Feasibility Study on Forecasting Water Level Fluctuation of the Senanayaka Samudra Reservoir

Abstract— **The Senanayake Samudraya Reservoir in Ampara District of Sri Lanka is a crucial piece of water management infrastructure. It supports various sectors, including agriculture, industry, and domestic water needs. The country experiences variable rainfall patterns throughout the year due to its tropical climate and diverse topography. Catchment area of the reservoir is 994.22 sq.km and command area is 120,254 ac (488.66 sq.km). Data for the reservoir was collected from irrigation department, Ampara and 26-year (1990-2015) rainfall and temperature data collected from Department of Meteorology and Irrigation department. This study developed a comprehensive water level forecasting system for the Reservoir to improve water resources management system. Both Hydrologic Engineering Centre-Hydrologic Modelling System (HEC-HMS) and Soil Conservation Service-Curve number (SCS-CN) methods were used to simulate the surface inflow and compared, with SCS-CN proving more reliable for this study. Then, the base flow of the reservoir was determined. The Long Short-Term Memory (LSTM) recurrent neural network (RNN) was employed to forecast water level fluctuations. The model performance was evaluated based on the computed statistical parameters. The performance of model is very good with Coefficient of Determination (R2) = 0.998, Mean Square Error (MSE)= 0.0357 and Root Mean Squared Error (RMSE)= 0.189. Finally, it can be concluded that the model can be used effectively in forecasting water level fluctuations, providing valuable insights for reservoir management.**

I. Introduction

Senanayaka Samudraya (formerly Gal Oya Reservoir) is Sri Lanka's largest and most important reservoir. This distinction stems from its association with the Galoya Multipurpose Irrigation System, a unique project whose construction began in 1949 and was completed in 1953.In the Ampara District, agriculture provides 95% of the population's livelihood. This tank is the heart of the Ampara District's economy, supplying more than 70% of the freshwater required to cultivate 120,000 acres of paddy fields during both Maha and Yala seasons. The reservoir has a storage capacity of approximately 950 MCM, with a catchment area of 994.22 km² and a command area of 120,254 acres (488.66 km²). Around 15% of the country's annual rice requirement is supplied by this scheme, highlighting its national significance [[14]].

The Reservoirs in Sri Lanka stands as a critical water management infrastructure, serving multiple purposes including irrigation, hydropower generation, and flood control. It supports various sectors, including agriculture, industry, and domestic water needs. It also plays an important role in flood control and generating electricity. However, efficiently managing this reservoir depends on accurately forecasting water level fluctuations. These fluctuations are influenced by complex water flow processes, such as how rain affects the amount of water entering the reservoir.

The country experiences variable rainfall patterns throughout the year due to its tropical climate and diverse topography. Traditional forecasting methods often rely on simplistic models that cannot capture the complexities of the water system, leading to inaccurate and unreliable predictions. Recent advances in machine learning, particularly Long Short-Term Memory (LSTM) recurrent neural networks, have shown strong potential in hydrological forecasting. LSTM models are capable of capturing both short-term fluctuations and long-term dependencies, making them highly suitable for predicting reservoir water levels where inflow depends on multiple interlinked climatic factors.

Senanayaka Samudraya Reservoir faces challenges in effectively managing water level, particularly amidst the uncertainties posed by changing climatic patterns and increasing water demands. The increasing variations in rainfall and temperature present a significant threat to the reservoir water level and disrupting the delicate balance of water supply and demand. The effective reservoir management plans are limited by lack of a complete precise impact of various climate factors. Therefore, Accurate forecasting of water level fluctuations is essential for optimizing reservoir operations, ensuring efficient water allocation, and mitigating potential risks associated with floods and droughts. The primary objective of this study is to develop a comprehensive water level forecasting system for the Senanayake Samudraya Reservoir to improve water resources management.

II. Literature Review

Estimating stream flow or runoff from a catchment is essential for predicting flood levels, ensuring water supply, designing storage systems, planning irrigation, and forecasting water resources for power generation. Rainfall, a fundamental component of the hydrological cycle, can be directly measured, but runoff, influenced by rainfall, requires estimation using rainfall data, which is more readily available ([[10]], [[11]], [[9]]). Key factors affecting runoff from a watershed include precipitation patterns, catchment area size and shape, soil composition, land usage, and terrain topography [[12]]. Land use, land cover (LULC), and soil type exert a significant impact on hydrological processes, surpassing catchment size and shape, in generating stream flow ([[2]], [[13]], [[8]]).

Shashi Ranjan and Vivekanand Singh have shown that the HEC-HMS model can effectively capture hydrological dynamics when combined with geographic information systems (GIS) for analyzing land use, soil characteristics, and slope data [[1]]. Previous research highlights the model’s robustness, particularly when evaluated with statistical indices like the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and RMSE-observations standard deviation ratio (RSR). These metrics have demonstrated the HEC-HMS model's capacity to perform well at daily, monthly, and seasonal scales, with monthly models typically yielding better predictive accuracy. Despite some limitations in daily models, the consensus in the literature emphasizes that HEC-HMS is a reliable tool for hydrological simulations, making it a popular choice for forecasting runoff and streamflow in various river basins.

A research performed to predict the inflow of the Koyna reservoir by utilizing a conceptual model and the Hydrologic Engineering Centre’s Hydrologic Modelling System (HEC-HMS; version 4.8). They utilized the Soil Conservation Service Curve Number (SCS-CN) method for loss assessment, the SCS Unit hydrograph method for converting surplus precipitation into direct runoff, and suitable time intervals for channel routing in the HEC-HMS Model. The model's performance was assessed using metrics like Relative Error (%), Root Mean Square Error (RMSE), Correlation Coefficient (r), and Nash Sutcliffe Efficiency (NSE). Additionally, comparisons were made between simulated and observed hydrographs, as well as scatter plots. After a thorough investigation, it was concluded that the HEC-HMS model's overall performance was satisfactory and reliable, indicating its suitability for comparable [[3]].

This Study conducted on Runoff Estimation for Darewadi Watershed using Soil Conservation Service–Curve Number (SCS-CN) Method. The SCS runoff curve number approach was used to estimate runoff. Geographic Information Systems (GIS) and Remote Sensing (RS) were used to apply overlay methods in order to calculate runoff from the watershed. The study utilized 20 years of daily rainfall data. The study indicated that the SCS-CN model is capable of accurately predicting surface runoff depth [[4]].

Forecasting water levels in reservoirs, rivers, and other water bodies is critical for effective water resource management, flood prediction, and mitigation. LSTM networks applied to rainfall-runoff modeling and found significant improvements in forecast accuracy compared to traditional hydrological models. Their study highlighted the ability of LSTMs to capture both short-term fluctuations and long-term trends in water levels [[6]].

A case Study conducted a case study on the Tisza River, a lowland river in Central Europe, demonstrating the effectiveness of the LSTM model for predicting water levels across various time horizons. In their research, the LSTM model consistently outperformed other approaches, including baseline models, linear regression, and even Multilayer Perceptron models. The key advantage of LSTM over these methods is its built-in memory mechanism, which allows the model to retain information from previous time steps, making it highly suitable for multivariate input data with variable lengths. This ability to capture long-term dependencies is particularly relevant in hydrological forecasting, where water levels are influenced by a combination of factors such as inflow, rainfall, temperature, and evaporation [[5]].

The LSTM-Attention-LSTM model developed to address limitations in traditional methods, particularly for long and complex sequences. This model integrates two LSTM networks in an encoder-decoder framework with an attention mechanism, allowing it to focus on key information in long input sequences, thereby improving the accuracy of multivariate time series forecasts. Their study showed that the LSTM-Attention-LSTM model significantly outperforms conventional models, especially in long time-step forecasting. The attention mechanism enables the model to weigh different time steps dynamically, improving its ability to predict complex patterns [[7]].

For hydrological forecasting, this model is highly relevant as it captures the intricate relationships between variables like inflow, rainfall, and evaporation, which are essential in water level prediction.

III. METHODOLOGY

A. Hydrological Data Screening

Data collection involved compiling daily rainfall records from 12 rainfall stations located within and around the Senanayake Samudra catchment area. All 12 stations were considered in the analysis, but the completeness of the dataset varied between stations. Missing values were checked, and stations with more than 10% missing records were excluded. For the remaining stations, missing daily values (approximately 3–5% of the dataset) were filled using the Inverse Distance Weighting (IDW) interpolation method. Daily mean rainfall was then calculated as a weighted average of rainfall across all available stations, with weights based on the distance of each station to the corresponding sub-basin centroid. Software setup included the installation of Notepad and the Anaconda Distribution. Within the Anaconda command prompt, a Python environment was created and activated. Python 3.6 was selected for analysis. . A custom Python script was written to automate rainfall preprocessing, including cleaning, gap-filling, and assigning daily mean rainfall values to each sub-basin centroid for integration into the HEC-HMS model. Exploratory data analysis, as outlined by [20], was performed including Welch’s t -test. The resulting data from these analyses were then employed for subsequent hydrological analyses.

B. Development of Basin Model using HEC-HMS

Creating a basin model in HEC-HMS involves the process of defining the physical and hydrological characteristic of a watershed within the HEC-HMS’s framework to simulate its hydrological behavior.

C. Basin Delineation and Terrain Processing

Terrain data was created and linked into the basin model, using the terrain data the boundaries of the watershed was delineated. The DEM data imported to create necessary hydrological features such as streams, sub basins and flow paths within the watershed.

D. Assigning parameterization and hydrological methods

The simple canopy method was selected for estimating interception losses and loss methods was specified to characterize the processes of infiltration and surface run off.

SCS curve number was assigned and Lag time was assigned to reflect the time taken to traverse the basin and reach the outlet. Sub basin area, longest flow path, basin slopes were extracted from HEC-HMS model. Impervious areas were calculated within the basin.

Rainfall data, processed as described earlier, was linked to each sub-basin centroid to provide spatially distributed input for the hydrological simulations.

E. Estimation of the SCS-CN method parameter

The most used empirical method developed by Soil Conservation Service Curve Number (SCS-CN) was used to estimate runoff value. The SCS equation with the relation of rainfall and retention parameter

$$Q = \left(\frac{(P-0.2S)^2}{(P+0.8S)}\right) \quad (1)$$

$$S = \left(\frac{25400}{CN}\right) - 254 \quad (2)$$

Where,
Q = daily runoff in mm; P= daily rainfall in mm;
S = potential maximum retention parameter in mm.
CN = weighted curve number.

F. Antecedent Moisture Condition (AMC)

Antecedent moisture condition is a crucial factor for deciding the final CN value. Antecedent moisture condition refers to the amount of water present in the soil at a given time [19]. Three antecedent soil moisture conditions namely AMCI, AMCII & AMCIII were developed by the SCS according to conditions of the soil and rainfall limits for inactive and growing seasons.

G. Water Balance Equation

In this study the water balance equation was utilized to simulate the storage changes of the Senenayake Samudra reservoir. The water balance equation which integrates the primary hydrological components influencing reservoir storage, is expressed as follows:

$$\frac{dS}{dt} = I - E - O - L \quad (3)$$

Where: $\frac{dS}{dt}$-Change in storage (m³/s).
I-Cumulative Inflow,
E-Evaporation, O- Outflow from the reservoir
L- Losses due to see page
For the purpose of this study, seepage losses (L) were neglected (Reference to literature review)

H. Cumulative Inflow Calculation

To determine the inflow (I), the following equation was applied:

$$I = \frac{dS}{dt} + R_0 \quad (4)$$

Where: R_0= Water released (sluice and spill) + Evaporation

I. Change in Storage (dS/dt)

The change in storage was calculated using the collected data on the beginning and end of the day water level from the Irrigation Department. By applying the area-capacity diagram.

J. Water Release

Data on water releases (through sluices and spills) was also collected from the irrigation department.

$$E_L = E_M \times A_{SR} \times P_C \quad (5)$$

Where: E_L - Evaporation losses; E_M - Monthly Evaporation; A_{SR} - Average Surface area of the reservoir; P_C - Pan coefficient (0.8)

K. Base Flow Calculation

The base flow was determined using the following equation:

Base Flow = Cumulative Inflow - Surface Inflow (From the selection of inflow from the comparison of HEC-HMS and SCS-CN method)

This comprehensive methodology in the calculation of cumulative inflow (including surface flow and base flow) using the water balance equation enabled the forecasting of water level fluctuations in the Senanayake Samudra reservoir, utilizing various RNN

L. LSTM-Based RNN for Water Level Prediction

The mathematical foundations of an LSTM-based Recurrent Neural Network (RNN) used to predict water levels based on input features such as inflow, rainfall, evaporation, and temperature. The Figure **1** and Figure **2** illustrate the flow of data through the input, hidden (LSTM), and output layers.

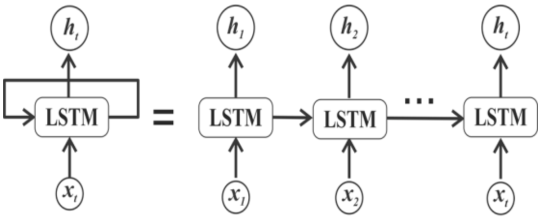

Figure 1 - Schematic representation of the recurrent neural network

Where, $X_1, X_2, \ldots, X_t$ are model inputs and $h_1, h_2, \ldots, h_t$ are model outputs

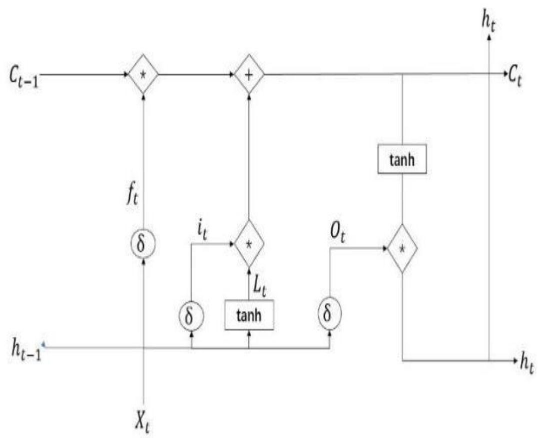

Figure 2 - Schematic representation of the structure of the long short-term memory (LSTM)

Where, cell f_t is the forget gate, i_t is the input gate, L_t is the cell update, C_t is the cell state and O_t is the output gate.

M. Input Layer

The input layer consists of multiple features related to the water level prediction: Inflow, Sluice+Spill, Rainfall, Evaporation, Temperature (Max/Min), Water Level Each time step t in the input sequence contains a vector X_t of these features.

N. Hidden Layer (LSTM Mechanism)

The hidden layer in the LSTM cell processes the input data over time, updating its internal memory (cell state) and hidden state. The LSTM works as follows:

- Forget Gate: $f_t = \delta(W_f\,[h_{t-1}, X_t\,] + b_f\,)$ determines how much of the previous cell state to retain. where δ is the sigmoid activation function.
- Input Gate: $i_t = \delta(W_i[h_{t-1}, X_t\,] + b_i)$ controls how much of the current input to write to the cell state.
- Candidate Cell State: $L_t = \tanh(W_c[h_{t-1}, X_t\,] + b_c)$ represents the candidate values for the new cell state.
- Cell State Update: $C_t = f_t \times C_{t-1} + i_t \times L_t$ updates the cell state with the information from the forget and input gates.
- Output Gate: $O_t=\delta(W_o[h_{t-1}, X_t]+ b_o)$determines how much of the cell state to output to the hidden state.
- Hidden State Update: $h_t = O_t \times \tanh(C_t\,)$ is the updated hidden state passed to the next time step.

O. Output Layer

The output layer uses the final hidden state ht from the LSTM to make the prediction: $\hat{y}_t = (W_{out} \times h_t + b_{out})$ This produces the predicted water level based on the learned patterns in the input data.

IV. Data and Study Area

Data for the reservoir was collected from irrigation department, Ampara and 26year (1990-2015) rainfall and temperature data were collected from Department of Meteorology (DOM) and Irrigation Department (ID). Catchment area of the reservoir is 994.22 sq.km and command area is 120,254 ac (488.66 sq.km).

TABLE I. Table 1 - Data sources and resolution

Data type	Temporal resolution	Data source
Rainfall	Daily	DOM, ID
Evaporation	Monthly	Climate Engines
Water Release	Daily	ID
Topographic	1:50000	Ministry of Agriculture (CSIAP)
Soil Map	1:50000	(CSIAP)
Land use	1:50000	(CSIAP)

The Figure **3** shows a map of the study area with 12 rainfall gauging stations marked. The selected stations cover a significant extent of the Senenayake Samudra catchment area, which is crucial for forecasting water level fluctuations.

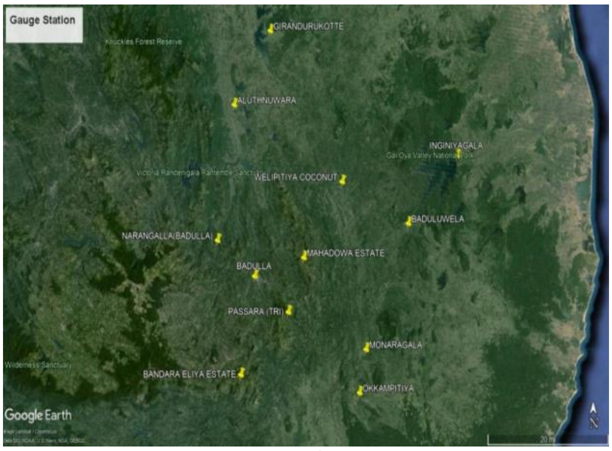

Figure 3 - Location of rain gauge stations

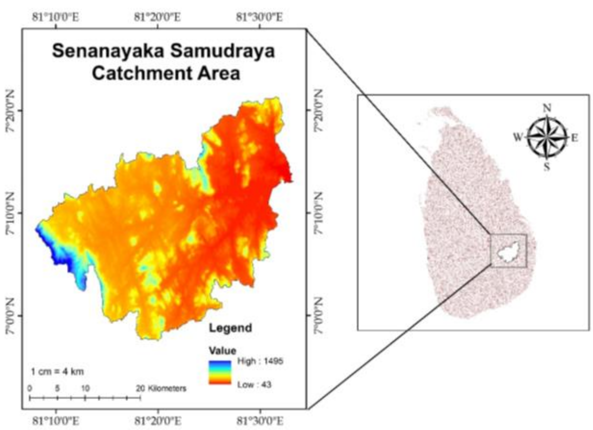

Figure 4 - Location of the Senanayake Samudraya Catchment Area

V. Analysis

The Figure **5** represents the digital elevation model (DEM) of the Senenayake Samudra catchment area extracted from ArcGIS.

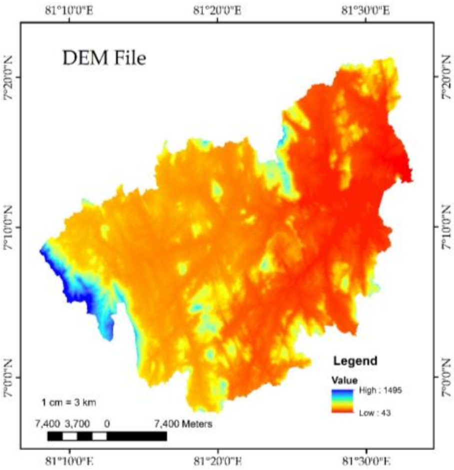

Figure 5 - Digital Elevation Model (DEM)

Figure **6** and Figure **7** show the generated soil map and land use map of the Senenayake Samudra catchment area.

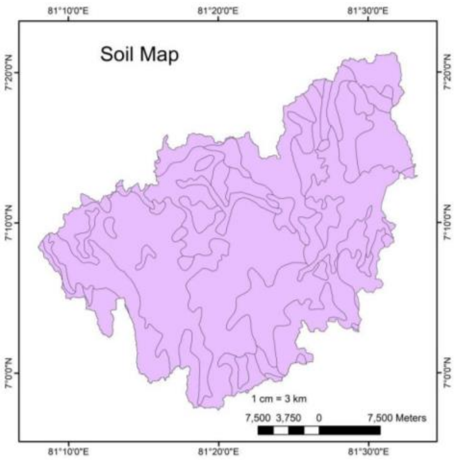

Figure 6 - Soil Map

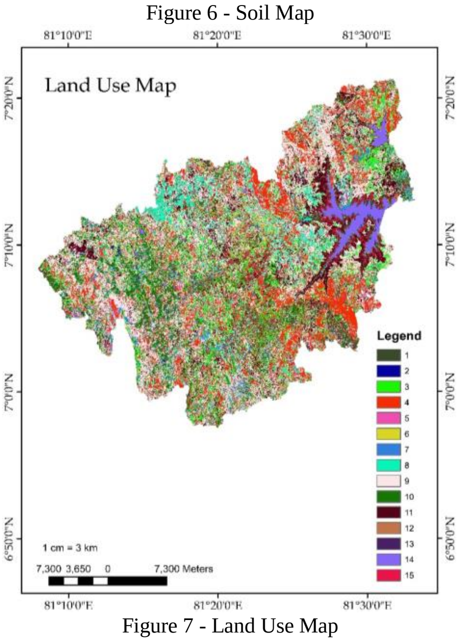

Figure 7 - Land Use Map

The Curve Number (CN) Grid was generated by integrating both the soil map and land use map. Figure **8** provides a spatially explicit representation of runoff potential across the basin in the Senenayake Samudura catchment area.

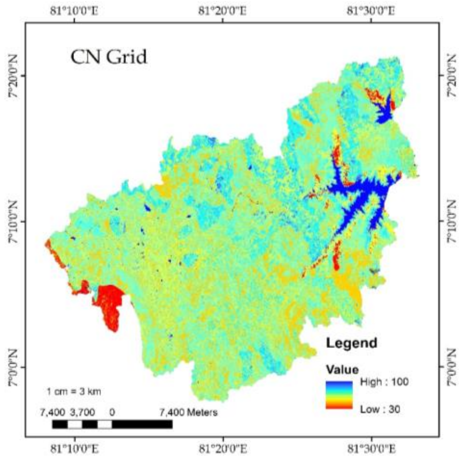

Figure 8 - Curve Number (CN) Map

A. Assigning Parameters in HEC-HMS Model

Assigning lag time for basin model involves analyzing various factors such as topography, soil type, land cover and drainage characteristics. Table 3 was prepared to calculate the necessary inputs to the basin model. This analysis considers how rainfall moves through the basin and Table 2 shows the details of initial abstraction rates of sub catchments.

TABLE 2 - DETAILS OF INITIAL ABSTRACTION RATES OF SUB CATCHMENTS

NO	Subbasin	Ia (inch)	Ia (mm)
1	Subbasin1	0.600983	15.26497
2	Subbasin2	0.55941	14.20902
3	Subbasin3	0.502346	12.75959
4	Subbasin4	0.473647	12.03064
5	Subbasin5	0.47813	12.14451
6	Subbasin6	0.484009	12.29383
7	Subbasin7	0.546506	13.88124
8	Subbasin8	0.271927	6.906944
9	Subbasin9	0.172473	4.380804

TABLE II. TABLE 3 - DETAILS OF LAG TIME ASSIGNING FOR PREPARATION OF BASIN MODEL

Subbasin	CN	L(ft)	Slope of basin (Y)	Y%	S (inch)	Tc (hr)	Lagtime (hr)	Lagtime (min)
Subbasin1	76.894	55621.64	0.172290	17.229	3.004916	3.491206	2.094724	125.6834
Subbasin2	78.143	56840.81	0.177770	17.777	2.797052	3.369044	2.021426	121.2856
Subbasin3	79.925	117514.4	0.117120	11.712	2.51173	7.026148	4.215689	252.9413
Subbasin4	80.85227	92130.35	0.084380	8.438	2.368236	6.617277	3.970366	238.222
Subbasin5	80.706	132864	0.156900	15.69	2.390652	6.534432	3.920659	235.2396
Subbasin6	80.515	21127.78	0.179270	17.927	2.420046	1.41269	0.847614	50.85684
Subbasin7	78.539	99154.28	0.171920	17.192	2.732528	5.283032	3.169819	190.1892
Subbasin8	88.031	24588.08	0.073710	7.371	1.359635	1.91824	1.150944	69.05665
Subbasin9	92.061	14892.91	0.023130	2.313	0.862363	1.942835	1.165701	69.94207

The basin was delineated into nine sub-catchments as shown in the Fig. 9

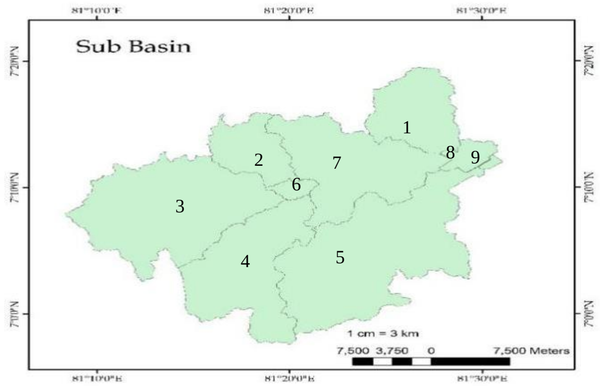

Fig. 9 - Sub-Basin Delineation

Fig. 10 illustrartes the physical characteristics of a watershed, including streams, subbasins, reservoirs, and other hydrologic features. The model will be used to simulate how rainfall is converted into runoff.

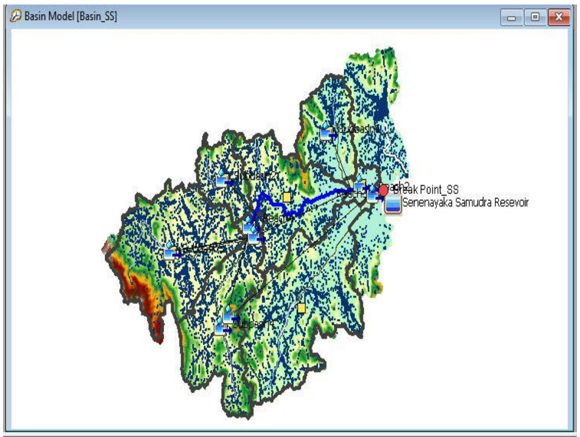

Fig. 10 -Basin Model Generated by the HEC-HMS (Version 4.11)

VI. RESULT

The Fig. 11 Shows simulated inflow generated by the HEC-HMS for the period of 1990-2015 represents model's predictions based on the input parameters and equations. It shows a relatively stable baseline with occasional spikes in inflow rates over the period.

Peaks in inflow are prominent, particularly around early 1990s, late 1990s, early 2000s, and mid-2000s. These peaks indicate significant rainfall or runoff events leading to higher inflow rates. The inflow values show a consistent pattern of low to moderate values with distinct high peaks. This suggests that the HEC-HMS model captures a range of inflow conditions, from regular low inflows to episodic high inflows.

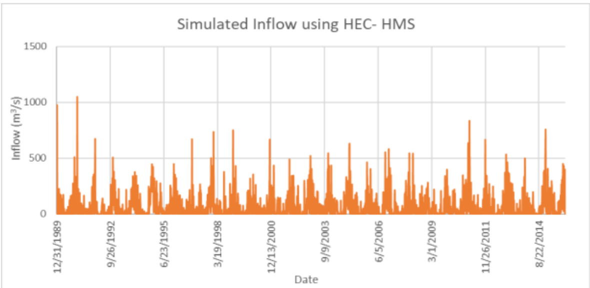

Fig. 11 - Simulated Inflow Using HEC-HMS Model

The Fig. 12 illustrates Simulated SCS-CN inflow graph shows high variability in inflow rates over the period from 1990 to 2015.There are several notable peaks, indicating periods of high inflow. It shows a more dynamic range of inflow rates with frequent peaks over the same period. The inflow peaks are more pronounced and occur more frequently compared to the HEC-HMS model. This indicates that the SCS-CN method may be more sensitive to variations in rainfall and runoff.

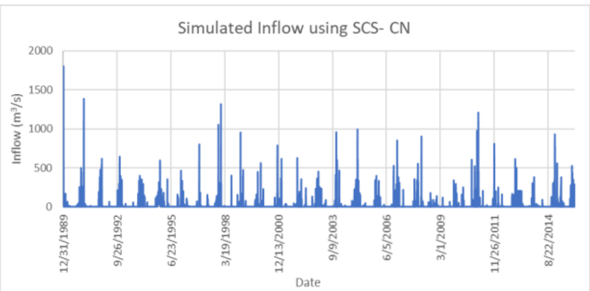

Fig. 12 - Simulated Inflow Using SCS-CN Method

The Figure 13 and Figure 14 display the comparison between rainfall and inflow as calculated by the HEC-HMS and SCS-CN methods.

The Figure 13, which utilizes the HEC-HMS method, shows a relatively stable relationship between rainfall and inflow, with inflow peaks aligning closely with rainfall peaks, suggesting that the HEC-HMS model accurately reflects the direct impact of rainfall on inflow rates.

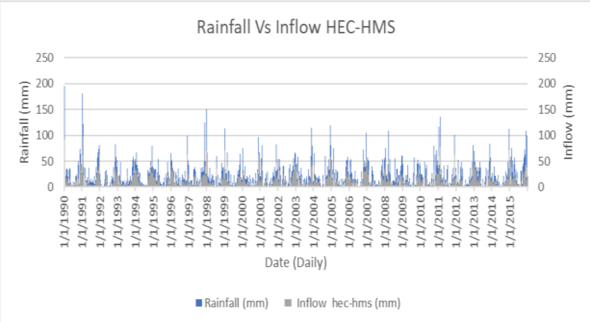

Figure 13 - Comparison of Rainfall with Calculated Inflow Using HEC-HMS

The Figure 14, using the SCS-CN method, illustrates a more pronounced and frequent fluctuation in inflow rates. This suggests that the SCS-CN method is more sensitive to rainfall variations, capturing higher inflow peaks more frequently than the HEC-HMS model. This heightened sensitivity indicates that the SCS-CN method may be better suited for detecting rapid changes in inflow due to sudden rainfall events. However, it also suggests a higher degree of variability in the inflow data, which could imply the need for careful calibration to avoid overestimation in certain periods.

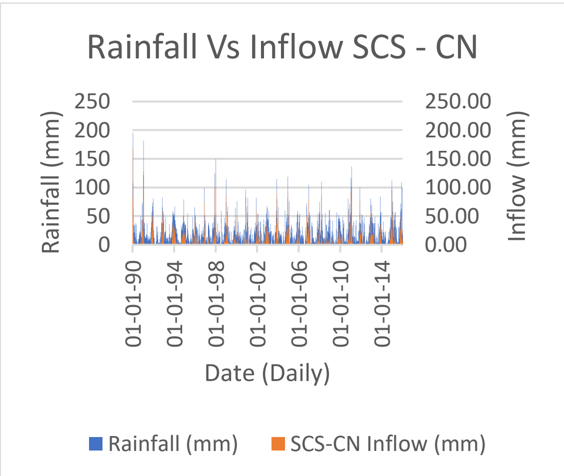

Figure 14 - Comparison of Rainfall with Calculated Inflow Using SCS-CN Method

The Figure 15 displays cumulative inflow for the Senanayake Samudra Reservoir from 1990 to 2015, calculated using the water balance equation, shows a consistent pattern with notable inflow peaks at intervals. The water balance equation incorporates changes in reservoir storage, water releases, and evaporation to determine the cumulative inflow.

The graph highlights several periods of sharp increases in inflow, particularly in the early 1990s, mid-1990s, early 2000s, and around 2010. These peaks suggest significant rainfall or runoff events that caused a surge in inflow. Between these peak events, the inflow remains at moderate or low levels, indicating stable reservoir conditions during less extreme weather periods.

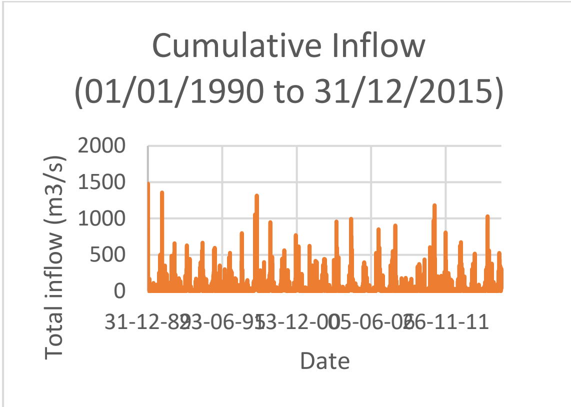

Figure 15 - Cumulative Inflow

The Figure 16 Shows base flow of the Senanayake Samudra Reservoir was determined by subtracting surface inflow from the cumulative inflow over time. The graph reveals periodic fluctuations in base flow, with peaks occurring during specific periods, likely corresponding to seasonal rainfall or runoff events.

Overall, the base flow maintains relatively lower values between these peaks, suggesting that natural groundwater or subsurface inflows contribute steadily to the reservoir's water levels. The variation in base flow highlights the reservoir's capacity to manage consistent water supply during non-peak times and maintain stability during less extreme conditions.

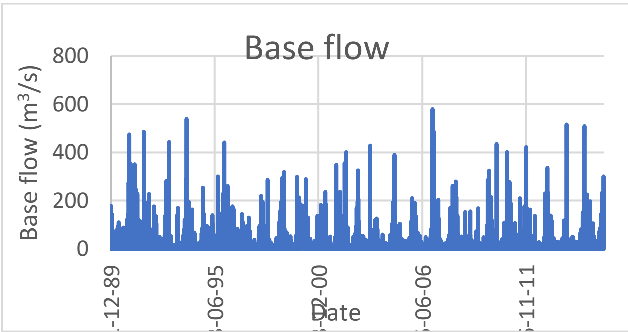

Figure 16 - Base Flow of the Senanayake Samudra Reservoir

1) Correlation analysis

Correlation analysis for the all the attributes were identified. Figure 17 shows the relationship between the all the attributes by using the heatmap.

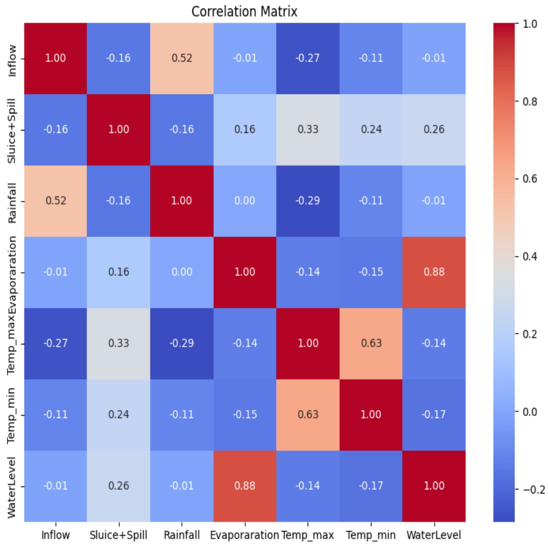

Figure 17 - Attributes Correlation Analyze with Heatmap

The Figure 18 model's loss per epoch graph is crucial for understanding the training dynamics and overall performance of the neural network. Initially, the loss is high, indicating significant prediction errors. As training progresses, the loss decreases rapidly, showing that the model is learning and improving its predictions. Eventually, the loss stabilizes at a lower value, signalling that the model has converged and additional training offers minimal improvement. This steady decrease and eventual stabilization in loss highlight the model's effectiveness in learning from the data and optimizing its predictive accuracy.

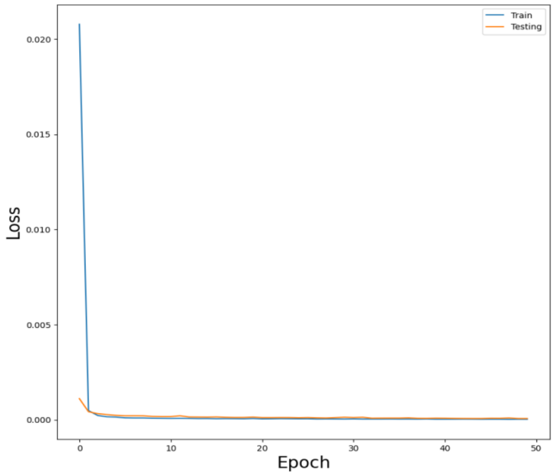

Figure 18 - Model's Loss Per Epoch Graph

The Figure 19 model analyzes patterns and trends in the past water level data and learns to make predictions about future water level. By processing sequences of historical water level measurements, the RNN captures temporal dependencies and learns to anticipate how water level will change over time. The predicted water level represents the model's best estimate of what the future water level will be, given the information available from the training data. While the prediction may not be perfect and can be influenced by factors not captured in the training data, it serves as a valuable tool for anticipating and planning for future water level fluctuations in the reservoir.

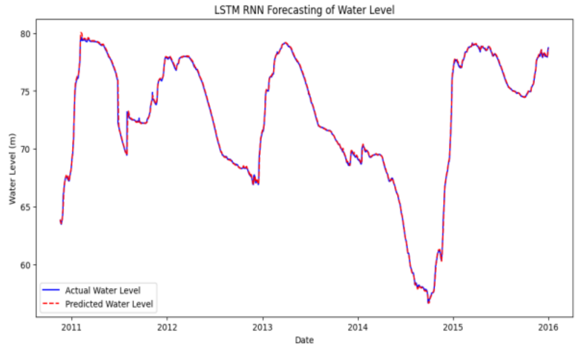

Figure 19 - Forecasting of Water Level Fluctuations Graph Generated Using RNN

The Figure 20 illustrates a graph based on predicted water levels of the Senenayake Samudra reservoir for January 2016 the water level predictions start at a higher value and exhibit a gradual decrease over the course of the month, with a notable drop in the middle of the month before stabilizing towards the end.

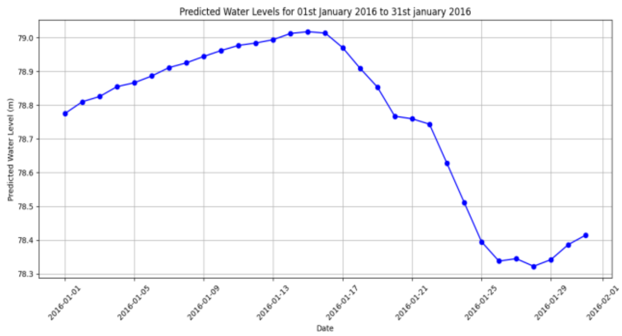

Figure 20 - Prediction of Water Level Fluctuations of Senenayake Samudra Reservoir

Figure 21 illustrates the comparison between Actual and predicted Water Level Fluctuation for the Senenayake Samudra Reservoir during January 2016.The close alignment between the actual and predicted water levels reflects the model’s effectiveness and indicating a well-fitted model in forecasting water level fluctuations.

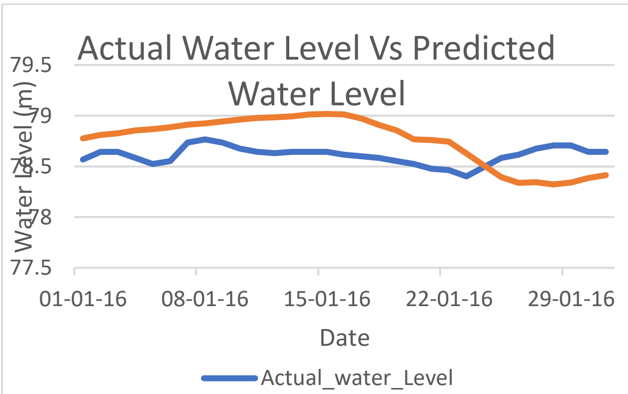

Figure 21 - Actual and Predicted Water Level Fluctuation in January 2016

Beyond the January 2016 validation, the analysis was extended to assess monthly and annual variations of water level fluctuations over the 26-year dataset. Results indicate that the reservoir exhibits strong seasonal signals, with peak water levels typically occurring during the Maha season (October–March) and notable declines during the Yala season (April–September). Annual fluctuations were within the range of 0.4–0.6 m on average, with higher variability in years of extreme rainfall. This highlights the ability of the model to capture both short-term (monthly) and long-term (annual) variations, thereby reinforcing its utility for operational reservoir management.

Calibration of the hydrological parameters was performed using observed inflows, evaporation, and release data. The model was iteratively tuned to minimize errors between simulated and observed water levels. Sensitivity analysis revealed that rainfall input and curve number values exerted the strongest influence on predicted inflows, whereas evaporation and sluice releases had secondary but still measurable effects. This process ensured robustness of the model before applying the LSTM forecasting framework.

B. *Model's Performance*

The MSE value is 0.0357. This means that the model's predictions deviate from the actual value. The RMSE (Root Mean Squared Error value) value is 0.189. This indicates that the model's predictions have an average error of approximately 0.189 units, providing a measure of the model's accuracy in forecasting water level fluctuations. Coefficient of Determination value is 0.998. The model fits the data well and captures the relationships between the independent variables and water level fluctuations effectively.

Overall, the results indicate that the LSTM and RNN model is performing well in forecasting water level fluctuations in the reservoir. The small MSE and RMSE values suggest that the model's predictions are relatively accurate, while the high value indicates a strong explanatory power of the independent variables in the model. This implies that your model is robust and provides valuable insights into the factors influencing reservoir dynamics.

VII. CONCLUSION

Overall, the results indicate that RNN (LSTM) model is performing well in forecasting water level fluctuations in the Senenayake Samudra reservoir. It provides valuable guidance for water resource management and decision-making processes, facilitating sustainable and efficient utilization of the reservoir's water resources. This research successfully assessed the feasibility of forecasting water level fluctuations in the Senanayake Samudra Reservoir using hydrological modeling and machine learning techniques.

The study developed a comprehensive water level forecasting framework by integrating the HEC-HMS model, the SCS-CN method, and time-series forecasting models such as LSTM and RNN.

The results demonstrated that the SCS-CN method provided a more reliable estimation of inflow, which was further utilized for water level prediction.

The LSTM and RNN models achieved excellent forecasting performance, with MSE = 0.0357, RMSE = 0.189, and R^2 = 0.998, demonstrating their suitability for water level prediction.

VIII. RECOMMENDATION

By accurately forecasting reservoir water levels, this study provides valuable insights for water resource management, irrigation planning, and flood control strategies.

The study highlights the importance of addressing variable rainfall and temperature patterns driven by climate change in reservoir management strategies.

The developed model can aid policymakers and reservoir managers in making informed decisions to ensure sustainable water management practices amid climate variability and increasing water demands.

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