Available online at www.CivileJournal.org

Civil Engineering Journal

(E-ISSN: 2476-3055; ISSN: 2676-6957)

Vol. 11, No. 01, January, 2025

Machine Learning and the GR2M Model for Monthly Runoff Forecasting

Natapon Kaewthong [1], Torlap Kanplumjit [1], Naras Kwanthong [2], Kritsana Sureeya [3], Chayanat Buathongkhue [4*]

[1] *Department of Civil Engineering, Faculty of Engineering Rajamangala University of Technology Srivijaya, Songkhla 90000, Thailand.*

[2] *Faculty of Engineering and Technology Rajamangala University of Technology Srivijaya, Trang 92150, Thailand.*

[3] *Research assistant, Rajamangala University of Technology Srivijaya, Songkhla 90000, Thailand.*

[4] *College of Industrial Technology and Management, Rajamangala University of Technology Srivijaya, Nakhon Si Thammarat 80210, Thailand.*

Received 04 August 2024; Revised 09 December 2024; Accepted 15 December 2024; Published 01 January 2025

Abstract

This article presents the results of an analysis of monthly rainfall into monthly runoff using Machine Learning algorithms, including Multiple Linear Regression, Multilayer Perceptron, and Support Vector Machine, which were compared with the GR2M hydrologic model to identify the most suitable approach for rainfall-runoff analysis in watersheds in the lower southern region of Thailand. This region is characterized by its unique geographic location at the border between Thailand and Malaysia. It faces challenges due to uncertainty in rainfall data, measured only on the Thai side, leading to a lack of corresponding data from Malaysia. The analysis found that the Machine Learning Support Vector Machine algorithm consistently provided the most accurate results across all sub-basins. Sub-basin TU02 achieved an MAE of 2.63 mm/month, while sub-basin X.119A had an MAE of 68.10 mm/month, sub-basin X.184 had an MAE of 145.05 mm/month, and sub-basin X.274 had an MAE of 66.08 mm/month. This research demonstrated the utility of advanced algorithms in rainfall-runoff analysis for areas with partial or incomplete data coverage. The findings confirm that the Machine Learning Support Vector Machine algorithm outperformed the Hydrologic Model (GR2M) in terms of accuracy and reliability. Therefore, this study concludes that applying the Machine Learning Support Vector Machine algorithm is an optimal approach for runoff prediction in the southern region of Thailand and provides a framework for potential applications in other areas with similar data and geographic challenges.

Keywords: Hydrologic Model; Runoff Forecasting; Machine Learning; GR2M; Thailand.

1. Introduction

The hydrologic assessment of rainfall-runoff is a complex process, especially in watersheds with national boundaries, where the constraints of rainfall measurements due to such boundaries can affect the accuracy of runoff estimates. Key factors contributing to errors include the lack of comprehensive temporal data for model calibration [1, 2] and the incompleteness of constants used in analytical processes [3, 4]. Furthermore, variability in inconsistent rainfall data increases the risk of errors, especially in regions with diverse geographical features, such as surface runoff loss and streamflow changes due to land-use modifications [5], soil permeability variations [6, 7], and evapotranspiration [8, 9]. Another issue to consider is climate and land use changes, which affect the water balance in river basins, locally and globally. Such changes are likely to increase the intensity of heavy rainfall and the frequency of flood events. For

* Corresponding author: chayanat.b@rmutsv.ac.th

http://dx.doi.org/10.28991/CEJ-2025-011-01-022

example, studies in the Yellow River basin [10], Kunhar [11], and Fujiang [12] found that changes in rainfall and land use affected water flow in the basin [13]. Moreover, changes in water resource management patterns also play an important role in mitigating the impacts of this variability, especially in vulnerable areas [10, 12].

In terms of model evaluation, various models such as HEC-HMS [14, 15], SWAT [16, 17], NAM [18, 19], and GR2M [20-22] are currently being used to estimate rainfall and runoff. Model performance comparisons, such as HEC-HMS with SWAT [23, 24] and GR2M [25], demonstrate the need to select an appropriate model to increase accuracy [26]. Meanwhile, the application of Machine Learning (ML), such as MLR, MLP, and SVM, in runoff forecasting has become increasingly popular due to its ability to handle more data than traditional hydrologic models [27, 28].

For Thailand, GR2M and ML have been applied to forecast runoff in the upper southern region [29-31]. However, the border area between Thailand and Malaysia, the Lower Part of the Peninsula – East Coast River basin of Thailand, is still an area of geographic complexity and limited rainfall data from Malaysia, resulting in high error rates for runoff analysis accuracy. Therefore, using ML algorithms is an important alternative because several studies confirm that ML can improve accuracy better than the GR2M model in certain cases [29, 32]. This study aims to explore the efficiency of GR2M and ML in forecasting runoff in the border basin between Thailand and Malaysia, which has never been analyzed before. The focus is on selecting the most appropriate model for warning flood risk areas and supporting water resource management during flash floods or droughts. In the future, rainfall forecasts provided by the Thai Meteorological Department and the Hydro-Informatics Institute (Public Organization) could be incorporated into the system to predict runoff in advance if the model achieves high accuracy. This integration would enhance the disaster warning system, enabling timely and accurate alerts for flood-prone areas. The expected results are models that improve runoff forecasting, support long-term water management, promptly warn of disasters, and reduce the impact on life, property, and ecosystems in risk areas, with the potential to be applied in other regions with similar topography and data limitations.

2. Study Area and Data Set

This study focuses on the lower eastern coast of Thailand, which forms a transboundary basin between Thailand and Malaysia. It is located in the southernmost part of Thailand, consisting of Pattani, Yala, Narathiwat, and parts of Songkhla provinces [33, 34]. The western and southern parts of the basin are adjacent to the Sankalakhiri mountain range, the border between Thailand and Malaysia. The direction of the river flow is from the south to the north and flows into the Gulf of Thailand. Most of the area is forested and mountainous, while the lower part of the basin is flat. The average elevation of the basin is between 0 and 1,535 MSL. The basin area measures 10,605 square kilometers, with the north and east bordering the Gulf of Thailand, the west bordering the Songkhla Lake Basin, and the south bordering Malaysia [35]. The southwest monsoon and northeast monsoon influence the area. In addition, occasional tropical depressions and typhoons come from the South China Sea, resulting in different seasons: the rainy season occurs from May to January, and the hot season occurs from February to April.

Monthly meteorological and hydrological data were collected from various central agencies, such as climate data and evaporation data from the Meteorological Department(TMD) and Hydro-Informatics Institute (Public Organization: HII), with monthly rainfall at 8 stations: BTGH(2017-2023), TU02(2017-2023), VLGE35(2017-2023), STH019(2017-2023), STH013(2017-2023), STH014(2017-2023), BUKT(2018-2023), STH021(2018-2023), and runoff data from 2 agencies, the Royal Irrigation Department(RID) and the Electricity Generating Authority of Thailand(EGAT), consisting of 4 stations: X.184, X.119A, X.274, TU02. Runoff data also came from the Royal Irrigation Department at 3 stations: X. 184 Saiburi River (SBR), X.119A Golok River (KLR-1), and X.274 Golok River (KLR-2). From the Electricity Generating Authority of Thailand, data came from 1 station at TU02 Pattani River (Pattani River: PTR), as shown in Figure 1.

In summary, the physical geographical characteristics of the studied river basin are as follows. The river basin area (A) had values of 225.49–1260.04 square kilometers. The main river (L) length ranged from 23.58 to 69.52 kilometers (Table 1). The length of the main river to the center of gravity of the basin (Lc) was 5.52 - 31.52 kilometers. The slope of the basin (S) was 0.00108-0.02649. The From Factor (FF) was 0.2320 - 0.4055, and the Elongation ratio (ER) was between 0.5434 - 0.7183. The From Factor (FF) is the ratio of watershed area to the square of the watershed length. The elongation ratio is the ratio of the diameter of a circle in the same area as the basin to the maximum basin length (1.128A0.5/L), as shown in Table 2.

Table 1. Summary of physical geographical characteristics at water monitoring stations

No.	Runoff Station	Period	Sub-Basin	A (km^2)	L (km)	Lc (km)	S	FF	ER
1	X.184	2017-2023	SBR	1260.04	69.52	21.67	0.00108	0.2607	0.5760
2	X.119A	2018-2023	KLR-1	913.39	62.74	31.52	0.02649	0.2320	0.5434
3	X.274	2017-2023	KLR-2	225.49	23.58	5.52	0.00993	0.4055	0.7183
4	TU02	2017-2023	PTR	729.17	43.56	21.16	0.00367	0.3844	0.6993

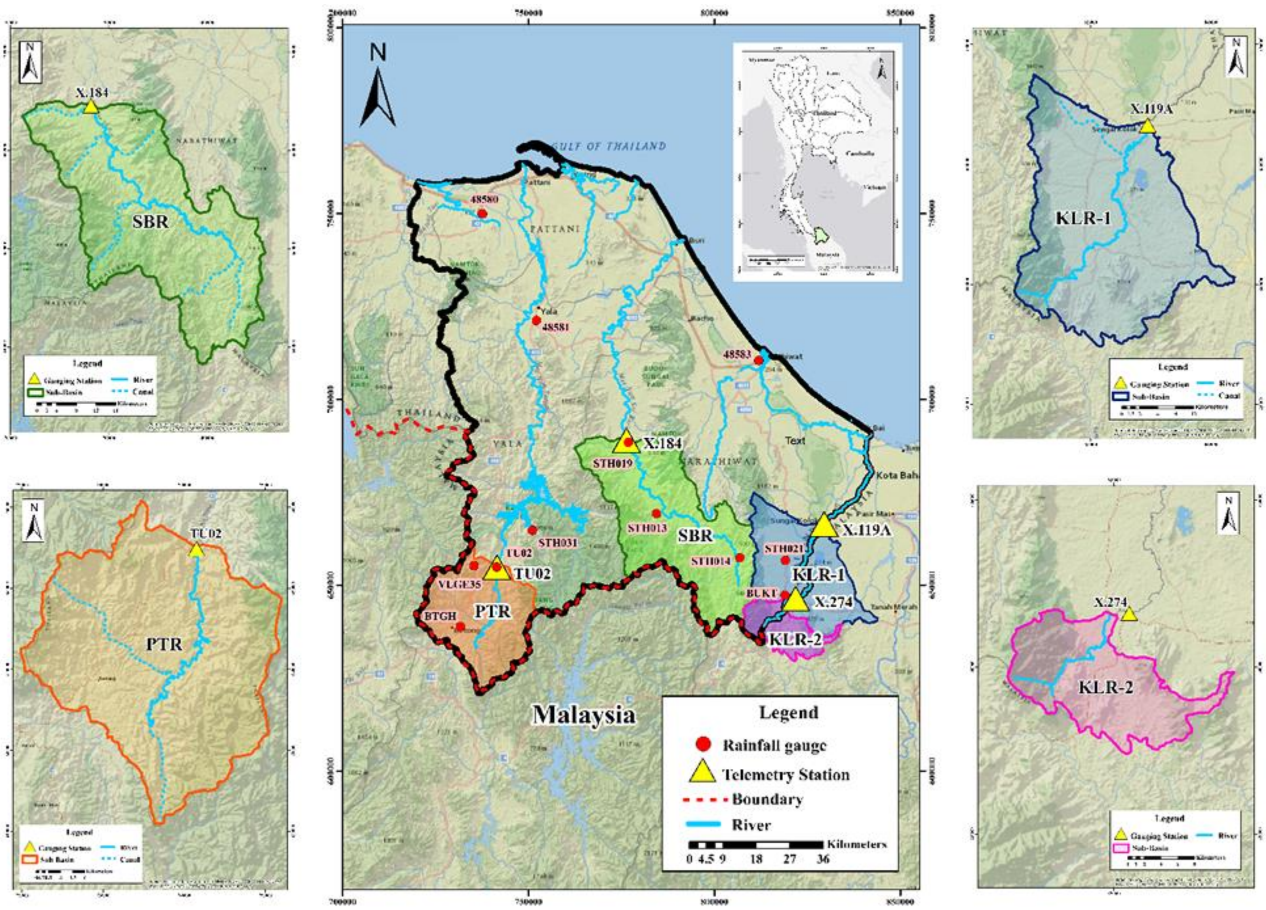


Figure 1. Location of rainfall and runoff stations in the study area

Table 2. Proportion of rain gauge stations affecting sub-basins

Runoff Station	Sub-basin	Rain Gauge Stations	Area (sq. km)	Weightage factor: wf
X.119A	KLR-1	BUKT	525.94	0.576
		STH021	322.35	0.353
		STH014	65.10	0.071
TU02	PTR	BTGH	460.44	0.632
		TU02	145.81	0.200
		VLGE35	122.92	0.169
X.184	SBR	STH013	528.87	0.420
		STH014	442.79	0.351
		STH019	266.14	0.211
		BUKT	22.24	0.018
X.274	KLR-2	BUKT	225.49	1.000

3. Methodology and Prediction Model

3.1. Methodology

This article studies the prediction of monthly runoff using three data variables: monthly rainfall, monthly evaporation, and monthly runoff. It is the foremost information for predicting monthly runoff. It starts by determining the proportion of influence of rain stations using the Thiessen polygon method. This study used 8 rain stations: BUKT, STH021, STH014, BTGH, TU02, VLGE35, STH013, and STH019. Then, all data are normalized so that the value of each variable is between 0 and 1. Then, that data will be entered into the model to create a runoff prediction model. In this study, 4 models were chosen for comparison of performance: multiple linear regression, multilayer perceptron, support vector machine, and GR2M. When the model construction was completed, the results were compared to the performance of the models by using the correlation coefficient and mean absolute error, as shown in Figure 2.

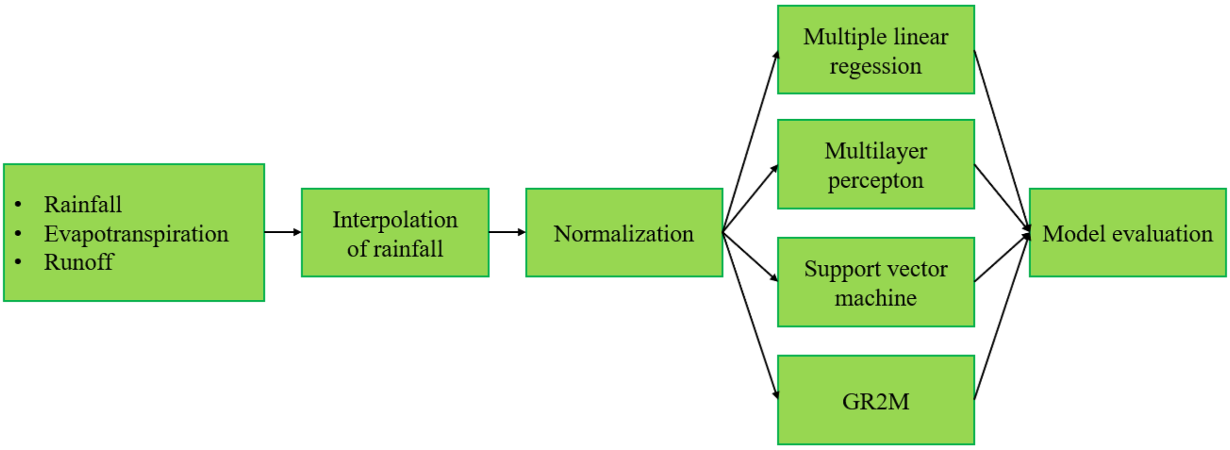


Figure 2. Block diagram of the modeling processes

3.2. Multiple Linear Regression

Multiple linear regression is a data analysis tool used to identify the relationship between a dependent variable and multiple independent variables. It takes advantage of the linear nature of these relationships to make predictions. A multiple linear regression equation represents the quantitative relationship between variables and can be presented as an equation, such as Equation 1 below.

$$y_i = \beta_0 = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n + \epsilon \quad (1)$$

where y_i is the dependent variable, β_0 and β_i are the intercept and coefficient of regression, respectively, x_i represents an independent variable, and ϵ is the error term [36].

3.3. Multilayer Perceptron

There are many types of artificial neural networks (ANN), including the multi-layer perceptron (MLP) [37], which comprises multiple layers of fully connected nodes. An MLP is composed of an input layer, one or more hidden layers, and an output layer, as illustrated in Figure 3. Activation functions play a crucial role by introducing non-linearity to the model and are applied to the nodes of the hidden and output layers [38-40]

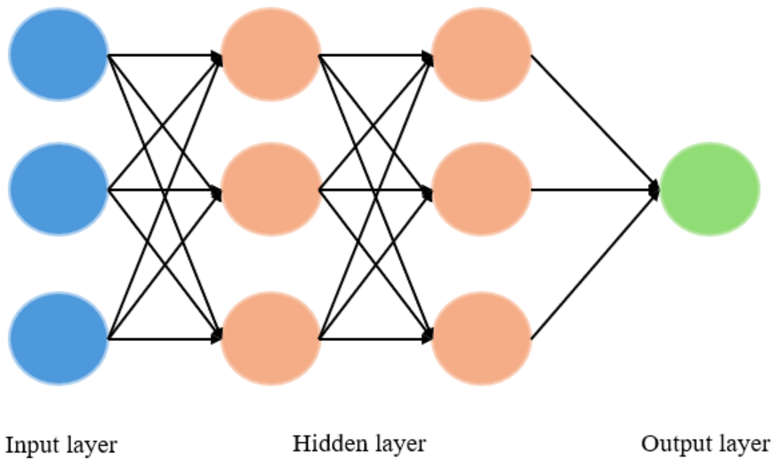


Figure 3. Multilayer perceptron

3.4. Support vector machine

The Support Vector Machine (SVM) is a widely prevalent supervised learning algorithm for regression and classification analysis. One of the key features of SVM is its ability to apply kernel functions to handle data that are linearly indivisible in the original dimensions. Commonly used kernel functions include linear, polynomial, and radial basis functions (RBF). The main goal of SVM is to find the most suitable hyperplane to separate the data into distinct clusters by optimizing the distance between the hyperplane and the nearest data point from each cluster. This distance is called the "margin," and the data points are called the "support vectors," as shown in Figure 4 [41].

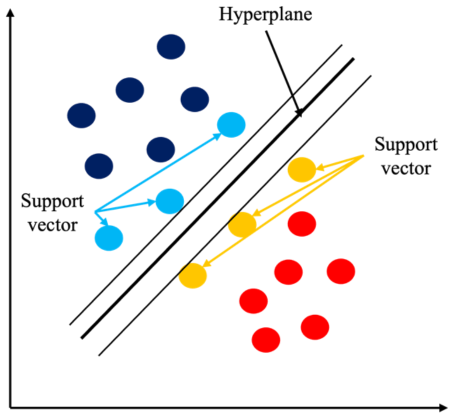


Figure 4. Support Vector Machine

3.5. GR2M

The GR2M model is a simple-to-use monthly rainfall and runoff model developed in the late 1980s with only two parameters: the ability to keep moisture in the soil (X_1) and the water exchange coefficient (X_2). The model requires three observed meteorological and hydrological inputs, including monthly rainfall, evapotranspiration, and runoff. Figure 5 shows the structure of the GR2M model, and the calculations for monthly rainfall and runoff are given in Equations 2 to 9 [42-44].

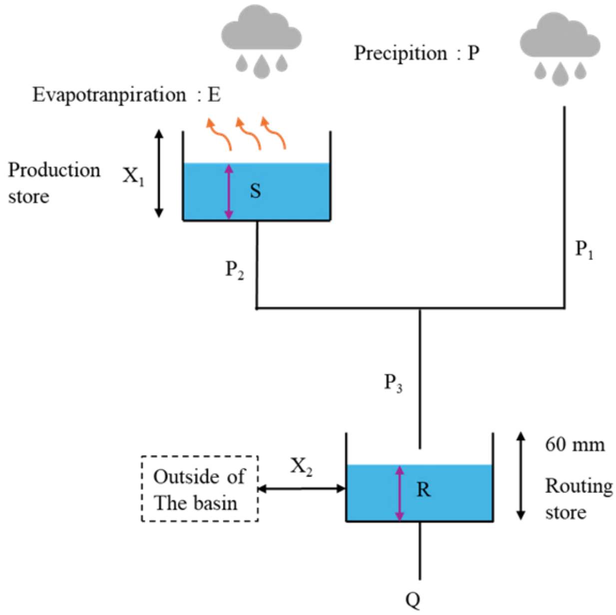


Figure 5. Structure of the GR2M model [31]

$$S_1 = \frac{S+X_1\varphi}{1+\varphi\frac{S}{X_1}} \text{ with } \varphi = \tanh(\frac{P}{X_1}) \tag{2}$$

$$P_1 = P + S + S_1 \tag{3}$$

$$S_2 = \frac{S_1(1-\psi)}{1+\psi(1+\frac{S_1}{X_1})} \text{ with } \psi = \tanh(\frac{E}{X_1}) \tag{4}$$

$$S = \frac{S_2}{(1+(\frac{S_2}{X_1})^3)} \tag{5}$$

$$P_3 = P_1 + P_2 \tag{6}$$

$$R_1 = R + P_3 \tag{7}$$

$$R_2 = X_2 \times R_1 \tag{8}$$

$$Q = \frac{R_2^2}{R_2+60} \tag{9}$$

where S_1 is the storage component, P is precipitation, E is evaporation, S is accumulated storage, S_1 is the primary storage component (Production store), S_2 is a secondary storage component (Routing store), P_1 is net precipitation in the first step, P_2 is net precipitation passing through S_2, P_3 is additional precipitation-related flow contributing to runoff, R_1 is total runoff in the first step, R_2 is total runoff in the final step, Q is the discharge rate, X_1 is a system capacity parameter for storage and non-linear relationships, and X_2 is the coefficient related to the transformation from R_1 to R_2.

3.6. Model Evaluation

In this research, statistical indicators were used to evaluate the performance of each model using two methods comprising mean absolute error (MAE), which considers the average absolute error between the observed and simulated values, and correlation coefficient (r), which is the linear relationship between two variables.

$$MAE = \frac{\sum_{i=1}^{n}|R_{Obs}-R_{Pred}|}{n} \tag{10}$$

$$r = \frac{\sum_{i=1}^{n}(R_{Obs}-\bar{R}_{Obs})(R_{Pred}-\bar{R}_{Pred})}{\sqrt{\sum_{i=1}^{n}(R_{Obs}-\bar{R}_{Obs})^2}\sqrt{\sum_{i=1}^{n}(R_{Pred}-\bar{R}_{Pred})^2}} \tag{11}$$

where R_{obs} is observed runoff, R_{pred} is predicted runoff, n is the amount of data or number of time periods, $\bar{R}_{obs}$ is average actual runoff, $\bar{R}_{pred}$ is average predicted runoff.

4. Results and Discussion

4.1. Thiessen Polygon

In Figure 6, the weighting factor (wf) of the rain gauge stations in the area is analyzed using the Thiessen Polygon method to estimate the average rainfall in each sub-basin using data from 8 rain gauge stations: BUKT, STH021, STH014, BTGH, TU02, VLGE35, STH013, and STH019.

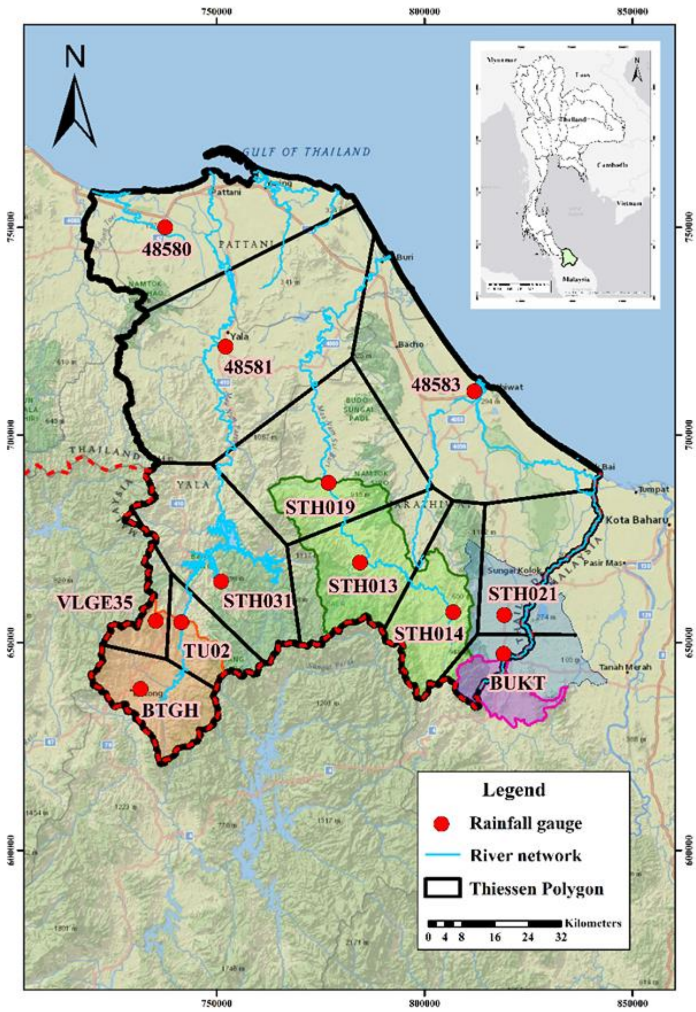


Figure 6. Thiessen polygon

Table 2 shows the details of the weighting factor (wf), which can be used to calculate the average rainfall in each sub-basin. It was found that each sub-basin had a different share of rain gauge stations, resulting in different weighting factor (wf) values for rainfall monitoring stations. For example, the KLR-1 sub-basin has three rainfall monitoring stations: BUKT, STH021, and STH014. It was found that BUKT has the highest weighting factor (wf) value of 0.576, followed by STH021 with a wf value of 0.353 and STH014 with a wf value of 0.071.

4.2. Compression Prediction Runoff Model

This research developed a model for forecasting monthly runoff volume from 8 rain gauge stations and evaporation data in 4 sub-basins, namely PTR, KLR-1, SBR, and KLR-2. The study compared the results of 4 models, consisting of Multiple Linear Regression (MLR), Multilayer Perceptron (MLP), Support Vector Machine (SVM) with Kernel Functions of Linear, Polynomial, and Radial Basis Function (RBF), and the GR2M model. The results can be considered for each sub-basin as follows:

The monthly runoff forecast results in the Pattani River Sub-basin (PTR) found that training the model using the support vector machine with a Radial Basis Function kernel: SVM(rbf) kernel had the best prediction performance with an MAE value of 2.47 mm/month, and the model testing using multi-layer perceptron: MLP and support vector machine with the linear kernel: SVM(linear) had the best prediction performance with MAE value of 2.61 and 2.63 mm/month, respectively, which provides higher accuracy than the GR2M method with an MAE value of 7.33. The details are shown in Figures 7 to 11, and Table 3.

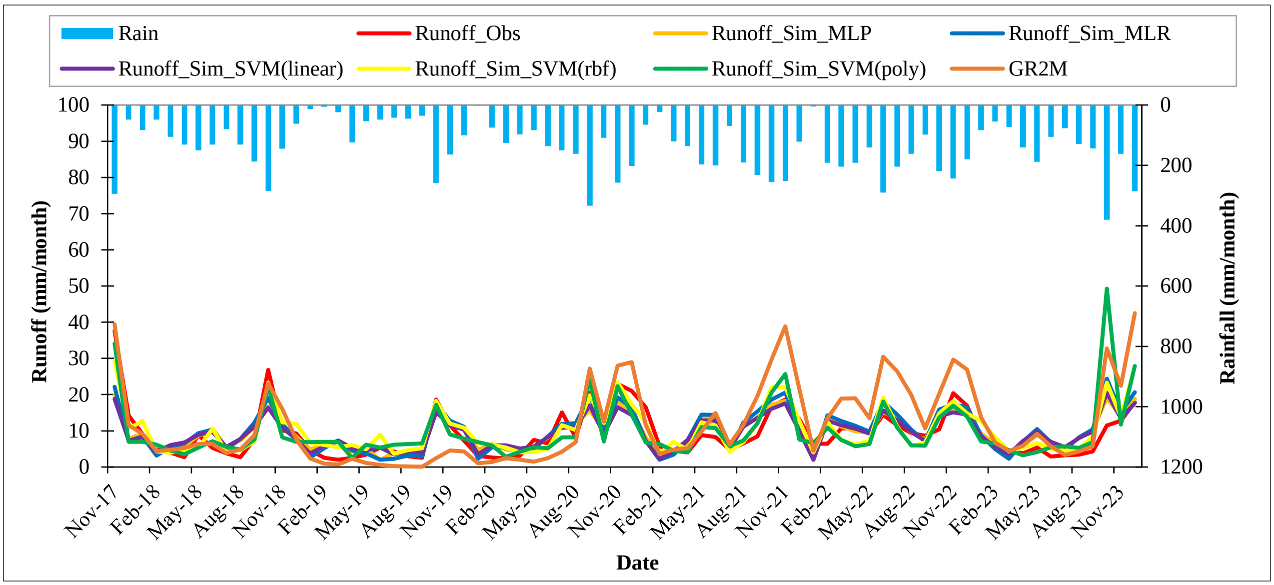


Figure 7. Pattani River Sub-basin (PTR)

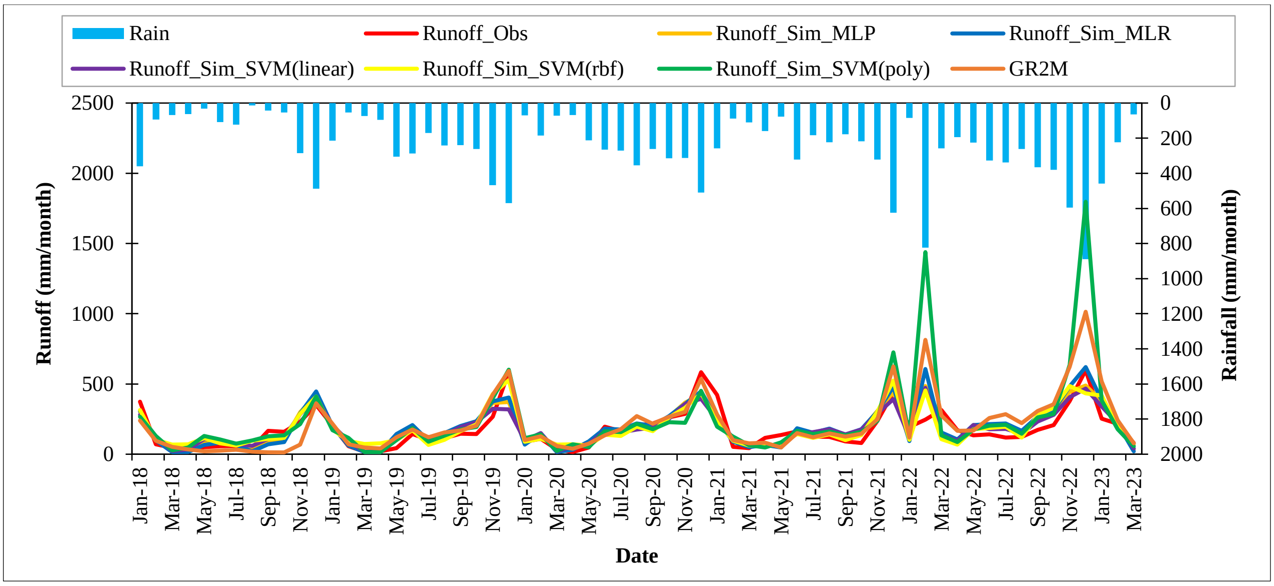


Figure 8. Golok River Sub-basin, Central Part (KLR-1)

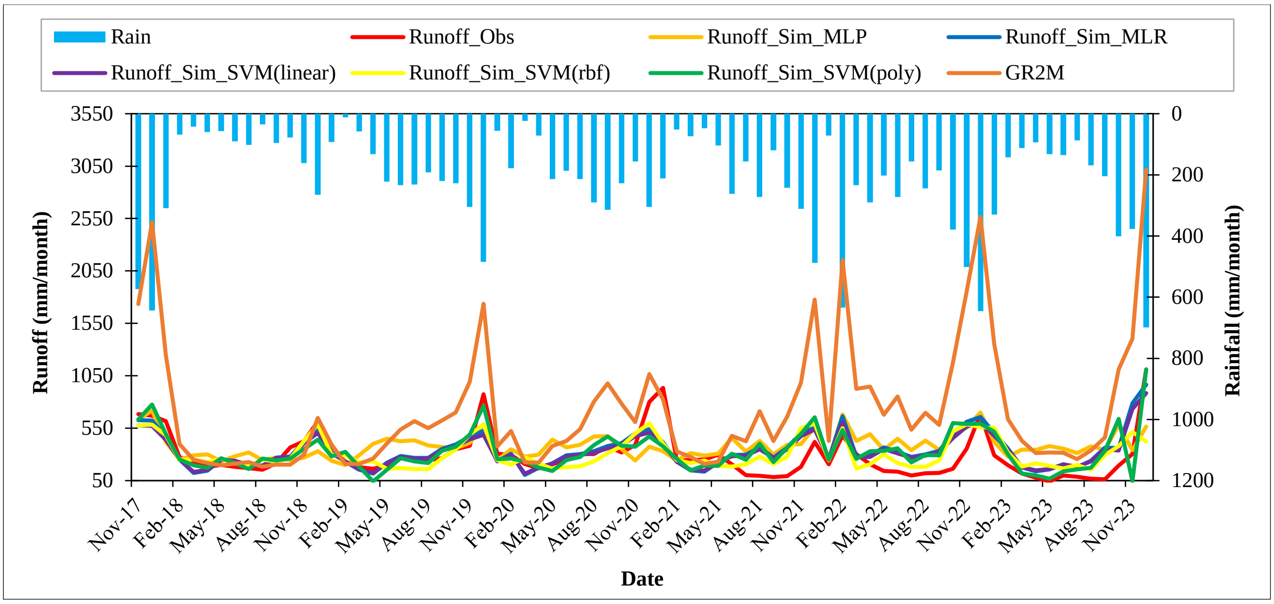


Figure 9. Saiburi River Sub-basin (SBR)

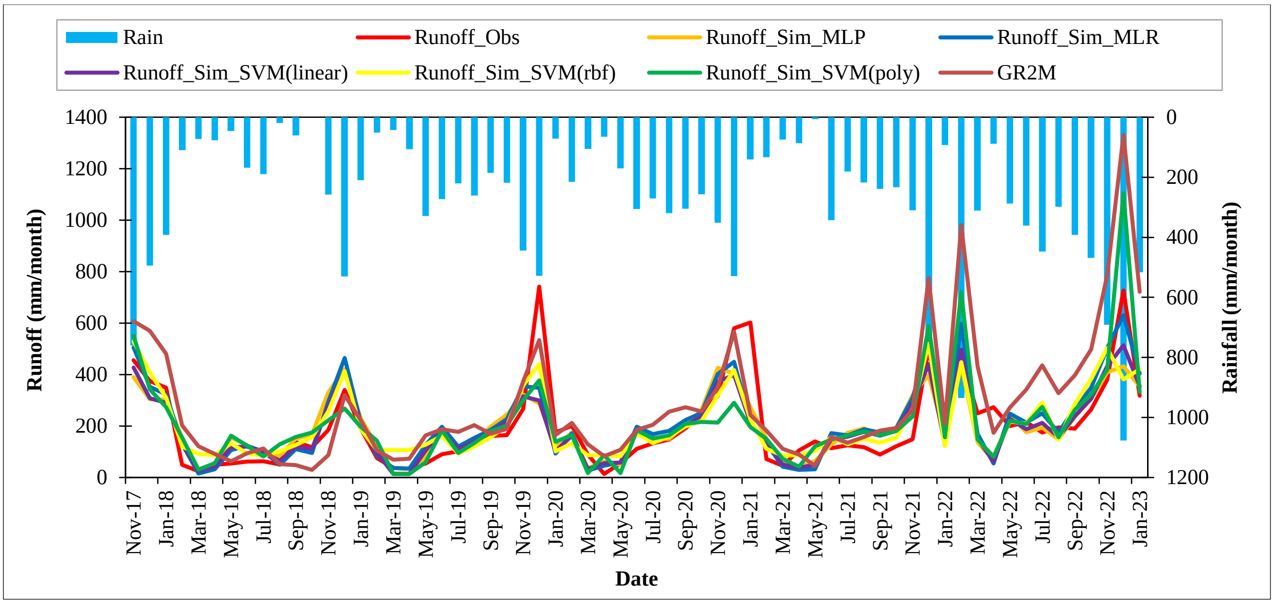
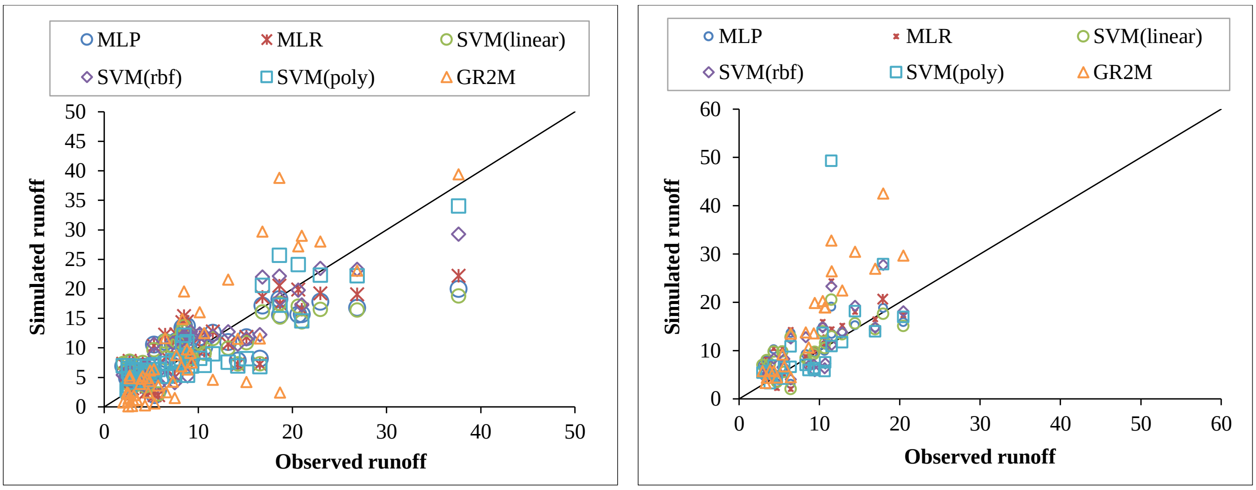


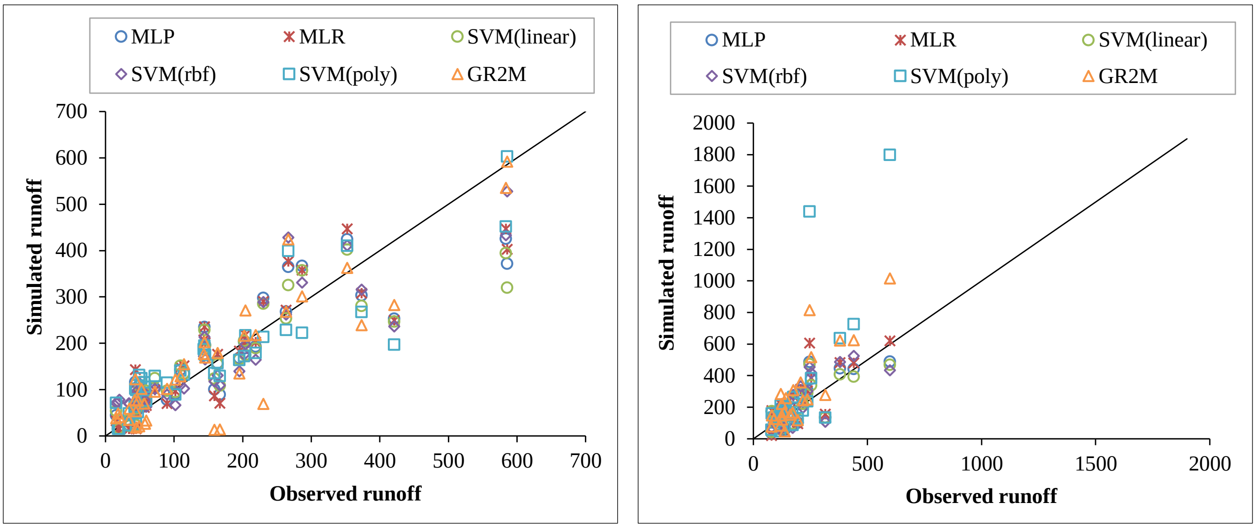
Figure 10. Golok River Sub-basin, Upper Part (KLR-2)



A. Train **B. Test**

Figure 11. Pattani River Sub-basin (PTR)

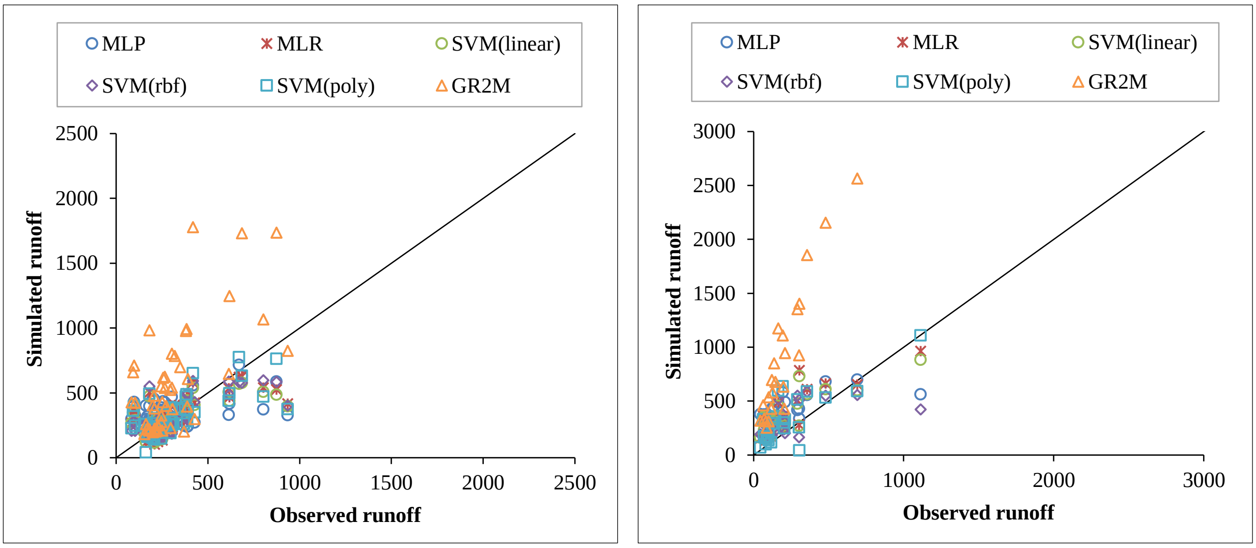
The monthly runoff forecast results in the Golok River Sub-basin, Central Part **(**KLR-1) found that training the model using the support vector machine with a polynomial kernel: SVM(poly) offered the best prediction performance, with an MAE value of 45.04 mm/month. Testing the model using the support vector machine with a linear kernel: SVM(linear) will have the best prediction performance, with an MAE value of 68.10 mm/month which gives higher accuracy than the GR2M method with an MAE value of 116.45. The details are shown in Figures 8 and 12, and Table 3.



A. Train **B. Test**

Figure 12. Golok River Sub-basin, Central Part (KLR-1)

The monthly runoff forecast results in the Saiburi River Sub-basin (SBR) found that training the model using the support vector machine with a linear kernel: SVM(linear) had the best prediction performance, with an MAE value of 91.85 mm/month. Testing the model using the support vector machine with a polynomial kernel: SVM(poly) will have the best prediction performance, with an MAE value of 145.05 mm/month which gives higher accuracy than the GR2M method with an MAE value of 736.80. The details are shown in Figures 9 and 13, and Table 3.



A. Train **B. Test**

Figure 13. Saiburi River Sub-basin (SBR)

The monthly runoff forecasting results in the Golok River Sub-basin, Upper Part (KLR-2) found that training the model and testing the model using a support vector machine with linear kernel: SVM (linear) will have the best prediction performance, with MAE values of 59.35 and 66.08 mm/month, respectively, which gives higher accuracy than the GR2M method, which has an MAE value of 175.95. The details are shown in Figures 10 and 14, and Table 3.

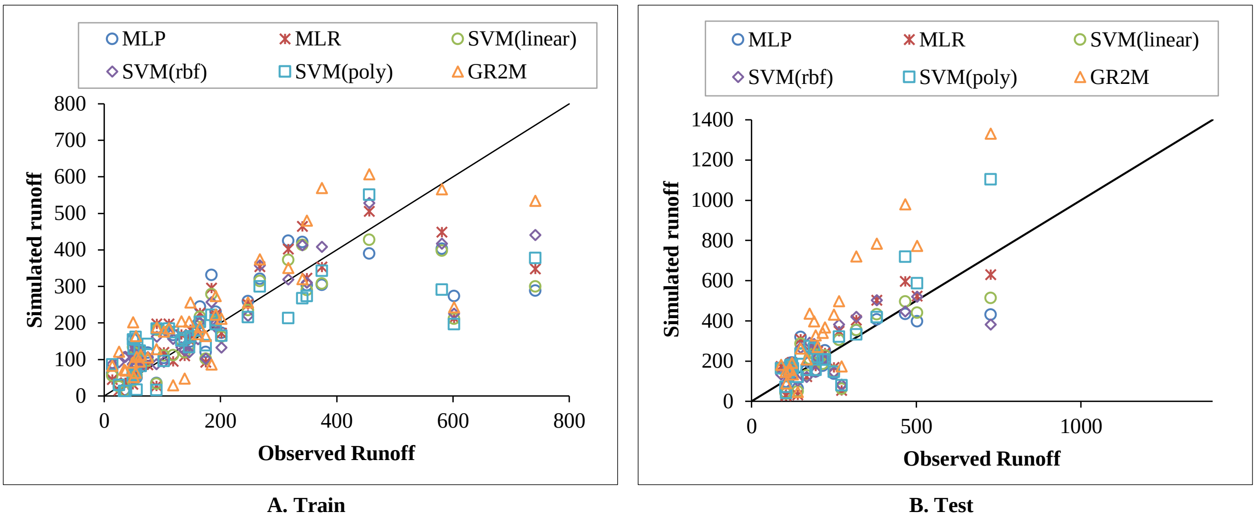


Figure 14. Golok River Sub-basin, Upper Part (KLR-2)

Table 3. Performance comparison

			MLP	MLR	SVM (linear)	SVM (rbf)	SVM (poly)	GR2M
PTR	Train	R	0.84	0.82	0.82	0.93	0.88	0.83
		MAE	3.13	3.21	3.25	2.47	2.65	3.96
	Test	R	0.79	0.76	0.75	0.77	0.54	0.91
		MAE	2.61	3.33	2.63	3.32	4.09	7.33
KLR-1	Train	R	0.89	0.89	0.88	0.91	0.90	0.89
		MAE	45.45	46.74	48.21	46.70	45.04	45.76
	Test	R	0.77	0.79	0.76	0.75	0.78	0.85
		MAE	73.11	82.97	68.10	77.65	172.67	116.45
SBR	Train	R	0.41	0.70	0.70	0.74	0.69	0.67
		MAE	144.48	92.77	91.85	91.99	96.48	305.58
	Test	R	0.64	0.84	0.84	0.57	0.79	0.93
		MAE	231.93	166.86	159.19	157.77	145.05	736.80
KLR-2	Train	R	0.77	0.79	0.79	0.85	0.77	0.82
		MAE	65.76	61.52	59.35	60.05	67.75	75.48
	Test	R	0.76	0.85	0.83	0.74	0.93	0.95
		MAE	72.61	77.55	66.08	70.96	77.19	175.95

As a comparison, it was found that both studies support that SVM(rbf) had the highest efficiency in forecasting monthly runoff when the results were compared with the research [31], especially in areas with complex or low-quality data such as the PTR and KLR-1 river basins. In this research, SVM(rbf) had the lowest MAE (2.47 mm/month and 45.04 mm/month), and the research [28] gave an average NSE of 0.595 and average r of 0.805, which were the best in the validation step. Both studies also showed that Kernel Functions significantly affected the accuracy of SVM, with SVM(rbf) being suitable for non-linear data. At the same time, GR2M, despite being easy to use, gave significantly lower results than other MLS (average NSE of 0.566 and average r of 0.760), especially in cases where the data had low correlation between variables.

5. Conclusion

This article studies the development of models to predict runoff in the lower eastern region of southern Thailand, which consists of 4 sub-basins comprising the PTR sub-basin, KLR-1 sub-basin, SBR sub-basin, and KLR-2 sub-basin. In this paper, 4 models are used to predict monthly runoff: multivariate linear regression, multi-class perceptron, support vector machine, and GR2M. In the PTR sub-basin, SVM(rbf) gives the lowest MAE (2.47 mm/month) and the highest r (0.93), which means the best forecasting performance in the Training Phase. MLP and SVM(linear) have the lowest MAE (2.61 mm/month), but SVM(rbf) has a higher r-value of 0.77, indicating a more accurate prediction in terms of a linear relationship. GR2M has the lowest MAE and r, indicating that its performance is unsuitable in this basin for the Testing Phase. Therefore, the model SVM(rbf) is the most suitable for training, and MLP/SVM(linear) has equivalent predictive ability in testing. In the KLR-1 sub-basin, SVM(poly) gave the lowest MAE (45.04 mm/month) and the highest r value (0.91) for the Training Phase. In the Testing Phase, SVM(linear) had the lowest MAE (68.10 mm/month), but SVM(rbf) had a higher r-value (0.77), and GR2M had the highest MAE (116.45 mm/month), indicating the lowest performance. Therefore, SVM(poly) is the most suitable for training, but SVM(linear) performs best in the Testing Phase. In the SBR sub-basin, SVM(linear) gave the lowest MAE (91.85 mm/month) and the highest r value (0.84) for the Training Phase. For the Testing Phase, SVM(poly) gave the lowest MAE (145.05 mm/month), with GR2M having the highest MAE (736.80 mm/month), indicating the lowest performance. Although SVM(linear) performed best in the training phase, SVM(poly) provided more accurate predictions in the testing phase. In the KLR-2 sub-basin, SVM(linear) gave the lowest MAE (59.35 mm/month) and the highest r value (0.95) for the Training Phase. For the Testing Phase, SVM(linear) gave the lowest MAE (66.08 mm/month) and the highest r value (0.83), while GR2M had the highest MAE (175.95 mm/month), indicating the lowest performance. From the results in this sub-basin, SVM(linear) was found to be the most suitable model in both the training and testing phases.

Simpler watersheds like PTR and KLR-2 benefited from kernels such as RBF and Linear due to their ability to efficiently model uniform hydrological patterns. In contrast, more diverse and complex watersheds, such as KLR-1 and SBR, required the flexibility of Polynomial Kernel to account for their variability and structured non-linear dynamics. These results emphasize the necessity of choosing a kernel that aligns with the distinct hydrological features of each watershed to maximize predictive accuracy.

The results of the accuracy analysis for each model in this research can be used with the 3-day rainfall forecast data prepared by the Thai Meteorological Department and the Hydro-Informatics Institute (Public Organization) of Thailand to use with this model to forecast water volume in the future, which will help increase the efficiency of disaster warning systems in both Thailand and Malaysia. In addition, such integration may help develop a natural disaster monitoring system in flood-prone border areas of ASEAN member countries, enabling timely and accurate warning of flood-prone areas to reduce potential damage in ASEAN member countries.

6. Declarations

6.1. Author Contributions

Conceptualization, B.C. and K.A.N.; methodology, KW.N., S.K., and K.A.N.; software, K.W.N. and S.K.; validation, B.C., K.A.N., and S.K.; formal analysis, B.C. and K.A.N.; investigation, B.C. and K.A.N.; resources, B.C. and K.A.N.; data curation, B.C., K.T., and S.K.; writing—original draft preparation, K.A.N. and B.C.; writing—review and editing, K.A.N. and B.C.; visualization, K.T. and S.K.; supervision, B.C. and K.A.N.; project administration, K.A.N.; funding acquisition, K.A.N. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

This article is a part of research called “Enhanced Community Capacity for Water Management for Consumption and Agriculture with IoT Technology Innovation in Conjunction with the Public Participation Process: A Case Study of Khok Pho District, Pattani Province”, which received funding and support from the Rajamangala University of Technology Srivijaya, to which the authors would like to express their gratitude.

6.4. Acknowledgements

The data used in this research were obtained from the Hydro-Informatics Institute (Public Organization), the Electricity Generating Authority of Thailand, the Royal Irrigation Department, and the Southern Meteorological Center (East Coast), for which the research team would like to express its gratitude. The main researcher is solely responsible for the data analysis results and is not affiliated with the data providers mentioned previously.

6.5. Conflicts of Interest

The authors declare no conflict of interest.

7. References

[1] Perrin, C., Oudin, L., Andreassian, V., Rojas-Serna, C., Michel, C., & Mathevet, T. (2007). Impact of limited streamflow data on the efficiency and the parameters of rainfall—runoff models. Hydrological Sciences Journal, 52(1), 131–151. doi:10.1623/hysj.52.1.131.

[2] Song, S., Ye, Z., Zhou, Z., Chuai, X., Zhou, R., Zou, J., & Chen, Y. (2024). Impacts of climate change and land cover factor on runoff in the Coastal Chinese Mainland region. Geography and Sustainability, 5(4), 526–537. doi:10.1016/j.geosus.2024.04.003.

[3] Alshammari, E., Abdul Rahman, A., Rainis, R., Abu Seri, N., & Ahmad, F. (2024). Investigation of Runoff and Flooding in Urban Areas based on Hydrological Models: A Literature Review. International Journal of Geoinformatics, 20(1), 3033. doi:10.52939/ijg.v20i1.3033.

[4] Zope, P. E., Eldho, T. I., & Jothiprakash, V. (2016). Impacts of land use–land cover change and urbanization on flooding: A case study of Oshiwara River Basin in Mumbai, India. CATENA, 145, 142–154. doi:10.1016/j.catena.2016.06.009.

[5] Mekonnen, Y. A., & Manderso, T. M. (2023). Land use/land cover change impact on streamflow using Arc-SWAT model, in case of Fetam watershed, Abbay Basin, Ethiopia. Applied Water Science, 13(5), 111. doi:10.1007/s13201-023-01914-5.

[6] Chaves, M. T. R., Farias, T. R. L., & Eloi, W. M. (2024). Comparative analysis of bioretention design strategies for urban runoff infiltration: a critical overview. Ecological Engineering, 207, 107352. doi:10.1016/j.ecoleng.2024.107352.

[7] Chen, H.-E., Chiu, Y.-Y., Tsai, T.-L., & Yang, J.-C. (2020). Effect of Rainfall, Runoff and Infiltration Processes on the Stability of Footslopes. Water, 12(5), 1229. doi:10.3390/w12051229.

[8] Love, D., Uhlenbrook, S., Corzo-Perez, G., Twomlow, S., & van der Zaag, P. (2010). Rainfall–interception–evaporation–runoff relationships in a semi-arid catchment, northern Limpopo basin, Zimbabwe. Hydrological Sciences Journal, 55(5), 687–703. doi:10.1080/02626667.2010.494010.

[9] Wang, D., & Alimohammadi, N. (2012). Responses of annual runoff, evaporation, and storage change to climate variability at the watershed scale. Water Resources Research, 48(5), W05546. doi:10.1029/2011wr011444.

[10] Wang, Y., Xu, H.-M., Li, Y.-H., Liu, L.-L., Hu, Z.-H., Xiao, C., & Yang, T.-T. (2022). Climate Change Impacts on Runoff in the Fujiang River Basin Based on CMIP6 and SWAT Model. Water, 14(22), 3614. doi:10.3390/w14223614.

[11] Waheed, A., Jamal, M. H., Javed, M. F., & Idlan Muhammad, K. (2024). A CMIP6 multi-model based analysis of potential climate change effects on watershed runoff using SWAT model: A case study of Kunhar river basin, Pakistan. Heliyon, 10(8), e28951. doi:10.1016/j.heliyon.2024.e28951.

[12] Lan, H., Zhao, Z., Li, L., Li, J., Fu, B., Tian, N., Lai, R., Zhou, S., Zhu, Y., Zhang, F., Peng, J., & Clague, J. J. (2024). Climate change drives flooding risk increases in the Yellow River Basin. Geography and Sustainability, 5(2), 193–199. doi:10.1016/j.geosus.2024.01.004.

[13] Zhang, H., Wang, B., Liu, D. L., Zhang, M., Leslie, L. M., & Yu, Q. (2020). Using an improved SWAT model to simulate hydrological responses to land use change: A case study of a catchment in tropical Australia. Journal of Hydrology, 585, 124822. doi:10.1016/j.jhydrol.2020.124822.

[14] Janicka, E., Kanclerz, J., Agaj, T., & Gizińska, K. (2023). Comparison of Two Hydrological Models, the HEC-HMS and Nash Models, for Runoff Estimation in Michałówka River. Sustainability, 15(10), 7959. doi:10.3390/su15107959.

[15] Souley Tangam, I., Yonaba, R., Niang, D., Adamou, M. M., Keïta, A., & Karambiri, H. (2024). Daily Simulation of the Rainfall–Runoff Relationship in the Sirba River Basin in West Africa: Insights from the HEC-HMS Model. Hydrology, 11(3), 34. doi:10.3390/hydrology11030034.

[16] Busico, G., Colombani, N., Fronzi, D., Pellegrini, M., Tazioli, A., & Mastrocicco, M. (2020). Evaluating SWAT model performance, considering different soils data input, to quantify actual and future runoff susceptibility in a highly urbanized basin. Journal of Environmental Management, 266, 110625. doi:10.1016/j.jenvman.2020.110625.

[17] Tasdighi, A., Arabi, M., & Harmel, D. (2018). A probabilistic appraisal of rainfall-runoff modeling approaches within SWAT in mixed land use watersheds. Journal of Hydrology, 564, 476–489. doi:10.1016/j.jhydrol.2018.07.035.

[18] Ghosh, A., Roy, M. B., & Roy, P. K. (2022). Evaluating the performance of MIKE NAM model on rainfall–runoff in lower Gangetic floodplain, West Bengal, India. Modeling Earth Systems and Environment, 8(3), 4001–4017. doi:10.1007/s40808-021-01347-6.

[19] Nannawo, A. S., Lohani, T. K., Eshete, A. A., & Ayana, M. T. (2022). Evaluating the dynamics of hydroclimate and streamflow for data-scarce areas using MIKE11-NAM model in Bilate river basin, Ethiopia. Modeling Earth Systems and Environment, 8(4), 4563–4578. doi:10.1007/s40808-022-01455-x.

[20] Fathi, M. M., Awadallah, A. G., & Aldahshoory, W. (2023). An Improved Monthly Water Balance GR2M Model with a Seasonally Variable Parameter. Journal of Hydrology, 617, 129127. doi:10.1016/j.jhydrol.2023.129127.

[21] Mendez, M., Calvo-Valverde, L.-A., Imbach, P., Maathuis, B., Hein-Grigg, D., Hidalgo-Madriz, J.-A., & Alvarado-Gamboa, L.-F. (2022). Hydrological Response of Tropical Catchments to Climate Change as Modeled by the GR2M Model: A Case Study in Costa Rica. Sustainability, 14(24), 16938. doi:10.3390/su142416938.

[22] Sadio, C. A. A. S., Faye, C., Pande, C. B., Tolche, A. D., Ali, M. S., Cabral-Pinto, M. M. S., & Elsahabi, M. (2023). Hydrological response of tropical rivers basins to climate change using the GR2M model: the case of the Casamance and Kayanga-Géva rivers basins. Environmental Sciences Europe, 35(1), 113. doi:10.1186/s12302-023-00822-4.

[23] Chekole, A. G., Belete, M. A., Fikadie, F. T., & Wubneh, M. A. (2024). Evaluate the performance of HEC-HMS and SWAT models in simulating the streamflow in the Gumara watershed, Ethiopia. Sustainable Water Resources Management, 10(1), 26. doi:10.1007/s40899-023-00997-x.

[24] Fanta, S. S., & Sime, C. H. (2021). Performance assessment of SWAT and HEC-HMS model for runoff simulation of Toba watershed, Ethiopia. Sustainable Water Resources Management, 8(1), 1-16. doi:10.1007/s40899-021-00596-8.

[25] Kate Flores Zuñiga, S., Junior Santos de la Cruz, E., & Santos Hurtado, S. (2022). Comparative analysis of GR2M, Temez and HEC-HMS Hydrological Models for runoff estimation in a high Andean basin. 2022 Congreso Internacional de Innovación y Tendencias En Ingeniería (CONIITI), 1–6. doi:10.1109/coniiti57704.2022.9953651.

[26] Gichamo, T., Nourani, V., Gökçekuş, H., & Gelete, G. (2023). Ensemble rainfall–runoff modeling of physically based semi-distributed models using multi-source rainfall data fusion. Journal of Water and Climate Change, 15(2), 325–347. doi:10.2166/wcc.2023.084.

[27] Mohammadi, B. (2021). A review on the applications of machine learning for runoff modeling. Sustainable Water Resources Management, 7(6), 98. doi:10.1007/s40899-021-00584-y.

[28] Singh, A. K., Kumar, P., Ali, R., Al-Ansari, N., Vishwakarma, D. K., Kushwaha, K. S., Panda, K. C., Sagar, A., Mirzania, E., Elbeltagi, A., Kuriqi, A., & Heddam, S. (2022). An Integrated Statistical-Machine Learning Approach for Runoff Prediction. Sustainability, 14(13), 8209. doi:10.3390/su14138209.

[29] Ditthakit, P., Pinthong, S., Salaeh, N., Binnui, F., Khwanchum, L., Kuriqi, A., Khedher, K. M., & Pham, Q. B. (2021). Performance Evaluation of a Two-Parameters Monthly Rainfall-Runoff Model in the Southern Basin of Thailand. Water, 13(9), 1226. doi:10.3390/w13091226.

[30] Ditthakit, P., Pinthong, S., Salaeh, N., Binnui, F., Khwanchum, L., & Pham, Q. B. (2021). Using machine learning methods for supporting GR2M model in runoff estimation in an ungauged basin. Scientific Reports, 11(1), 19955. doi:10.1038/s41598-021-99164-5.

[31] Ditthakit, P., Pinthong, S., Salaeh, N., Weekaew, J., Thanh Tran, T., & Bao Pham, Q. (2023). Comparative study of machine learning methods and GR2M model for monthly runoff prediction. Ain Shams Engineering Journal, 14(4), 101941. doi:10.1016/j.asej.2022.101941.

[32] Iamampai, S., Talaluxmana, Y., Kanasut, J., & Rangsiwanichpong, P. (2024). Enhancing rainfall–runoff model accuracy with machine learning models by using soil water index to reflect runoff characteristics. Water Science & Technology, 89(2), 368–381. doi:10.2166/wst.2023.424.

[33] Aedasong, A., Roongtawanreongsri, S., Hajisamae, S., & James, D. (2019). Ecosystem Services of a Wetland in the Politically Unstable Southernmost Provinces of Thailand. Tropical Conservation Science, 12. doi:10.1177/1940082919871827.

[34] Benharoon, S. Y. (2013). Building a Culture of Peace in Muslim Community in Southern Thailand through Family Communication. Procedia - Social and Behavioral Sciences, 91, 522–531. doi:10.1016/j.sbspro.2013.08.450.

[35] Anuar, A. R., & Harun, A. (2018). Malaysia-Thailand Cross Border Trade and Cross Border Special Economic Zone Potential: A Case Study of Rantau Panjang-Sungai Kolok Cross Border Town. Journal International Studies, 14. doi:10.32890/jis2018.14.8.

[36] Uyanık, G. K., & Güler, N. (2013). A Study on Multiple Linear Regression Analysis. Procedia - Social and Behavioral Sciences, 106, 234–240. doi:10.1016/j.sbspro.2013.12.027.

[37] Ahmed, A. A. M. (2022). Development of deep learning hybrid models for hydrological predictions. Ph.D. Thesis, University of Southern Queensland, Queensland, Australia.

[38] Patle, G. T., Chettri, M., & Jhajharia, D. (2020). Monthly pan evaporation modelling using multiple linear regression and artificial neural network techniques. Water Supply, 20(3), 800-808. doi:10.2166/ws.2019.189.

[39] Kassem, Y., Gökçekuş, H., Çamur, H., & Esenel, E. (2021). Application of artificial neural network, multiple linear regression, and response surface regression models in the estimation of monthly rainfall in Northern Cyprus. Desalination and Water Treatment, 215, 328-346. doi:10.5004/dwt.2021.26525.

[40] Prins, N. W., Sanchez, J. C., & Prasad, A. (2014). A confidence metric for using neurobiological feedback in actor-critic reinforcement learning based brain-machine interfaces. Frontiers in Neuroscience, 8. doi:10.3389/fnins.2014.00111.

[41] Vapnik, V. N. (2000). The Nature of Statistical Learning Theory. Springer, New York, United States. doi:10.1007/978-1-4757-3264-1.

[42] Kabouya, M. (1990). Rainfall-runoff modeling at monthly and annual time steps in northern Algeria. Ph.D. Thesis, University of Paris South Orsay, Orsay, France.

[43] Makhlouf, Z., & Michel, C. (1994). A two-parameter monthly water balance model for French watersheds. Journal of Hydrology, 162(3–4), 299–318. doi:10.1016/0022-1694(94)90233-x.

[44] Mouelhi, S., Michel, C., Perrin, C., & Andréassian, V. (2006). Stepwise development of a two-parameter monthly water balance model. Journal of Hydrology, 318(1–4), 200–214. doi:10.1016/j.jhydrol.2005.06.014.