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Prediction on Flood Risk in Batu Pahat using Spatial Analysis Approach

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Abstract

Floods are among the most frequent and destructive natural disasters in Malaysia, particularly affecting regions such as Batu Pahat, Johor, due to its low-lying terrain, rapid urbanization, and climate variability. The conventional flood prediction methods often fail to capture the spatial variability of flood risks, limiting their accuracy for localized assessments. This research aims to determine flood prediction in Batu Pahat hydrology station by using geospatial tools, implement the clustering analysis in categorizing the flood risk levels based on the rainfall intensity across multiple hydrology stations, and to predict the rainfall intensity in 2025 by using simple exponential smoothing (SES). This research employs geospatial tools like Local Moran's I and *k*-means clustering to analyse normalized rainfall data from 11 hydrology stations. Clustering methods were used to identify spatial patterns and categorize flood risks. SES was applied for predictive modelling of rainfall intensity. The findings reveal significant spatial clustering of rainfall intensity in urban areas, highlighting them as high-risk zones due to impermeable surfaces and poor drainage systems. Stations were categorized into low, medium, and high-risk zones, with SES predictions indicating the smoothing constant ($\alpha = 0.0915$) for Station 1 and the smoothing constant ($\alpha = 0.2183$) for Station 9 produce more efficient and better forecast in 2025 where the predicting rainfall intensities of 75.4 mm and 78.6 mm, respectively. The insights provide a foundation for improved urban planning, resource allocation, and disaster preparedness.

1. Introduction

Floods are one of the most frequent and devastating natural disasters, causing significant social, economic, and environmental impacts globally [1]. In Malaysia, low-lying regions like Batu Pahat, Johor, are particularly vulnerable due to a combination of factors such as rapid urbanization, insufficient drainage infrastructure, and climate variability [2]. Despite efforts to manage flood risks, the increasing frequency and severity of flood events underscore the limitations of existing mitigation strategies. Accurate flood prediction is essential for enhancing early warning systems, urban planning, and resource allocation, particularly in flood-prone areas.

Spatial analysis offers a robust approach for identifying high-risk zones, understanding contributing factors, and visualizing potential flood scenarios [3]. By integrating geospatial tools and predictive modelling techniques, this study seeks to address gaps in current methodologies and contribute to more effective flood management strategies in Batu Pahat.

Flooding is a recurring issue in Batu Pahat, Johor, caused by rapid urbanization, low-lying terrain, and seasonal monsoons [4]. These floods disrupt communities, economies, and the environment [5]. Despite existing flood management efforts, key gaps hinder effective prediction and mitigation. Conventional models lack accuracy because they fail to account for spatial factors such as land use changes, hydrology, and topography [6]. While techniques like Geographic Information Systems (GIS) have improved flood predictions elsewhere, their use in Batu Pahat is underdeveloped [7]. Additionally, no studies compare the reliability of spatial analysis models to conventional methods, making it hard to justify adopting advanced approaches [8]. Current efforts are reactive, providing limited support for proactive flood mitigation. Without a spatial analysis-based model, local authorities cannot accurately assess risks or allocate resources effectively.

Batu Pahat, located in the western part of Johor, Malaysia, spans an area of 187,702 hectares and consists of 14 sub-districts. Governed by the Majlis Perbandaran Batu Pahat (MPBP) and Majlis Daerah Yong Peng (MDYP), it is a rapidly developing district with significant economic activities in manufacturing, trade, and agriculture [9]. However, its geographic location and urban development make it highly susceptible to flooding, particularly during the monsoon season [10]. The district's rivers, including Sungai Batu Pahat and its tributaries, play a central role in its hydrological network but are often overwhelmed during heavy rainfall due to inadequate drainage and pollution [11].

Flooding is a recurring challenge in Batu Pahat, largely attributed to its low-lying terrain and urbanization. Heavy rainfall during monsoon seasons leads to river overflows, while insufficient drainage infrastructure exacerbates waterlogging [12]. Tidal influences further complicate the flood management landscape. Key areas such as Taman Universiti and Parit Raja are especially vulnerable due to poor drainage and rapid development [13]. The combined impact of physical and human-induced factors highlights the urgency of adopting comprehensive flood mitigation strategies.

Predictive modelling has been central to flood risk assessment in Malaysia. The use of ARIMA models has demonstrated efficacy in short-term water level forecasting, such as for rivers like Sungai Melaka [14]. Deep learning techniques, including Long Short-Term Memory (LSTM) networks, have shown high accuracy in multivariable flood predictions [15]. Additionally, logistic regression integrated with Geographic Information Systems (GIS) has been effective in urban flood hazard assessments, providing reliable identification of high-risk zones [16]. Real-time forecasting systems, such as the Fuzzy Inference System, have been successfully implemented in river basins like Kelantan to enhance disaster preparedness [17]. These methods collectively underscore the importance of combining statistical, machine learning, and geospatial techniques for precise flood prediction.

Spatial analysis plays a pivotal role in flood risk management. Techniques such as Local Moran's I enable the identification of spatial clusters and patterns, highlighting areas with heightened flood susceptibility. K-means clustering has proven effective in categorizing flood risks into distinct levels, facilitating targeted interventions. Tools like the Analytic Hierarchy Process (AHP) integrate environmental factors, such as slope and river proximity, to prioritize high-risk zone [18]. Hybrid models combining Support Vector Machines (SVM) and Index of Entropy (IoE) have achieved high predictive accuracy in mapping flood susceptibility [19]. These approaches demonstrate the utility of geospatial tools in enhancing our understanding of flood dynamics and informing proactive mitigation strategies.

The study is conducted with the specific objectives such as follows; 1) to determine flood prediction in Batu Pahat hydrology station by using geospatial tools; 2) to implement the clustering analysis in categorizing the flood risk levels based on the rainfall intensity across multiple hydrology stations and 3) to predict the rainfall intensity in 2025 by using simple exponential smoothing.

2. Materials and Methods

The methodology adopted for this research were designed to address spatial analysis by employing various method such as Local Moran's I, *k*-means clustering, and predict the flood risk by using simple exponential smoothing method. The analysis is conducted using statistical software tools, specifically Minitab and Microsoft Excel. Minitab is utilized for its advanced statistical analysis capabilities, while Microsoft Excel serves as a supplementary tool.

2.1 Normalizing Data

Floods are among the most frequent and destructive natural disasters in Malaysia, particularly affecting regions like Batu Pahat, Johor, due to its low-lying terrain, rapid urbanization, and climate variability. This study integrates spatial analysis techniques to predict flood risks by using rainfall data collected from 11 monitoring stations in Batu Pahat. The dataset, obtained from the Department of Irrigation and Drainage (DID), spans from 2003 to 2022 and includes measurements such as rainfall intensity and water levels.

Rainfall data collected at various intervals were normalized to a standard 60-minute duration to ensure comparability across stations. The normalization process involved calculating adjusted values through Eq. (1) and Eq. (2).

$$Duration = Hours \times 60 \tag{1}$$
$$Duration = Days \times 24 \times 60 \tag{2}$$

However, the durations such as 5Min, 15Min, 30Min, and 60Min were converted into minutes directly for uniformity. Each rainfall value was normalized to the 60-minute standard by using Eq. (3).

$$Value\ Adjusted = 60 \times \frac{Value}{Duration} \tag{3}$$

A new column was created to store the normalized values. This column ensures that all rainfall values represent the estimated intensity for a 60-minute period. This normalization allowed for consistent spatial analysis and ensured that differences in durations did not bias the results.

2.2 Spatial Clustering

Spatial clustering was performed using k-means and Local Moran's I. Local Moran's I is a statistical measure used to identify spatial clusters and outliers in the data [20]. It quantifies how similar a station's rainfall intensity is to its neighbouring stations, providing insights into spatial dependence. The calculation of Local Moran's I was followed by Eq. (4) [21];

$$I_i = z_i \sum_j w_{ij} z_j \tag{4}$$

where:

I_i is the Local Moran's I for station i,
z_i is the Standardized value of rainfall for station i,
w_{ij} is the Spatial weight between station i and j,
z_j is the Standardized value of rainfall for neighbouring station j.

The k-means clustering technique was used to group rainfall stations based on intensity and geographic proximity, optimizing the number of clusters using the Elbow Method through Eq. (5) [22];

$$WSS = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{5}$$

where:

C_i is the set of data points in cluster i,
u_i is the centroid of cluster i,
x is an individual data point,
$\|x - \mu_i\|^2$ is the squared Euclidean distance between data point and cluster centroid.

Local Moran's I assessed spatial autocorrelation, revealing significant clustering patterns and identifying high-risk zones requiring targeted interventions. These methods allowed for a granular understanding of flood risk distribution across the study area.

2.3 Simple Exponential Smoothing

SES was employed to forecast rainfall intensity for the year 2025. This time-series method emphasizes recent observations through Eq. (6) [23];

$$l_T = \alpha y_T + (1 - \alpha) l_{T-1} \tag{6}$$

where:

l_T represents the forecast for the next time period,
y_T is the observed value at time T,

l_{T-1} is the forecast for the current time period,
α represents the smoothing constant.

SES is particularly suited for datasets with no discernible trends or seasonality [24]. To evaluate the accuracy of the forecasts, metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD) were calculated through the Eq. (7) and Eq. (8) respectively [25].

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{T}|y_t - l_{T-1}| \tag{7}$$

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{T}(y_t - l_{T-1})^2 \tag{8}$$

where:
n represents the number of observations,
y_T is the observed value at time T,
l_{T-1} is the forecast for the current time period.

3. Results and Discussions

The analysis is conducted to provide a demographic characteristic of rainfall stations, analyses spatial clustering patterns, evaluates the effectiveness of the Simple Exponential Smoothing (SES) model, and integrates these findings to provide actionable insights for flood risk management in Batu Pahat. The ensuing discussion will shed light on the strengths, limitations, and practical implications of each approach, guiding the reader through a nuanced understanding of the forecasting landscape employed in this study.

3.1 Demographic

Table 1 shows the 11 rainfall monitoring stations in Batu Pahat are distributed across urban and rural areas, ensuring comprehensive data collection. This geographic spread captures variations in rainfall intensity influenced by topography and land use, enabling a localized assessment of flood risks.

Table 1 Coordinates of 11 Stations in Batu Pahat

No	Stations	Latitude	Longitude
1	Pintu Kawalan Sembrong	1.875000	103.054167
2	Ladang Union	2.130556	103.050278
3	Pintu Kawalan Separap	1.920833	102.928333
4	Kerja Air Parit Sulong	1.981944	102.925000
5	Rumah Pengawas Parit Raja	1.869444	103.112500
6	Pintu Pasang Surut Senggarang	1.745833	103.056944
7	Ladang Yong Peng	2.070833	103.152778
8	Ladang Sri Gading	1.840278	103.020833
9	SMK Munshi Sulaiman	1.866944	102.981944
10	Pintu Kawalan Parit Saidi	1.737500	103.108333
11	Pintu Pasang Surut Sungai Rengit	1.666944	103.148611

A visual representation of the spatial distribution of the 11 rainfall monitoring stations in Batu Pahat is provided in Fig. 1. Each station is geolocated using its specific latitude and longitude coordinates, ensuring accurate mapping across the district. The map highlights the strategic placement of these stations to capture diverse rainfall patterns across urban and rural regions, contributing to a robust dataset for flood risk analysis.

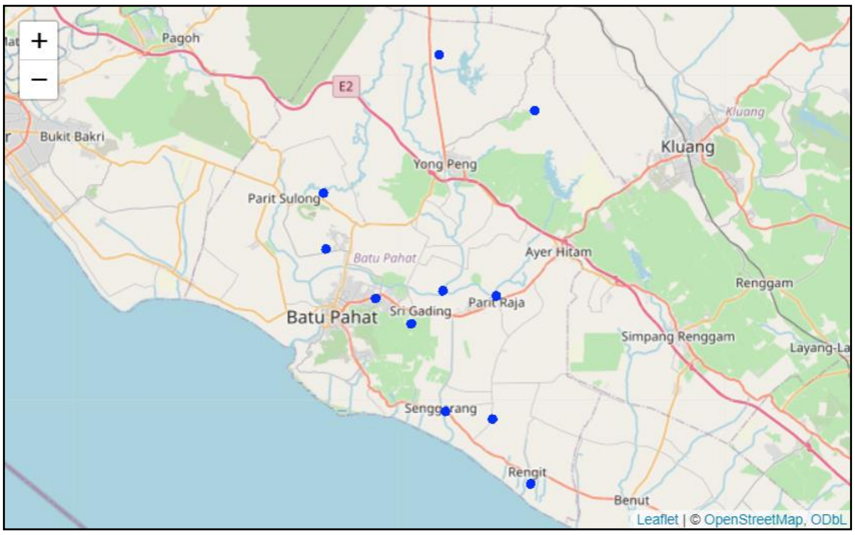


Fig. 1 Stations Mapping in Batu Pahat

3.2 Flood Prediction by Using Spatial Analysis

The spatial analysis was conducted to predict flood risk levels in Batu Pahat based on rainfall intensity data across 11 monitoring stations. The primary tool for this analysis was Local Moran's I, a geostatistical method used to identify spatial autocorrelation and clustering patterns. By integrating spatial data with rainfall intensity values, the study explored the spatial distribution of flood risks (see Fig. 2).

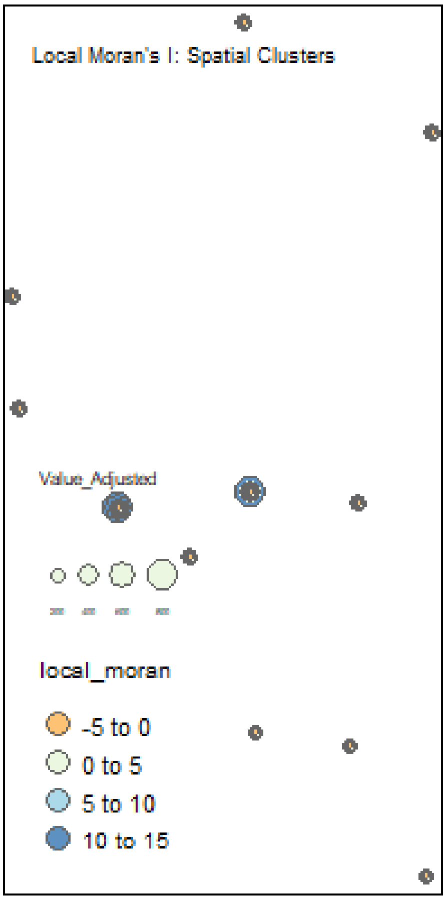


Fig. 2 *Thematic Map (tmap) Visualization*

Meanwhile, Fig. 2 shows the thematic map that provides a clear representation of the Local Moran's I values for different locations within the study area. Each point on the map corresponds to a station, with the size and colour of the points reflecting two variables; Value Adjusted represents the circle size that increases with the adjusted value for each station, possibly indicating the rainfall intensity or another related metric. Meanwhile for Local Moran's I represents the colour gradient represents the range of Local Moran's I values, categorized into four bins such as negative spatial autocorrelation (-5 to 0), weak positive spatial autocorrelation (0 to 5), moderate positive spatial autocorrelation (5 to 10), and strong positive spatial autocorrelation (10 to 15).

Stations with dark blue markers (10 to 15) signify areas with significant clustering, either high or low, based on flood-related variables like rainfall or elevation. These clusters might be hotspots for flood risks. Stations with lighter colours or orange shades reflect areas with weak clustering or contrast with their surroundings. These stations may be located at transitional or diverse zones in terms of risk levels.

3.3 Flood Prediction by Using Clustering

The k-means clustering was employed to categorize the flood risk levels of the 11 stations based on rainfall intensity. The k-means algorithm is widely used in data analysis for partitioning data into meaningful clusters by minimizing the within-cluster sum of squares (WSS) (see Table 2).

Table 2 Within Sum of Squares Values (WSS)

k	Within Sum of Squares (WSS)
1	13362649.6
2	7370514.3
3	3952378.6
4	2710073.8
5	1455031.4
6	1038036.6
7	705401.2
8	541027.1
9	442017.8
10	358875.1

The k-means clustering algorithm was performed with values of k ranging from 1 to 10 to determine the most appropriate number of clusters for categorizing flood risk levels. The analysis involved calculating the total within-cluster sum of squares (WSS) for each k, with the results stored for further evaluation. To ensure consistency and reliability of the results, the parameter nstart was set to 25, meaning the algorithm was run 25 times with different initial centroid positions for each value of k. This approach minimizes the risk of suboptimal clustering caused by random centroid initialization.

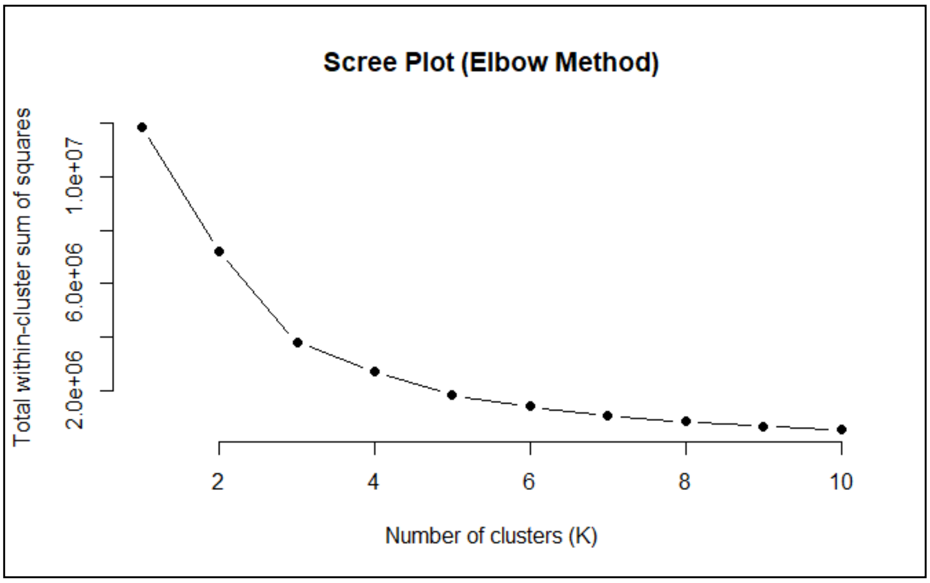


Fig. 3 *Scree plot*

From the results in Table 2 and Fig. 3, it was observed that $k = 3$ provided a meaningful balance between minimizing WSS and ensuring interpretability of the results. This suggests that the stations can be grouped into three flood risk levels. Based on the clustering for $k = 3$, the stations were categorized into three flood risk levels such as low risk, medium risk, and high risk. The categorization was achieved by assigning each station to the cluster with the nearest centroid.

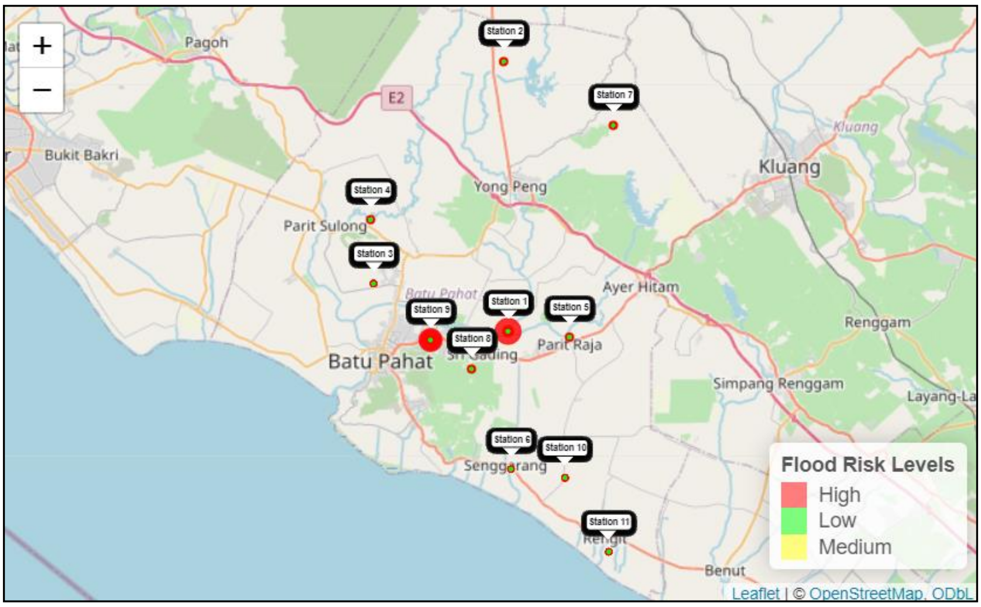
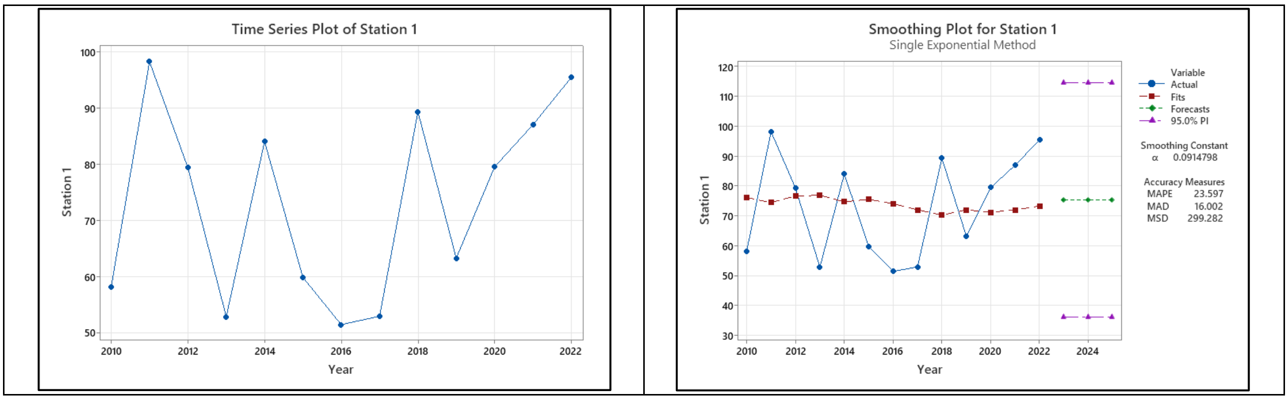


Fig. 4 Leaflet Plot of Flood Risk

From the observations in Fig. 4, stations 1 and 9, located closer to the urban center of Batu Pahat, are classified as having a high flood risk since the radius of the red circle is bigger than other stations. The stations 3, 4, and 6 are categorized under medium flood risk. However, the stations 1, 2, 5, 7, 10, and 11 are categorized as having low flood risk.

3.4 Flood Prediction by Using Simple Exponential Smoothing

The Simple Exponential Smoothing (SES) is used to predict rainfall intensity for the year 2025 across the study area. SES is a widely used time series forecasting technique that assigns exponentially decreasing weights to past observations, emphasizing recent data while smoothing random fluctuations.



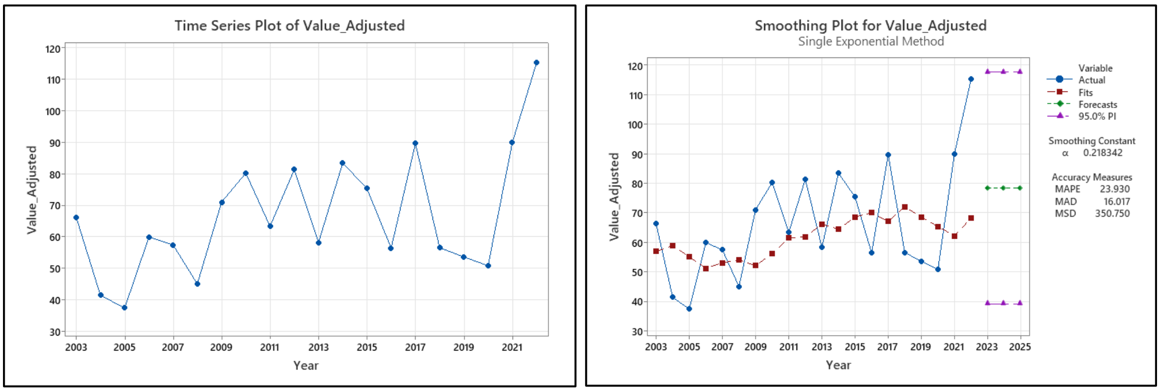
(a) (b)

Fig. 5 Prediction of Rainfall Intensity for Station 1 (Pintu Kawalan Sembrong) in 2025
(a) Time Series Plot; (b) Smoothing constant $\boldsymbol{\alpha = 0.0915}$

Table 3 Results for Pintu Kawalan Sembrong (Station 1)

Year	Rainfall Intensity	Smoothed Estimate Level	Forecast	Forecast Error
2010	58.20	74.5232	76.1668	-17.9668
2011	98.20	76.6891	74.5232	23.6768
2012	79.40	76.9371	76.6891	2.7109
2013	52.90	74.7382	76.9371	-24.0371
2014	84.00	75.5855	74.7382	9.2618
2015	59.90	74.1506	75.5855	-15.6855
2016	51.50	72.0785	74.1506	-22.6506
2017	53.00	70.3332	72.0785	-19.0785
2018	89.30	72.0683	70.3332	18.9668
2019	63.30	71.2662	72.0683	-8.7683
2020	79.50	72.0194	71.2662	8.2338
2021	87.00	73.3898	72.0194	14.9806
2022	95.40	75.4033	73.3898	22.0102

Based on Fig. 5(a), there is no trend and no seasonality, thus the model for SES can be denoted as $y_t = \beta_0 + \varepsilon_t$. Table 3 produce the result of smoothed level for $\alpha = 0.0915$. Meanwhile, Fig. 5(b) shows the forecasting results for year 2023 until 2025 when the smoothing constant α was set to 0.0915, and the predicted rainfall intensity in 2025 is 75.4. The model produced a smoother fit that closely tracked the overall trend of the actual data.



(a) (b)

Fig. 6 Prediction of Rainfall Intensity for Station 9 (SMK Munshi Sulaiman) in 2025
(a) Time Series Plot; (b) Smoothing constant $\boldsymbol{\alpha = 0.0915}$

Table 4 Results for SMK Munshi Sulaiman (Station 9)

Year	Rainfall Intensity	Smoothed Estimate Level	Forecast	Forecast Error
2003	66.30	58.9989	56.9595	9.3405
2004	41.50	55.1782	58.9989	-17.4989
2005	37.50	51.3183	55.1782	-17.6782
2006	60.00	53.2139	51.3183	8.6817
2007	57.50	54.1497	53.2139	4.2861
2008	45.10	52.1738	54.1497	-9.0497
2009	71.10	56.3062	52.1738	18.9262
2010	80.30	61.5450	56.3062	23.9938
2011	63.40	61.9500	61.5450	1.8550
2012	81.40	66.1968	61.9500	19.4500
2013	58.30	64.4726	66.1968	-7.8968
2014	83.50	68.6271	64.4726	19.0274
2015	75.40	70.1059	68.6271	6.7729
2016	56.50	67.1351	70.1059	-13.6059
2017	89.70	72.0620	67.1351	22.5649

2018	56.60	68.6860	72.0620	-15.4620
2019	53.70	65.4139	68.6860	-14.9860
2020	50.90	62.2449	65.4139	-14.5139
2021	90.00	68.3050	62.2449	27.7551
2022	115.30	78.5660	68.3050	46.9950

Based on Fig. 6(a), there is no trend and no seasonality, thus the model for SES can be denoted as $y_t = \beta_0 + \varepsilon_t$. Table 4 produce the result of smoothed level for $\alpha = 0.2183$. Meanwhile, Fig. 6(b) shows the forecasting results for year 2023 until 2025 when the smoothing constant α was set to 0.2183, and the predicted rainfall intensity in 2025 is 78.6. The model produced a smoother fit that closely tracked the overall trend of the actual data.

In addition, the accuracy metrics, including Mean Absolute Percentage Error (MAPE), Mean Average Deviation (MAD), and Mean Square Deviation (MSD), were calculated to evaluate the reliability of the SES predictions (see Table 5).

Table 5 Summary of Accuracy Metrics

Station	MAPE	MAD	MSD	Forecast	Model
Station 1	23.6%	16.0	299.2	75.4	$l_T = (0.0915)y_T + (0.9085)l_{T-1}$
Station 9	23.9%	16.0	350.8	78.6	$l_T = (0.2183)y_T + (0.7817)l_{T-1}$

Based on Table 5, the results indicate that Station 1 (Pintu Kawalan Sembrong) achieves the lowest MAD and MAPE, with values of 16.0 and 23.6%, respectively, when using the optimal smoothing constant of $\alpha = 0.0915$. These metrics suggest that the forecast for Station 1 is both accurate and consistent, with minimal deviation between the observed and predicted values. The relatively low MAPE indicates that the model performs well in forecasting, with errors being small in proportion to the actual rainfall values. On the other hand, Station 9 (*SMK Munshi Sulaiman*) also achieves a competitive level of accuracy, with the lowest MAPE recorded at 23.9% and the lowest MAD at 16.0, using the optimal smoothing constant of $\alpha = 0.2183$. However, the higher Mean Squared Deviation (MSD) of 350.8 for Station 9 reflects larger squared errors, which could indicate the presence of outliers or greater variability in the rainfall data for this station. Despite this, the low MAPE and MAD suggest that the model is still effective in capturing the overall trend of rainfall for Station 9.

4. Conclusion

This study successfully integrated spatial analysis, clustering techniques, and simple exponential smoothing to predict and manage flood risks in Batu Pahat. The spatial analysis using Local Moran's I identified significant clustering patterns, with high positive spatial autocorrelation (10–15) indicating flood-prone hotspots, while weaker correlations marked transitional or low-risk areas. K-means clustering classified the 11 stations into three distinct flood risk levels, identifying Stations 1 and 9 in urban centers as high-risk zones. SES was employed to predict rainfall intensity for 2025 using the optimal smoothing constants, $\alpha = 0.0915$ for Station 1 and $\alpha = 0.2183$ for Station 9. The forecasted rainfall intensities for 2025 were 75.4 mm for Station 1 and 78.6 mm for Station 9. The models achieved notable accuracy, with Station 1 exhibiting lower MAD (16.0) and MAPE (23.6%), while Station 9 recorded the lowest MAPE (23.9%) and MAD (16.0) despite a higher MSD (350.8). These findings underline the importance of using optimal smoothing constants to enhance prediction reliability and accuracy.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Norsyahmirul Amin Ruzlan, Mohd Asrul Affendi Abdullah;* ***data collection:*** *Norsyahmirul Amin Ruzlan;* ***analysis and interpretation of results:*** *Norsyahmirul Amin Ruzlan;* ***draft manuscript preparation:*** *Norsyahmirul Amin Ruzlan, Mohd Asrul Affendi Abdullah, Norziha Che Him. All authors reviewed the results and approved the final version of the manuscript.*

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Enhanced Knowledge in Sciences and Technology Vol. 5 No. 2 (2025) p. 473-483

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