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Flood Forecasting Analysis in Bandar Segamat Catchment Utilizing the Artificial Bee Colony Algorithm

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Abstract

Floods are one of the most devastating natural disasters in Malaysia. Therefore, flood forecasting is a critical component in managing and mitigating the adverse effects of floods, particularly in vulnerable areas such as Bandar Segamat catchment in Johor, Malaysia. This study presents an innovative approach to flood forecasting by employing the Artificial Bee Colony (ABC) algorithm, a nature-inspired optimization technique. By incorporating with MATLAB software, it can leverage its robust computational, visualization tools, modifications such as hybridization, dynamic parameter tuning, and adaptive strategies, the study demonstrates improved solution quality, faster convergence, and greater robustness. The aims are to identify parameters for flood forecasting in the Bandar Segamat catchment using the Artificial Bee Colony (ABC) algorithm and to develop a flood prediction model for the catchment area utilizing the ABC algorithm. The model has been adeptly employed to emulate future floods under typical circumstances, conditions incorporating 14 years of current rainfall data, temperature data, runoff, and Curve Number (CN) value. The findings underscore MATLAB's utility in optimization research and provide valuable insights for refining bio-inspired algorithms for practical applications. The projected flood probabilities manifest a more uniform schema in comparison to historical records, possibly signifying enhanced predictability of flood occurrences in the forecast interval attributable to refined modelling methodologies. Using this information, the organizations linked to flood oversight in Johor, notably in Bandar Segamat, can develop a proactive strategic framework for the next fourteen years to reduce the chances of floods.

1. Introduction

The region, characterized by its low-lying topography and susceptibility to monsoonal rainfall, has experienced devastating floods over the years, with the 2023 incident standing out as one of the most catastrophic. Continuous heavy rainfall inundated over 80% of the district's residential areas, forming isolated islands and displacing thousands of residents as shown in **Fig. 1** [1]. These events highlight the urgent need for innovative solutions to improve flood preparedness and management. Traditional forecasting methods often fall short in addressing the complexities of flood dynamics in such regions, prompting this study's focus on utilizing the Artificial Bee Colony (ABC) algorithm to develop a robust predictive model tailored to the Bandar Segamat catchment. The ABC algorithm, inspired by the foraging behavior of honeybees, offers significant advantages in optimizing complex systems [2]. It leverages robust computational techniques to process rainfall, temperature, and runoff data, enabling accurate flood predictions. This study integrates historical data and modern computational methods to create a model capable of assessing flood risks under varying climatic conditions. By doing so, it seeks to enhance the accuracy and timeliness of flood forecasts, providing vital insights for disaster management agencies in Johor.

Establishes a strong foundation for the study by exploring the global and local implications of flooding. Historical records from Johor, including the severe floods of 2006, 2011, and 2017, underscore the growing frequency and intensity of such events due to climate change and rapid urbanization [3]. Rainfall data, a critical input for flood forecasting, is analyzed for its variability and importance in predicting runoff and flood risks [4]. Additionally, the review discusses various flood forecasting methods, including machine learning models, Long Short-Term Memory (LSTM) networks, and Bayesian approaches. While these techniques offer unique advantages, they often require extensive data or computational resources. The ABC algorithm, in contrast, is highlighted for its adaptability and efficiency, making it particularly suitable for optimization tasks in flood forecasting [5]. In examines the impact of land use and soil characteristics on flood risks, emphasizing the importance of the Curve Number (CN) value in runoff calculations. By incorporating these parameters into the ABC algorithm, the model accounts for both hydrological and environmental factors that influence flooding. This integration aligns with recent advancements in flood forecasting, where bio-inspired algorithms like the ABC are increasingly used to refine predictive accuracy [6]. The methodology involves a comprehensive data normalization process to ensure uniformity and accuracy, followed by the implementation of the ABC algorithm in MATLAB software to optimize the forecasted parameters. This approach demonstrates how computational advancements can address the limitations of traditional flood forecasting methods.

In conclusion, this study not only highlights the vulnerabilities of Bandar Segamat to recurring floods but also provides a novel solution through the application of the ABC algorithm. By combining historical data with modern optimization techniques, the research offers a significant improvement in flood risk assessment and management. The findings underscore the potential of bio-inspired algorithms to enhance disaster preparedness and resilience, paving the way for their broader application in environmental engineering and sustainability. The insights gained from this study can aid policymakers, urban planners, and disaster management agencies in developing more effective strategies to mitigate the socioeconomic and environmental impacts of floods in Malaysia and beyond.

Fig. 1 *Flood hit Segamat district, forming 'small island' [1]*

2. Literature Review

A major issue that impacts many parts of the world is flooding. Water submerges an area, typically due to severe precipitation, snowmelt, or increasing sea levels. Apart from causing lives, floods can also seriously damage homes, businesses, infrastructure, and agriculture [7]. Flooding may have long-term effects in addition to its acute ones. It has the potential to pollute water sources and disperse disease. Floods frequently cause disruptions to the transit network, making it challenging to flee and obtain necessities and a complicated issue that needs to be solved by a multidisciplinary team. This includes initiatives to enhance urbanization and land use, as well as the deployment of early warning systems and flood prevention techniques [8]. In addition, it is imperative that people learn about floods and how to prevent and respond to these occurrences. There are numerous ways to reduce the possibility of flooding and the damage caused by it. These are a few of the most popular techniques. Creating flood control infrastructure, such as dikes, levees, and dams, can stop or divert floodwaters. These structures lessen the chance of flooding in communities downstream and also help to regulate water flow. Restricting development in flood-prone areas is one aspect of regulating floodplains. People and property are protected, and flood damage is decreased as a result [9].

To predict and simulate flood events, a number of flood modelling techniques are employed, each with advantages and disadvantages. Here are some of the most widely used techniques. By simulating the watershed's flow, a process called "hydrology modelling" makes predictions about the amount of water that will be available and its distribution throughout the terrain during a flood event [10]. Hydrology modelling has the advantage of simulating the effects of alterations in human activity and land use while accounting for the complex relationships between soil, water, and vegetation. Its drawbacks include relying on data that could be inaccurate or insufficient and how challenging it could be to employ on a big scale because of its computational complexity [11]. Hydraulic modelling predicts the depth and speed of water during a flood event by simulating the flow of water in a river or canal. One advantage of hydraulic modelling is that it can accurately predict water levels and velocities while accounting for the effects of infrastructure, such as dams and bridges. Among its drawbacks are its complexity, which can make it challenging to apply to large-scale applications, and its reliance on precise knowledge on the river or channel shape, which can be hard to come by. Water levels, velocities, and depth in a river or canal during a flood can be predicted by simulating the movement of water using physical equations and boundary conditions. Equations of fluid mechanics or finite element techniques can be used to generate these models analytically or numerically [12].

2.1 Study Area

The study covers the entire district of Segamat, which located in northern part of Johor between latitude 2° 29' 59.99" N and longitude 102° 48' 59.99" E. From November to March, the district is renowned for having regular floods from during the northeast monsoon season. The average annual rainfall is 2173 mm with an average temperature 23°C to 31°C [13]. In the highest region, with 2500 mm annual precipitation, the precipitation rate is usually higher and a larger part of the rainfall during the north-eastern monsoon season drops. A series of floods in the history of 100 years, from 1948, 4969, 1979, 1982, 1983, 1987, 1989, 1991, 2004, 2006 and 2007, were recorded. Flood incidents also occur. Heavy precipitation would lead to large sediments along the river shore during the Northeast monsoon season [14]. Seven (7) stations in each Segamat are illustrate in **Fig. 2**.

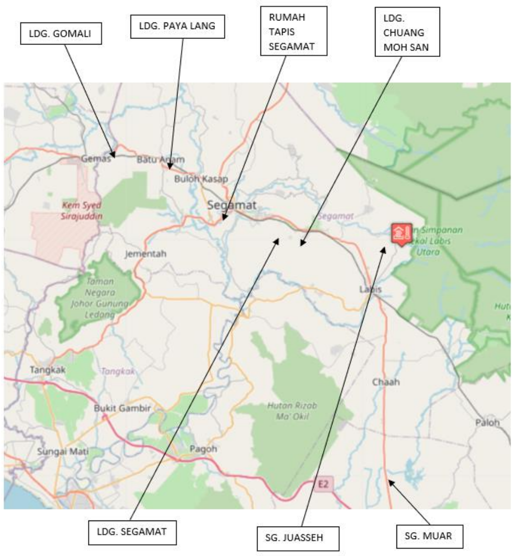

Fig. 2 Rainfall stations overview at Segamat

2.2 Review on Flood Forecasting Technique

Flood forecasting is indispensable in lessening the harmful effects of floods, a key responsibility in disaster preparedness. To deal with this dilemma, a wide spectrum of tactics has been established and employed, including cutting-edge strategies such as AI algorithms, time series data mining, and Bayesian methods. These tools not only increase the precision and effectiveness of flood prediction but also have a notable impact on advancing predictive abilities in the field of hydrology and readiness for natural disasters. The utilization of such advanced techniques contributes not only to improving flood prediction but also to strengthening the overall resilience and response mechanisms in the face of potential disasters [15]. The process of mapping and assessing flood events involves the utilization of remote sensing and geographic information system (GIS)-based models, which leverage satellite and aerial data for their operations. One major strength of this method lies in its capacity to integrate information from diverse sources, enabling the generation of precise insights into the characteristics and impacts of floods. Nonetheless, a significant disadvantage of this technique is its requirement for top-notch data, which might be challenging to acquire or not conveniently reachable. Additionally, the computational complexity associated with this modelling technique poses challenges in its implementation for large-scale applications, thereby limiting its widespread utility [12].

2.3 Artificial Bee Colony Algorithm (ABC)

Originate by Karaboga in 2005, the ABC algorithm, commonly referred to as the Artificial Bee Colony algorithm, is a meta-heuristic algorithm inspired by the intricate foraging patterns observed in honey bee colonies. The ABC algorithm is structured around three distinct categories of bees: employed bees, onlooker bees, and scouts, each playing a crucial role in the optimization process. The employed bees are responsible for scouring the vicinity of the food source stored in their memory and subsequently communicating their findings to the onlooker bees. These onlooker bees, in turn, meticulously evaluate the quality and fitness levels of the food sources identified by the employed bees, selecting only the most desirable options. Meanwhile, the scout bees are tasked with transitioning from the role of employed bees to explore new food sources, abandoning their current locations in favor of potentially more rewarding alternatives. It is imperative to note that the quantity of employed bees (Ne) or onlooker bees (No) employed within the ABC algorithm is directly correlated to the total number of solutions (Ns) present within the swarm, ensuring a balanced and efficient search process [2].

The application of the Artificial Bee Colony (ABC) algorithm, has been successfully employed in various optimization challenges, including flood forecasting and its associated areas. In a study conducted by Hongze Liu, the application of the ABC algorithm in the optimization of reservoir operation models for non-flood season flood dispatching and power generation was demonstrated, resulting in notable enhancements in power generation and water resource utilization efficiency [16]. These particular research showcases the significant potential of ABC algorithms in improving flood resource management practices. Furthermore, within the realm of flood control material scheduling, Banteng Liu and colleagues introduced a multi-objective scheduling algorithm called the Pareto ABC (MSA_PABC) to better distribute flood control materials. Their work displayed enhancements in material satisfaction rates and convergence rates for identifying optimal solutions [17]. These findings underscore the capacity of the ABC algorithm in addressing logistical obstacles linked to flood disaster management strategies. In another study by Jiuyuan Huo and Liqun Liu, the optimization of hydrological model parameters using a multi-objective ABC algorithm (RMOABC) for long-term runoff prediction was investigated, revealing the algorithm's efficiency and dependability in hydrological forecasting, a critical component in flood prediction practices [18].

Additionally, the combination of ABC algorithms with other computational methodologies has exhibited promising outcomes in the domain of flood forecasting. For example, the fusion of the backpropagation technique with bee colony optimization for rainfall prediction has showcased the potential to refine predictive accuracy through the optimization of initial weights and biases in neural network models [6]. As a whole, these research undertakings elucidate the adaptability and efficiency of the ABC algorithm and its modifications in the domain of flood forecasting and management. By optimizing operational models, streamlining resource allocation processes, and enhancing the precision of hydrological forecasts, the ABC algorithm plays a pivotal role in advancing flood forecasting methodologies, thereby presenting a promising trajectory for future research and practical implementation in disaster management strategies. The ABC algorithm commences by randomly producing an initial population of Ns solutions (X_1, X_2, ... X_{Ns}), with Ns representing the swarm size, and establishing a threshold (limit) along with the maximum cycle number (MCU). Subsequently, each employed bee creates a fresh candidate solution within the vicinity of its current location. Upon the generation of the new candidate solution, a prudent selection process ensues: in case the fitness of the new solution surpasses that of its parent, the employed bee will supplant the parent with the new solution; contrarily, the parent will persist. Following this, all employed bees disseminate the information concerning their food sources to the onlooker bees through waggle dances. Each onlooker bee assesses the nectar details from all employed bees and elects a food source contingent on a probability (Pi) associated with its nectar level. Should a position fail to exhibit enhancement beyond the limit, the food source is deserted. Subsequently, the scout bee identifies the new food source for substitution; only one scout bee is designated in each cycle [19].

3. Methodology

The methodology elaborates on the geographical positioning of the study, where a number of stations in Segamat, Johor were meticulously chosen. The historical data of precipitation was meticulously obtained and examined through the utilization of the artificial bee colony algorithm. Its focus on the subject of forecasting precipitation data, temperature data, flood probabilities and employing the Artificial Bee Colony algorithm (ABC) were carefully explored in this section. This comprehensive discussion reveals the detailed processes associated with managing rainfall data, temperature data and CN value for the study area. The methodology chart serves as a guideline aligning with the objectives outlined in Chapter 1, facilitating the smooth and efficient execution of the study's research. **Fig. 3** visually depicts the study's process, integrating the utilization of the Artificial Bee Colony algorithm to conduct the investigation.

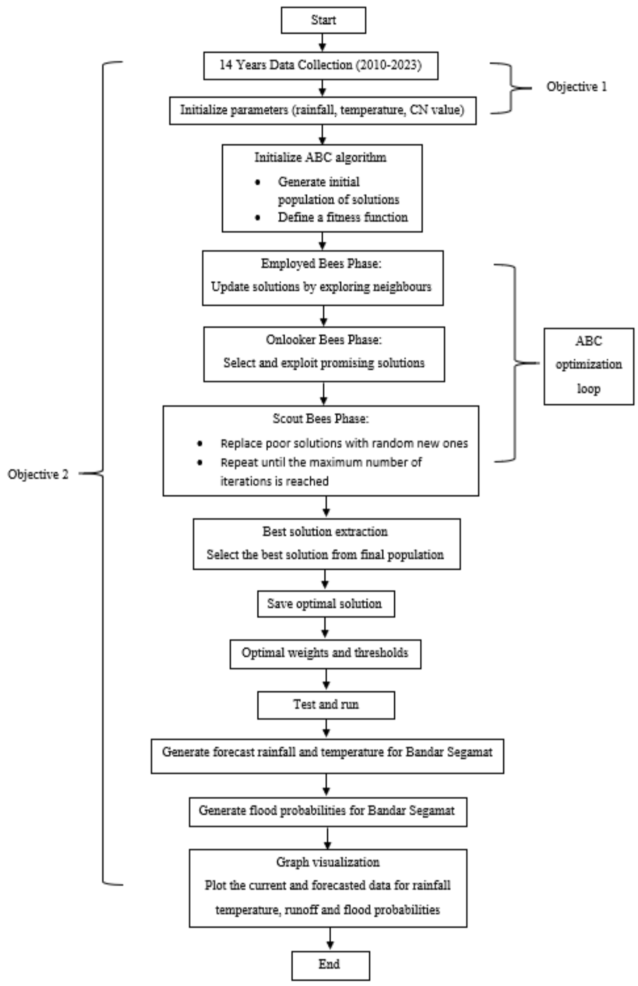

Fig. 3 Flowchart of utilizing ABC algorithm using MATLAB software

3.1 Study Area

In this study, there were three (3) rainfall stations were selected. The selected stations are Ldg. Segamat (0320251RF), Ldg. Paya Lang (0320281RF) and Ldg. Gomali (0320341RF). The annual average data was recorded in 14 years period which was from 2010 until 2023. Table 3.1 shows the selected stations in Segamat.

Table 1 *The selected rainfall stations in Segamat*

Stations No	Station ID	Stations Name
1	0320251RF	Ldg. Segamat
2	0320281RF	Ldg. Paya Lang
3	0320341RF	Ldg. Gomali

3.2 Study Area

A well-rounded and systematically planned approach for the proficient establishment of a sophisticated flood forecasting system that uses the MATLAB programming setup, which is strengthened by the application of the Artificial Bee Colony (ABC) algorithm, an optimization method inspired by the foraging behaviors of honeybees. This particular methodology integrates various crucial datasets, including but not limited to precipitation metrics, temperature readings, and Curve Number (CN) values, which collectively contribute to the formation of an intricate predictive model designed to anticipate flood events with a high degree of accuracy. The ABC optimization using MATLAB primarily consists of the following steps, as illustrated in **Fig. 3**:

Step 1: Collected historical data. The historical record consisted of rainfall: Annual rainfall (in millimeters), temperature: Average temperature (in degrees Celsius), and Curve Number (CN): Represented soil and land use characteristics and was used to calculate runoff.

Step 2: Normalized the data. Data normalization ensured uniformity in scale and improved algorithm performance. Each parameter were normalized to a range of [0,1] using (1):

$$\boldsymbol{Normalized\ Value} = \frac{Value - Min}{Max - Min} \tag{1}$$

Normalization constitutes a pre-processing technique employed to adjust data values into a uniform range, such as [0, 1]. This guarantees that all variables, irrespective of their initial scale, contribute equivalently to the computational procedure. In hydrological analysis and flood forecasting, datasets commonly represent elements such as rainfall, temperature, and CN values. Without normalization, variables with more substantial numerical ranges, such as rainfall, might overshadow the optimization procedure, resulting in skewed forecasts.

Chen et al. [20] illustrated, the significance of normalization when integrating heterogeneous datasets into machine learning models. By normalizing rainfall, temperature, and CN values, the inquiry assured that the Artificial Bee Colony (ABC) algorithm and Extreme Learning Machine (ELM) operated proficiently on a balanced dataset. This pre-processing phase enhanced convergence speed and precision in forecasting flood-associated parameters, rendering it a fundamental aspect of data preparation in flood forecasting frameworks.

Step 3: Initialized runoff calculation. The CN method was used to calculate runoff based on rainfall and CN values. This represented the maximum water retention capacity of the soil before runoff began. The formula was used to calculate maximum potential retention (S) using (2):

$$\boldsymbol{S} = \frac{25400}{CN} - 254 \tag{2}$$

This equation, rooted in the soil conservation service (SCS) Curve Number (CN) approach, predicts the utmost soil retention (S) before any runoff happens. The CN value is a pivotal parameter that encapsulates land utilization, soil classification, and antecedent moisture conditions. Recently, endeavours to enhance this methodology for improved applicability in ungauged catchments have been underscored in The Revised Curve Number Rainfall–Runoff Methodology for Predicting Runoff in Ungauged Basins [21]. This investigation underscores the necessity of modifying the conventional CN methodology to accommodate variability in hydrological conditions and augment flood prediction precision.

Then, runoff was calculated for each year using the formula in eqn. 3.3:

$$\boldsymbol{Runoff} = \frac{(Rainfall - 0.2S)^2}{Rainfall - 0.8S}, if\ Rainfall > 0.2S \tag{3}$$

If rainfall is less than 0.2S, runoff is set to zero. This equation computes the direct runoff produced from precipitation, considering the soil's retention capacity (S). If precipitation exceeds a defined threshold (0.2S), the excess water contributes to surface runoff. This methodology, anchored in the Curve Number framework, remains a fundamental element in hydrological modelling. Based on recent study, Wang et al. [2], integrated this equation with optimization strategies to increase the precision and dependability of flood forecasting systems. The investigation emphasizes the adaptability of the runoff equation in simulating various hydrological conditions.

Step 4: The Artificial Bee Colony (ABC) Algorithm were designed. The Mean Squared Error (MSE) was a frequently utilized benchmark for determining how accurately the prediction model functioned. In the context of the Artificial Bee Colony (ABC) algorithm, MSE appraises the adequacy of solutions, steering the optimization process to minimize variances between anticipated and observed values [22]. The study underscores how the ABC algorithm, coupled with sophisticated data decomposition techniques, markedly enhances the accuracy of hydrological forecasts.

The ABC algorithm optimizes the forecasting model by finding the best-fit parameters for rainfall, temperature, and runoff. First, initialize the parameters. Colony size: Number of bees (solution) in the population. Max iterations: Maximum number of optimization cycles. Limit: Number of cycles before abandoning an unproductive solution. Second, to generate initial population, it randomly initializes the population of solutions representing the forecasted values of rainfall, temperature and CN value for the prediction period. Then, the fitness function that measures the accuracy of the forecasted values were defined by comparing them with actual data. The mean squared error (MSE) were used as the fitness function as (4):

$$\boldsymbol{Fitness} = MSE\frac{1}{N}\sum(Predicted - Actual)^2 \quad (4)$$

For main algorithm phases, three (3) types of bees were deployed which is; Employed bees' phase: Each employed bee selects a neighbouring solution by modifying one parameter and evaluates its fitness. If the neighbour's fitness is better, it replaces the original solution. Onlooker bees' phase: Assign selection probabilities to solutions based on their fitness values. Onlooker bees select and exploit promising solutions. Scout bees' phase: Abandon solutions that fail to improve fitness within a predefined limit and replace them with new random solutions. These phases will repeat until convergence, which is the algorithm continues iterating through the phases until the maximum number of iterations is reached.

Step 5: Forecasting the flood parameters. The solution with the best fitness value was identified and represented the optimal forecast for rainfall, temperature, and CN value. Then, the normalized forecasted values were converted back to their original scale using (5):

$$\boldsymbol{Value} = \big(Normalized\ Value\ x\ (Max - Min)\big) + Min \quad (5)$$

The CN method was applied to calculate the forecasted runoff using the denormalized rainfall and CN values. Denormalization represents the reverse process of normalization, employed to restore scaled data to its original range following model predictions. This phase is imperative in rendering predictions comprehensible and actionable. For example, anticipated rainfall and runoff values, once denormalized, can be articulated in significant units such as millimetre, which are indispensable for decision-makers in flood probabilities administration.

Chen et al. [20] demonstrated that, denormalization assumed a pivotal function in converting the normalized outputs of the model back into real-world dimensions. This facilitated the application of the forecasted data in hydrological evaluations and decision-making methodologies. For instance, runoff forecasts computed employing the denormalized rainfall and CN values yielded actionable insights into potential flood probabilities. The research underscored that without denormalization, the model's outcomes would persist as abstract, constraining their practical efficacy in flood forecasting endeavours.

Thus, flood probabilities were defined as a weighted combination of rainfall, temperature and runoff using eqn. 3.6:

$$\boldsymbol{Flood\ Probabilities} = (0.4\ x\ Rainfall) + (0.3\ x\ Temperature) + (0.3\ x\ Runoff) \quad (6)$$

Flood probabilities often involves the integration of multiple factors, including precipitation, temperature condition, and surface runoff, into a comprehensive index. This weighted approach enables a comprehensive evaluation of flood vulnerability, taking into account the influence of each variable. The technique was employed in the AI-Driven Multiobjective Scheduling Algorithm for Flood Control Materials Based on Pareto Artificial Bee Colony [6], wherein the ABC algorithm refined the distribution of assets for flood mitigation. The investigation illustrated how the integration of hydrological information and artificial intelligence could enhance flood probabilities frameworks.

Step 6: Visualization and Analysis. The graph been plotted by following data on a time axis; Historical and forecasted rainfall, Historical and forecasted temperature, and runoff and flood probabilities. Then, the actual and forecast data is extracted into excel.

4. Result and Discussion

There are three (3) stations were chosen for taking the rainfall data, temperature data and CN value for sub-basin. The reason of the others station was not chosen it is because of data loss, equipment failure, site conditions, maintenance programs and so on. The chosen rainfall station is Ldg. Segamat station (0320251RF), Ldg. Paya Lang station (0320281RF) and Ldg. Gomali (0320341RF). By implement all of the data from 2010 to 2023 in the MATLAB software, the results for next 14 years were been displayed.

Table 2 *Sum of future rainfall, runoff, temperature and flood probabilities at Ldg. Segamat*

Future				
Years	Rainfall (mm)	Runoff (mm)	Temperature (°C)	Flood Probabilities
2024	2033.2	1928.9	26.8	1400
2025	2611.1	2506	25.5	1803.9
2026	1541.9	1439	26	1056.2
2027	2080.3	1975.9	26.4	1432.8
2028	1623.3	1519.9	25.8	1113
2029	1577.2	1473.9	26.4	1081
2030	1704.4	1600.8	27	1170.1
2031	2271.9	2167.1	26	1566.7
2032	1628.4	1524.9	26.4	1116.8
2033	1573	1469.7	26.1	1077.9
2034	2062	1957.6	26.1	1419.9
2035	1440	1337.2	25.8	984.9
2036	2293.9	2189.1	26.8	1582.3
2037	2112.6	2008.2	25.8	1455.2

The forecast data for rainfall, runoff, temperature, and flood probabilities at Ldg. Segamat reveals significant year-to-year variations, highlighting potential climate impacts on the region. High rainfall and runoff in 2025 and 2036, accompanied by elevated flood probabilities (1803.9 and 1582.3, respectively), indicate critical flood risk years requiring proactive management measures like improved drainage and early warning systems. Conversely, lower rainfall and runoff in 2035 (1440 mm and 1337.7 mm) correspond to reduced flood probabilities (984.9), suggesting a drier year with potential water scarcity concerns. Temperature fluctuations (25.5°C–27°C) influence evaporation rates, with warmer years like 2030 (27°C) potentially intensifying water stress despite adequate rainfall. These trends underscore the need for adaptive strategies balancing flood mitigation, water conservation, and climate resilience to manage both high-risk flood years and periods of reduced water availability effectively.

Table 3 Sum of future rainfall, runoff, temperature and flood probabilities at Ldg. Paya Lang

Future				
Years	Rainfall (mm)	Runoff (mm)	Temperature (°C)	Flood Probabilities
2024	1717.3	1634.2	26.1	1185
2025	1892.4	1809.1	25.6	1307.4
2026	1526.8	1444.1	25.9	1051.7
2027	1894.4	1811	25.9	1308.8
2028	1333.4	1333.4	25.8	974.1
2029	910.9	830.2	26.1	621.2
2030	1898.5	1815.1	26.6	1311.9
2031	1863.4	1780.1	26.4	1287.3
2032	1697.5	1614.5	25.7	1171
2033	999	917.9	26.1	682.8
2034	1337.1	1254.9	26.2	919.1
2035	1397.4	1314.9	26.4	961.3
2036	1650.5	1567.5	26.1	1138.3
2037	1902.7	1819.3	25.8	1314.6

The forecast data for rainfall, runoff, temperature, and flood probabilities at Ldg. Paya Lang highlights notable trends and relationships. Rainfall and runoff show significant annual fluctuations, with the lowest values in 2029 (910.9 mm rainfall and 830.2 mm runoff) and the highest in 2037 (1902.7 mm rainfall and 1819.3 mm runoff), indicating a strong correlation. Temperature remains relatively stable, ranging from 25.6°C to 26.6°C, suggesting limited variation compared to other variables. Flood probabilities align closely with rainfall and runoff trends, with higher probabilities observed during years of elevated rainfall and runoff, such as 2025 (1307.4) and 2027 (1308.8), and lower probabilities in years like 2029 (621.2). This analysis underscores the interdependence of these variables and highlights the importance of proactive flood risk management, especially during periods of expected high rainfall and runoff.

Table 4 *Sum of future rainfall, runoff, temperature and flood probabilities at Ldg. Gomali*

Future				
Years	Rainfall (mm)	Runoff (mm)	Temperature (°C)	Flood Probabilities
2024	575.8	498	26.2	387.6
2025	1845	1761.8	25.4	1274.2
2026	1771.1	1687.9	26	1222.6
2027	1474.4	1391.8	26.6	1015.3
2028	1692.2	1609.2	26	1167.4
2029	1286.2	1204	26.7	883.7
2030	1023	941.8	26.4	699.7
2031	1100	1019.2	25.6	753.7
2032	1499.5	1416.8	26	1032.6
2033	1596.8	1514	26.2	1100.8
2034	920.3	839.6	26.1	627.8
2035	1672.4	1589.4	25.8	1153.5
2036	1844.5	1761.2	25.5	1273.8
2037	1977.8	1894.4	26.6	1367.4

The forecast data for rainfall, runoff, temperature, and flood probabilities at Ldg. Gomali presents significant annual variability. Rainfall and runoff exhibit a fluctuating trend, with the lowest values in 2024 (575.8 mm rainfall and 498 mm runoff) and the highest in 2037 (1977.8 mm rainfall and 1894.4 mm runoff), indicating a strong correlation between these variables. Temperature remains relatively stable, ranging from 25.4°C to 26.6°C, showing minimal variation compared to rainfall and runoff. Flood probabilities also correspond closely with rainfall and runoff patterns, with higher probabilities observed during years of increased rainfall and runoff, such as 2025 (1274.2) and 2037 (1367.4), and lower probabilities in drier years, like 2024 (387.6) and 2034 (627.8). These results emphasize the direct relationship between rainfall, runoff, and flood risk, highlighting the importance of implementing adaptive flood mitigation strategies, particularly in years forecasted with high rainfall and runoff.

5. Conclusion

In conclusion, the flood represents Malaysia's most devastating natural catastrophe, and its effect have been experienced by the citizens of Bandar Segamat for an extended duration. The impact of floods has intensified recently due to alterations in land utilization and climatic variations. Consequently, the utilization of the Artificial Bee Colony algorithm implemented in MATLAB software for flood forecasting could serve as one of the remedial measures. The hydrological model of the Segamat river basin has been proficiently developed in this research. The model anticipated rainfall data, temperature data, runoff, and flood risk for the subsequent fourteen years. The model has been adeptly employed to emulate future floods under typical circumstances, conditions incorporating current rainfall data, temperature data, runoff, and Curve Number (CN) value. Utilizing this information, the key organizations linked to flood oversight in Johor, notably in Bandar Segamat, can develop a proactive strategic framework for the next fourteen years in Bandar Segamat to reduce the chances of floods that might influence the citizens in Bandar Segamat..

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