. 3967–3982, Aug. 2020, https://doi.org/10.5194/hess-24-3967-2020

[27] M. R. Ray and A. K. Sarma, "Importance of input parameter selection for synthetic streamflow generation of different time step using ann techniques," in *Proceedings of the International Conference on Neural Computation Theory and Applications*, SciTePress - Science and and Technology Publications, 2011, pp. 211–217. https://doi.org/10.5220/0003681802110217

[28] I. Dashora, S. K. Singal, and D. K. Srivastav, "Software Application for Data Driven Prediction Models for Intermittent Streamflow for Narmada River Basin, " *Int J Comput Appl*, vol. 113, no. 10, pp. 9–17, Mar. 2015, https://doi.org/10.5120/19860-1817

[29] S. Sathish and S. K. Khadar Babu, "Stochastic time series analysis of hydrology data for water resources," *IOP Conf Ser Mater Sci Eng*, vol. 263, p. 042140, Nov. 2017, https://doi.org/10.1088/1757-899X/263/4/042140