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Renuka Baglane

Ph.D. Scholar, Interfaculty
 Department of Irrigation
 Water Management, Mahatma
 Phule Krishi Vidyapeeth,
 Rahuri, Maharashtra, India

MS Mane

Professor and Head,
 Department of Irrigation and
 Drainage Engineering, Dr.
 ASCAET, MPKV, Maharashtra,
 India

DD Khedkar

Professor (CAS), IDE, MPKV,
 Rahuri, Maharashtra, India

Sunil Kadam

Interfaculty Department of
 Irrigation Water Management,
 Mahatma Phule Krishi
 Vidyapeeth, Rahuri - 413 722,
 Dist. Ahilyanagar,
 Maharashtra India

SK Ghodke

Assistant Professor,
 Department of Soil Sciences,
 IFD-IWM, MPKV, Rahuri,
 Maharashtra, India

Corresponding Author:

Renuka Baglane

Ph.D. Scholar, Interfaculty
 Department of Irrigation
 Water Management,
 Mahatma Phule Krishi
 Vidyapeeth, Rahuri,
 Maharashtra, India

Random forest-based reservoir inflow prediction for *Mula* reservoir, Maharashtra, India

Renuka Baglane¹, MS Mane², DD Khedkar³, Sunil Kadam⁴, SK Ghodke⁵

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ABSTRACT

Accurate reservoir inflow prediction is essential for effective reservoir operation and sustainable water resource management. This study developed a Random Forest (RF) model for monthly reservoir inflow prediction at *Mula* Reservoir, Maharashtra, India, using 432 monthly observations from June 1984 to May 2020. The model incorporated lagged reservoir inflow, rainfall, pan evaporation, reservoir-surface evaporation, and seasonally transformed month variables. Lag-correlation analysis identified relevant antecedent conditions, and a two-month lag period was selected for model development. An 80:20 chronological split was used for training and independent testing. The model achieved RMSE, R^2 and NSE values of 37.66 MCM, 0.89 and 0.89 for training, and 32.81 MCM, 0.85 and 0.85 for testing, respectively. Month sine and cosine variables jointly contributed approximately 55% of feature importance, followed by one-month lagged inflow. The model effectively captured seasonal and antecedent characteristics and has potential to support reservoir operation, irrigation planning and water resource management.

Keywords: Hydrological forecasting, Machine learning, Random Forest, Reservoir inflow

Introduction

Reservoirs play an important role in water-resource management by supporting irrigation, domestic and industrial water supply, hydropower generation, and flood and drought management. Reliable reservoir inflow forecasts are therefore essential for effective storage planning, water allocation, and reservoir operation (Solomatine *et al.*, 2008; Wang *et al.*, 2009; Yang *et al.*, 2017) [1, 2, 3]. In monsoon-dependent regions, inflow can vary considerably with seasonal rainfall and other hydro-meteorological conditions, making accurate forecasting particularly important (Mohammadi, 2021; Jahanbani *et al.*, 2024) [5, 4]. Reservoir inflow forecasting has traditionally relied on physically based hydrological models, conceptual approaches, and statistical techniques. Although these methods remain valuable, their performance may be influenced by model assumptions, parameterization, data requirements, and the complexity of hydrological processes (Solomatine *et al.*, 2008; Maier *et al.*, 2010) [1, 6]. Data-driven and machine-learning (ML) methods have consequently gained attention because they can learn complex and nonlinear relationships directly from historical observations (Wang *et al.*, 2009; Mosavi *et al.*, 2018; Xu *et al.*, 2021) [2, 7, 8]. Their application in hydrology has expanded with the increasing availability of hydro-meteorological data and advances in computational methods (Shen, 2018; Mohammadi, 2021) [9, 5]. Several ML techniques, including neural networks, support vector machines, ensemble methods, and deep-learning models, have been applied to rainfall-runoff and streamflow forecasting (Kratzert *et al.*, 2018; Zounemat-Kermani *et al.*, 2021; Jahanbani *et al.*, 2024) [10, 11, 4]. Among these, Random Forest (RF) is attractive because of its ability to represent nonlinear relationships, handle multiple predictors, and provide estimates of predictor importance. The RF algorithm was introduced by Breiman (2001) [12], and its theoretical properties and applications have been discussed extensively by Biau *et al.* (2016) [13]. RF and related ensemble approaches have been successfully applied to streamflow simulation, rainfall-runoff modelling, and flood prediction (Schoppa *et al.*, 2020; Tikhamarine *et al.*, 2020) [14, 15]. ML-based reservoir inflow forecasting has also shown promising results. Yang *et al.* (2017) [3] demonstrated the usefulness of ML models for monthly reservoir inflow forecasting, while subsequent studies incorporated climate information, satellite-derived variables, and antecedent hydrological conditions to improve forecasting performance (Tian *et al.*, 2022; Ibrahim *et al.*, 2023) [17, 16]. Recent studies have also emphasized the value of model interpretability and the continued development of ML and deep-learning approaches for long-term hydrological forecasting (Sushanth *et al.*, 2023; Ghenaati *et al.*, 2025) [19, 18]. In particular, previous studies have shown that lagged inflow and meteorological variables can provide useful information about catchment memory and current hydrological conditions (Kratzert *et al.*, 2018; Kratzert *et al.*, 2019; Tikhamarine *et al.*, 2020) [10, 20, 15].

The *Mula* Reservoir in Maharashtra is an important multipurpose reservoir serving irrigation, domestic, and industrial water requirements in the region. Previous research has examined its operation and water-allocation characteristics within the Upper Godavari Basin (Srivastava *et al.*, 2009; Paliwal *et al.*, 2020) [22, 21]. Its

strong seasonal inflow behaviour and availability of long-term hydro-meteorological observations make it a suitable case for evaluating data-driven inflow forecasting. Despite the growing use of ML for hydrological forecasting, model performance and predictor importance can vary considerably between catchments and datasets. Recent research has therefore highlighted the need to consider appropriate predictor selection, temporal structure, interpretability, and independent evaluation rather than focusing only on predictive accuracy (Nearing *et al.*, 2021; Xu *et al.*, 2021; Jahanbani *et al.*, 2024) [23, 8, 4]. A case-specific assessment of seasonal and antecedent variables is consequently important for developing reliable and interpretable reservoir inflow models. Accordingly, this study develops a Random Forest model for monthly reservoir inflow prediction at *Mula* Reservoir, Maharashtra, India, using long-term hydrological and meteorological observations. The study aims to evaluate the applicability of RF for monthly reservoir inflow prediction and its potential to support reservoir operation and water-resource management.

Materials and Methods

Study area

The *Mula* reservoir is a major multipurpose reservoir constructed across the *Mula* River, a tributary of the Godavari River, in Ahmednagar district, Maharashtra, India. The reservoir plays a vital role in supplying water for irrigation, domestic consumption, and industrial activities within the command area. It is one of the principal irrigation projects in western Maharashtra and supports agricultural production across a predominantly semi-arid region. The catchment experiences a tropical monsoon climate, characterized by three distinct seasons: summer (March–May), southwest monsoon (June–September), and winter (October–February). Large portion of the annual rainfall occurs during the southwest monsoon, resulting in highly seasonal inflow patterns. Consequently, reservoir inflows exhibit considerable interannual variability influenced by rainfall distribution, antecedent catchment conditions, and evaporation losses. These characteristics make the *Mula* reservoir an appropriate case study for evaluating machine learning-based inflow forecasting models.

Data collection

Monthly hydrological and meteorological data were collected for the *Mula* reservoir from the Water Resources Department, Government of Maharashtra. The dataset comprised continuous monthly observations from June 1984 to May 2020, resulting in 432 monthly records namely, monthly reservoir inflow in Million Cubic Metres (MCM), monthly rainfall in mm per month, monthly pan evaporation in mm per month, monthly evaporation from the reservoir surface in Million Cubic Metres (MCM). The data analysis and preprocessing, model development, data parameter optimization, and model performance evaluation was carried out using Python programming language of version 3.10. The analysis was performed in the Jupyter Notebook environment, which provides an interactive platform for data preprocessing, model implementation, visualization, and result interpretation.

Descriptive statistical analysis

The analysis was conducted for key parameters influencing reservoir inflow, rainfall, evaporation losses, and evaporation loss from reservoir. Statistical measures such as mean, median, mode, standard deviation, variance, minimum, maximum, range, skewness, and kurtosis were computed to evaluate the central tendency, dispersion, and distributional properties of the dataset. The correlation analysis of the selected variables for the prediction of reservoir inflow was performed to understand the driving variables affecting reservoir inflow. In the correlation analysis Pearson Correlation Coefficient was used to determine the degree of linear association between variables.

Random Forest (RF) model

Random Forest is an ensemble learning technique that constructs multiple decision trees using bootstrap sampling and random feature selection as shown in figure 1. It is developed by Breiman (Breiman, 2001) [12], RF is a powerful ensemble learning ML algorithm that can be constructed using multiple decision trees. The final prediction is obtained by averaging the outputs of individual trees. The RF model is capable of capturing complex non-linear relationships and reducing overfitting through aggregation. The selected hyperparameter values were determined through preliminary experiments conducted using the training data.

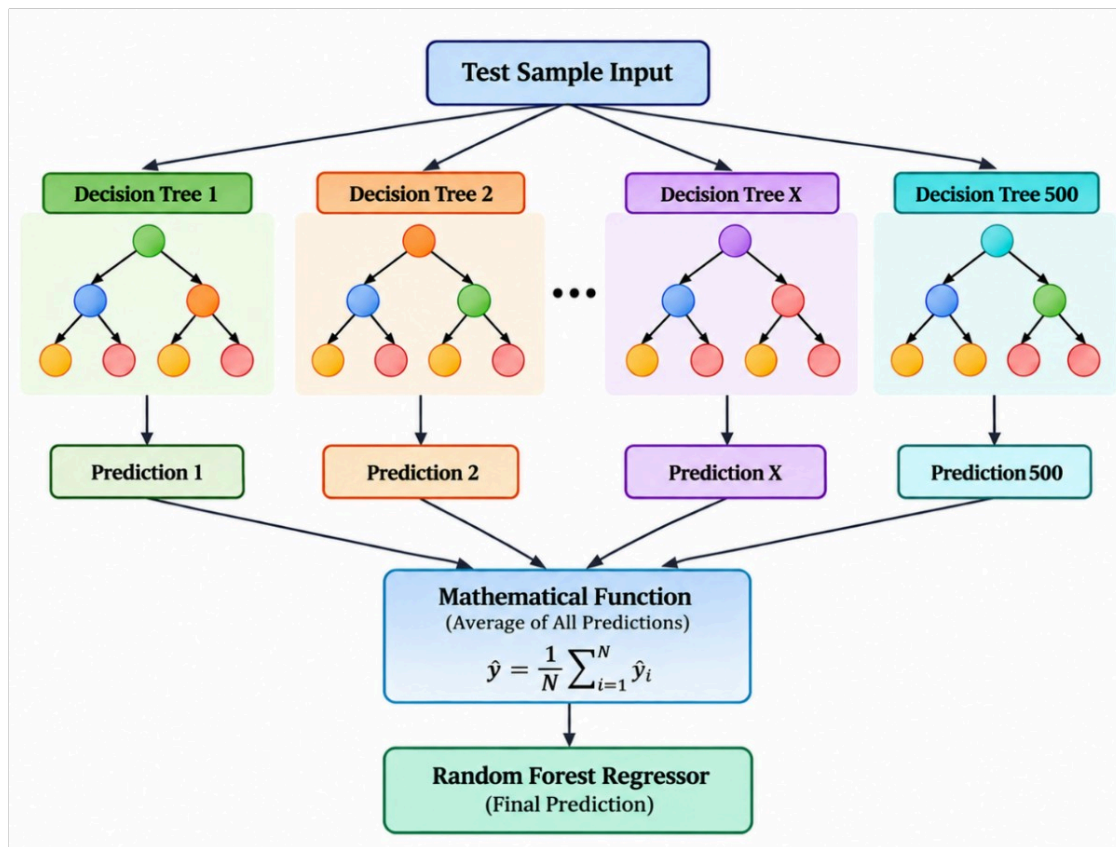


Figure 1. Schematic representation of the Random Forest regression model

Feature engineering

The modelling workflow included data preparation, lag-correlation analysis, feature engineering, chronological train-test splitting, RF fitting, prediction and performance evaluation. The monthly reservoir inflow was modelled as;

$$I_t = f(X_t)$$

where I_t is the monthly reservoir inflow during month t (MCM), and X_t represents the vector of predictor variables available for predicting month t . Lag-correlation analysis was performed for the preceding three months to identify relevant antecedent conditions. Considering the observed relationships and the importance of recent antecedent conditions, a two-month lag period was selected. Accordingly, lag-1 and lag-2 values of inflow, rainfall, pan evaporation and reservoir-sur-

face evaporation were used as predictors. The month number was transformed into sine and cosine variables to represent seasonal cyclicality. The final predictor matrix contained eleven variables: year, Month_sin, Month_cos, and lag-1 and lag-2 values of inflow, rainfall, pan evaporation and reservoir-surface evaporation. The response variable was current-month reservoir inflow. Thus,

$$\hat{I}_t = f(\text{Year}_t, \text{Month_cos}_t, \text{Month_sin}_t, I_{t-1}, I_{t-2}, R_{t-1}, R_{t-2}, E_{t-1}, E_{t-2}, E_{t-1}, E_{t-2})$$

Where $\hat{I}_t$ is the predicted inflow. After lag generation, the model-ready observations were divided chronologically into 80% training and 20% independent testing datasets. Predictor variables were used in their original numerical units without scaling. Figure 2 shows the flow chart of applied methodology for the study.

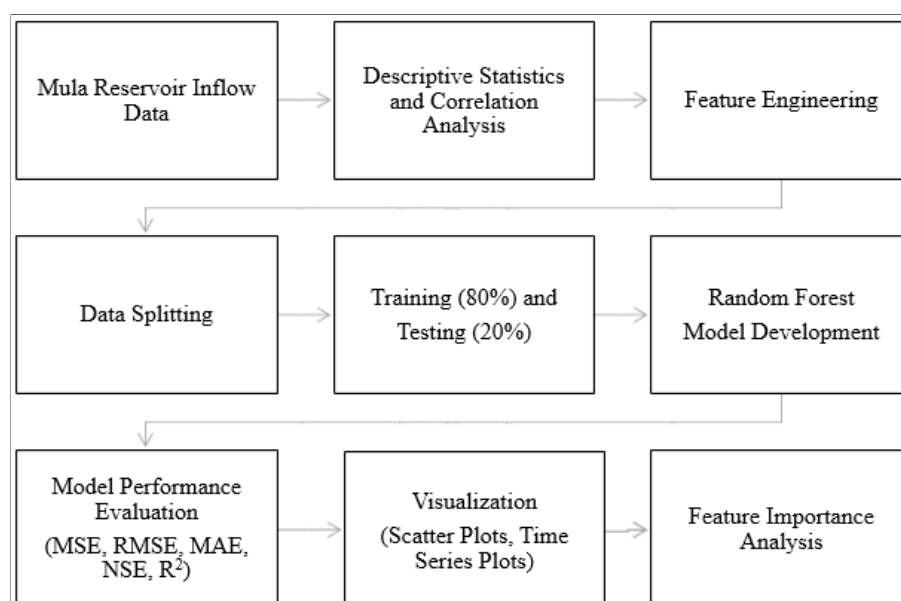


Figure 2. Methodological framework for monthly reservoir inflow forecasting using Random Forest model

Model development

Random Forest combines the predictions of multiple decision trees, enabling the model to capture nonlinear relationships between antecedent hydrometeorological conditions, seasonal variables and current reservoir inflow. Randomness is introduced during tree construction to increase diversity among individual trees, and their predictions

are aggregated to obtain the final output. In the present study, 500 trees were used, with bootstrap sampling enabled through the default RandomForestRegressor configuration. The model was executed using $n_jobs = -1$ to utilize all available processor cores for parallel computation. The other model parameters used in the study are presented in Table 1.

Table 1. Parameters of the developed Random Forest Model for Inflow Prediction

Hyperparameter	Value used	Role in the model
n_estimators	500	Number of decision trees in the forest
max_depth	10	Maximum depth allowed for each decision tree
min_samples_split	5	Minimum number of samples required to split an internal node
min_samples_leaf	2	Minimum number of samples required in a terminal leaf
random_state	42	Ensures reproducibility of the randomization
n_jobs	-1	Uses all available processor cores for parallel computation
max_features	Default	Python 3.10.10 and Scikit-learn 1.7.2 is used
Bootstrap	True	Bootstrap samples are used to construct individual trees

The Random Forest model was fitted using the training observations, with each decision tree learning the relationship between the eleven predictor variables and current-month reservoir inflow. The final prediction was obtained by averaging the predictions of all trees. The fitted model was then applied to both training and testing datasets to evaluate model fit and generalization. Feature importance was assessed using the impurity-based importance measure of the RF, with normalized scores used to determine the relative contribution of individual predictors to inflow prediction.

Model performance evaluation

The predictive performance of the developed model was evaluated using several statistical performance metrics that measure the degree of agreement between observed and predicted reservoir inflow values. In

the present study, the coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to assess and validate the performance of the RF model.

Results and Discussion

Descriptive statistical analysis

Table 2 presents the complete descriptive statistics for all four hydrometeorological variables computed over the full 432-month record (June 1984 – May 2020).

Table 2. Descriptive Statistics of Monthly Hydrometeorological Variables at Mula Reservoir

Statistical parameters	Inflow (MCM)	Rainfall (mm/month)	Pan evaporation (mm/month)	Reservoir evaporation (MCM)
Count	432	432	432	432
Mean	60.998	40.943	139.870	4.680
Median	0.706	4.000	118.750	4.309
Mode	0.000	0.000	87.000	2.002
Standard Deviation	109.323	64.876	65.948	1.811
Sample variance	11,951.47	4,208.92	4,349.13	3.280
Skewness	2.722	2.195	1.036	1.009
Kurtosis (Excess)	10.847	5.516	0.435	0.914
Minimum	0.000	0.000	35.000	1.709
Maximum	898.893	391.000	342.500	10.979
Range	898.893	391.000	307.500	9.270
Sum	26,351.01	17,687.50	60,423.77	2,021.68

The monthly inflow series exhibited a mean value of 60.998 MCM and a high standard deviation of 109.323 MCM and a coefficient of variation of 179.2%, indicating extremely high temporal variability. Such variability reflects the strong influence of seasonal rainfall patterns and the occurrence of extreme hydrological events within the catchment. Table 3 shows the lag correlation analysis for previous

three months were carried out for all variables. Considering the observed lagged relationships and the need to represent recent antecedent hydrometeorological conditions without introducing an unnecessarily long predictor window, a two-month antecedent period was selected for model development.

Table 3. Pearson Correlation Coefficients Between Lagged Predictor Variables and Current-Month Reservoir Inflow

Lag	Rainfall	Pan evaporation	Reservoir-surface evaporation	Reservoir inflow
1 month	0.409	-0.127	-0.285	0.577
2 months	0.18	0.275	0.043	0.138
3 months	-0.069	0.601	0.425	-0.145

Lag-correlation analysis was conducted for one- to three-month antecedent periods to examine the relationship between hydrometeorological conditions and current-month reservoir inflow. Rainfall and reservoir inflow showed the strongest relationships at a one-month lag, while some evaporation variables exhibited stronger relationships

at longer lags. Random Forest models with different antecedent windows were subsequently evaluated. Based on the lag-correlation results and model performance, a two-month antecedent window was selected for the final model. The Pearson correlation matrix among the hydrometeorological variables is presented in Table 4.

Table 4. Pearson Correlation Matrix of Monthly Hydrometeorological Variables

Variable	Inflow (MCM)	Rainfall (mm/month)	Pan evaporation (mm/month)	Reservoir evaporation (MCM)
Inflow (MCM)	1.000	0.501	-0.323	-0.300
Rainfall (mm/month)	0.501	1.000	-0.245	-0.293
Pan evaporation (mm/month)	-0.323	-0.245	1.000	0.835
Reservoir evaporation (MCM)	-0.300	-0.293	0.835	1.000

All correlations are statistically significant at $p < 0.001$ (two-tailed), given $n = 432$.

The moderate positive correlation between monthly rainfall and reservoir inflow indicates the important role of rainfall in generating reservoir inflow. However, the correlation is not very high because not all rainfall becomes runoff. Part of the rainfall is lost through interception, infiltration, soil moisture storage, and groundwater recharge. In addition, rainfall varies across the catchment, and monthly averages may not capture the timing and intensity of individual storms. Groundwater (baseflow) can also continue to contribute to reservoir inflow even during months with little rainfall.

Random Forest model

The Random Forest model was developed to predict monthly reservoir inflow using a feature engineered set of eleven predictor variables. The dataset was divided into training and testing subsets using an 80:20 chronological split. Out of 432 months, initial two months were dropped after lag month creation, 344 months (August 1984 to March 2013) were used to train the model and remaining 86 months (April 2013 to May 2020) were used for testing the model. The performance of developed RF Model to predict monthly reservoir inflow is depicted in table 5.

Table 5. RF model Performance for Training and Testing Reservoir Inflow Prediction

Dataset	MSE (MCM ²)	RMSE (MCM)	MAE (MCM)	R ²	NSE
Training	1418.99	37.66	16.12	0.89	0.89
Testing	1076.77	32.81	17.83	0.85	0.85

The model achieved an RMSE of 37.66 MCM and R² and NSE values of 0.89 on the training dataset, indicating that it explained about 89% of the variability in monthly reservoir inflow. On the testing dataset, the model produced an RMSE of 32.81 MCM with R² and NSE values of 0.85, demonstrating good prediction accuracy and strong generalization ability. The relatively small difference between the training and testing results suggests that the model did not overfit the data. Overall, the RF model effectively captured the nonlinear relationships between the selected input variables demonstrating good predictive performance for monthly reservoir inflow prediction. Figure 3 presents the temporal variation in observed and predicted reservoir inflow during the testing period. The predicted values generally followed the observed seasonal pattern, indicating that the model captured the major fluctuations in monthly inflow. Figure 4 presents

the relationship between observed and predicted inflow values. Most points were distributed around the 1:1 line, with a testing R² of 0.85, indicating that the model explained approximately 85% of the variability in the independent testing dataset.

The sensitivity of the RF model to the antecedent lag period was also examined. Extending the predictor window from two to three months reduced model performance. For the three-month lag specification, the model achieved an RMSE of 41.73 MCM, MAE of 20.55 MCM, R² of 0.758, and NSE of 0.758 on the testing dataset, compared with 32.81 MCM, 17.83 MCM, 0.85, and 0.85, respectively, for the two-month specification. The higher prediction errors and lower efficiency for the three-month specification indicate that extending the antecedent window did not improve prediction performance for the Mula Reservoir dataset.

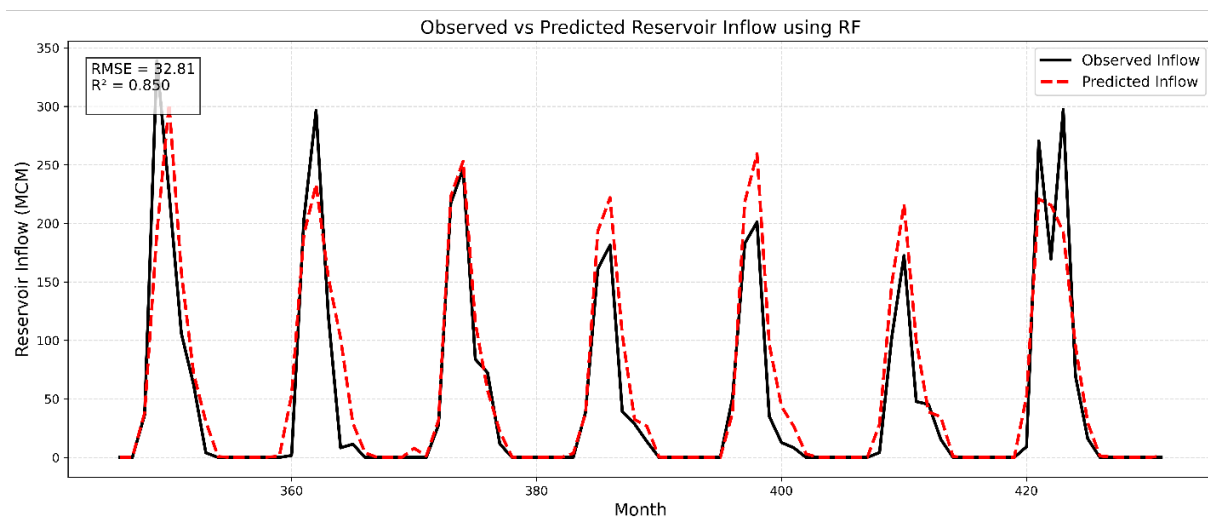


Figure 3. Variation in observed and predicted reservoir inflow using Random Forest model

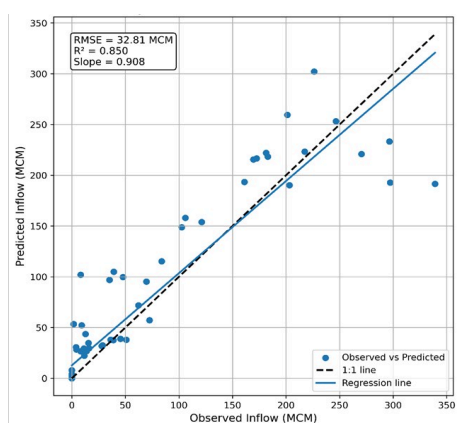


Figure 4. Observed versus Predicted reservoir inflow using RF model

The relative importance of the predictor variables in the developed RF model was evaluated to identify the variables that contributed

most to monthly reservoir inflow prediction. The results showed that the seasonal variables were the most influential predictors. Month_sin and Month_cos had importance values of 0.291 and 0.259, respectively, and together accounted for approximately 55.0% of the total feature importance. This indicates the strong seasonal pattern in reservoir inflow. The one-month lagged inflow was the third most important predictor for reservoir inflow, with an importance value of 0.227, highlighting the influence of recent antecedent inflow conditions on current-month inflow. Among the meteorological variables, two-month lagged reservoir evaporation (0.049) and one-month lagged rainfall (0.039) showed relatively higher importance. The remaining lagged variables had comparatively lower individual contributions. Overall, the feature importance analysis indicates that seasonality and recent antecedent inflow conditions were the dominant predictors of monthly reservoir inflow in the developed RF model. Table 6 shows the relative feature importance of predicting variables in the RF model.

Table 6. Feature importance of predictor variables in the Random Forest model

Rank	Predictor variable	Feature importance
1	Seasonality (sine-transformed month)	0.291
2	Seasonality (cosine-transformed month)	0.259
3	Previous-month reservoir inflow	0.227
4	Reservoir-surface evaporation – 2-month lag	0.049
5	Rainfall – 1-month lag	0.039
6	Pan evaporation – 2-month lag	0.033
7	Year	0.025
8	Rainfall – 2-month lag	0.021
9	Pan evaporation – 1-month lag	0.020
10	Reservoir-surface evaporation – 1-month lag	0.018
11	Reservoir inflow – 2-month lag	0.017

Conclusion

The Random Forest model effectively predicted monthly reservoir inflow at Mula Reservoir using antecedent hydrological, meteorological, and seasonal variables. The model achieved R^2 and NSE of 0.85 with an RMSE of 32.81 MCM on the independent testing dataset, indicating good predictive performance and generalization. Feature importance analysis showed that seasonality and previous-month inflow were the dominant predictors. The results are based on a single reser-

voir and a historical monthly dataset; therefore, further evaluation across different reservoirs, forecast periods, and predictor configurations is required to assess broader applicability. Overall, the developed model provides a useful approach for supporting reservoir operation and sustainable water resource management.

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