Nature Environment and Pollution Technology
An International Quarterly Peer-Reviewed Open Access Journal

p-ISSN: 0972-6268 | e-ISSN: 2395-3454 Vol. 25 | No. 3 | Article ID B4425 | 2026

RESEARCH ARTICLE https://doi.org/10.46488/NEPT.2026.v25i04.B4425 OPEN ACCESS

Modeling Temporal Persistence in Daily Pan Evaporation Using Interpretable Machine Learning

Jaydeep Kale† and Sanjaykumar Sharma
Department of Computer Science & Engineering, Oriental University, Indore, 453555, Madhya Pradesh, India
†Corresponding author: Jaydeep Kale; jaynkale@gmail.com

ARTICLE HISTORY

Received: 14-01-2026
Revised: 04-03-2026
Accepted: 20-03-2026

KEYWORDS

Pan evaporation
Temporal memory
Evaporation persistence
Machine learning
CatBoost

CITE THIS ARTICLE

Kale, J. and Sharma, S., 2026. Modeling temporal persistence in daily pan evaporation using interpretable machine learning. *Nature Environment and Pollution Technology*, 25(4), B4425. https://doi.org/10.46488/NEPT.2026.v25i04.B4425

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ABSTRACT

Accurate prediction of daily pan evaporation (Ep) is critical for irrigation management and water resource planning, yet it remains challenging due to strong temporal variability and persistence. Most available models are based primarily on contemporaneous meteorological variables and do not account for the inherent memory of evaporation. This paper systematically explores the impact of temporal memory on daily Ep by explicitly separating evaporation persistence from meteorological memory through a machine learning framework. A Categorical Boosting (CatBoost) model was used to analyze multi-year data from a semi-arid to sub-humid area in western-central India. The model used lagged Ep and meteorological variables at 1-, 3-, 7-, and 14-day timescales. The coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were used to evaluate model performance, while Random Forest and XGBoost were used for benchmarking. Feature importance and SHAP analyses provided interpretability. The findings indicate that the inclusion of a 1-day lag of pan evaporation substantially improves predictive performance, with RMSE decreasing to 0.83 mm. This improvement indicates strong short-term persistence in day-to-day evaporation. Longer evaporation lags degrade performance, whereas lagged meteorological variables provide modest additional improvement beyond evaporation memory. CatBoost demonstrated the most balanced performance among the evaluated models. Overall, the findings confirm that short-term evaporation persistence dominates temporal dependence in daily Ep, with meteorological memory playing a secondary role, thereby offering a physically interpretable and efficient framework for data-driven evaporation modeling.

1. INTRODUCTION

Evaporation is an essential part of the hydrological cycle (Kundzewicz 2008). It plays an important role in irrigation scheduling, reservoir management, and agricultural water management (Martínez Alvarez et al. 2008). Effective water resource planning requires accurate estimation of daily evaporation because water losses through evaporation directly affect water availability and crop production. In addition, evaporation is closely associated with climate change and global warming, as it accounts for a substantial portion of global precipitation redistribution (Zhou et al. 2021). Therefore, the accurate estimation and prediction of evaporation are important issues that remain to be resolved in the fields of hydrology and water resources engineering. Pan evaporation (Ep) is one of the most common and practical techniques for evaluating evaporative demand among the available options (Wang et al. 2023). Direct measurement of Ep is feasible using a simple evaporation pan, which makes it especially useful in data-scarce areas where radiation and other measurements of the energy balance are inaccessible. It has been widely adopted as a proxy measure of atmospheric evaporative demand due to its simplicity, low cost, and minimal data requirements. However, pan measurements are influenced by pan siting, maintenance problems, environmental exposure, and scale differences between the pan and natural water bodies, which may introduce uncertainty in daily evaporation records (Du et al. 2023).

Naturally, determining daily Ep is challenging due to the complex and nonlinear nature of evaporation processes (Goyal et al. 2014). Evaporation rates are influenced by diverse, interacting meteorological factors such as air temperature, relative humidity (RH), wind speed, and solar radiation, which can fluctuate significantly on a daily basis (Taheri et al. 2025). These abrupt variations, combined with seasonal changes, geographic location, and local climate conditions, further complicate the prediction of daily evaporation (Ghafouri-Azar & Lee 2023). Traditionally, Ep has been estimated using empirical and physically based models, including the Penman, Hargreaves-Samani, and FAO-56 Penman-Monteith methods (Ruiz-Ortega et al. 2024). These models are physically interpretable, grounded in fundamental principles, and computationally efficient. Nonetheless, they depend on simplifying assumptions about atmospheric processes and require accurate, comprehensive meteorological data such as temperature, radiation, humidity, and wind speed; inaccuracies in these data can drastically affect evaporation estimates (Irizarry-Ortiz & Harmsen 2023). While their performance is reasonable for seasonal or monthly estimates, their accuracy diminishes at the daily level due to their limited ability to capture short-term variability and nonlinear interactions (Moratiel et al. 2020). Furthermore, these models are highly sensitive to data quality; small measurement errors in wind speed or humidity can lead to substantial estimation uncertainties. They are also often site-specific and need recalibration when applied to different climatic regions, limiting their broader applicability (Xu & Singh 2002).

Evaporation has also been estimated using statistical and time-series methods, such as multiple linear regression and autoregressive methods. Although these models are simple and interpretable, their ability to capture nonlinear relationships and complex interactions between meteorological variables is usually constrained. Consequently, their forecasting ability remains limited in representing daily evaporation dynamics under rapidly changing weather conditions (Almedeij 2016).

Machine learning (ML) techniques have emerged as effective alternatives for evaporation prediction in recent years due to their ability to learn complex nonlinear relationships from data (Al Sudani & Salem 2022). Methods such as artificial neural networks, support vector regression, random forests (RF), and gradient boosting algorithms have shown high predictive accuracy compared to traditional empirical and statistical models (Fan et al. 2021). However, many studies on ML-based models primarily emphasize prediction accuracy and often overlook the temporal dynamics of the evaporation process. Typically, these studies use past meteorological variables or previous-day evaporation values to make predictions, but they frequently lack a systematic assessment of the contribution of individual variables and proper evaluation of lag durations (Phesa et al. 2024).

Ensemble tree-based algorithms such as RF, Extreme Gradient Boosting (XGBoost), and Categorical Boosting (CatBoost) have gained popularity due to their high predictive accuracy, ability to model nonlinear interactions, and robustness against multicollinearity and missing data (Agrawal et al. 2022). While these models deliver excellent predictions, they are often regarded as black-box predictors, limiting their use for exploring the temporal dynamics of evaporation, specifically the relative influence of evaporation persistence versus prior meteorological conditions.

Despite advances in empirical and machine learning methods for estimating Ep, the temporal variability of daily evaporation is still insufficiently studied. It remains unclear whether current evaporation is predominantly driven by its own persistence or by antecedent meteorological factors. The practice of incorporating lagged variables is frequently ad hoc, lacking systematic evaluation of optimal lag lengths (Phesa et al. 2024). This gap hampers interpretability and physical understanding, as most studies prioritize predictive performance over insights into temporal mechanisms.

To address these issues, this research introduces a systematic temporal-memory model for daily Ep prediction using ensemble machine learning approaches such as RF, XGBoost, and CatBoost. The framework rigorously examines different lag lengths to empirically distinguish between evaporation persistence and meteorological influence. Additionally, explainable machine learning techniques are employed to quantify the contributions of previous evaporation and relevant meteorological variables (Linardatos et al. 2021). The goal is to enhance evaporation estimates and deepen understanding of its temporal behavior. The overall methodology is illustrated in Fig. 1 and detailed in Section 2.

2. MATERIALS AND METHODS

2.1. Study Location and Climatic Characteristics

The meteorological data used in this study were acquired at the Bhagur station (19.31° N, 75.19° E), located in Maharashtra, India. The climate of Bhagur is semi-arid to sub-humid, with distinct wet and dry seasons that have a strong influence on the dynamics of daily evaporation. The station is part of the network maintained by the Office of the Chief Engineer, Planning and Hydrology, Nashik, Maharashtra. Access to the data was provided under an academic-use agreement, and the data are not publicly accessible. Evaporation measurements were recorded using a standard Class A pan installed at the meteorological station. The pan was placed in an open-field environment, and its siting was carried out in accordance with traditional guidelines. It is located in a flat area and is well exposed to sunlight and natural wind patterns. This arrangement reduces artificial shielding effects. Although detailed station metadata are not publicly available, the dataset underwent basic quality checks.

2.2. Data Description

The variables in the dataset are Ep, average wind speed (AWS), instantaneous wind speed (IWS), maximum air temperature (MAXT), minimum air temperature (MINT), pan water temperature (PWT), sunshine duration (SD), and RH. Each variable has two entries per day, except for SD. One of these values corresponds to 8:30 a.m., and the other corresponds to 5:30 p.m. The data are available for the period from 2007 to 2021.

2.3. Methodological Framework

The overall methodological framework adopted in this study is illustrated in Fig. 1. The workflow comprises eight consecutive steps, beginning with the preparation of the raw data and ending with the interpretation and reporting of the model. Each phase is described in detail below.

2.4. Raw Data Input

The meteorological dataset comprised Ep, AWS, IWS, MAXT, MINT, PWT, SD, and RH on a daily basis. The data were received in spreadsheet form and subsequently processed as discussed in the following section.

2.5. Data Preprocessing

The data were preprocessed to ensure temporal consistency, physical realism, and suitability for ML analysis (Maharana et al. 2022). The column containing measurement timestamps was first converted into a standard date-time format, and calendar dates were obtained. SD was originally measured hourly. To make the dataset consistent, SD observations were aggregated into a single daily value by summing all measurements recorded within each calendar day. The other features were recorded twice daily. For the analysis, these twice-daily values were then reduced to single daily values using physically meaningful rules. Ep values were summed over the day. MAXT and MINT were treated as extreme day-to-day variables. The daily MAXT was determined as the larger of the two MAXT values, while the daily MINT was determined as the smaller of the two MINT values. All other meteorological variables, such as RH, PWT, AWS, and IWS, were averaged over the day. Since the objective of this study was daily evaporation prediction rather than sub-

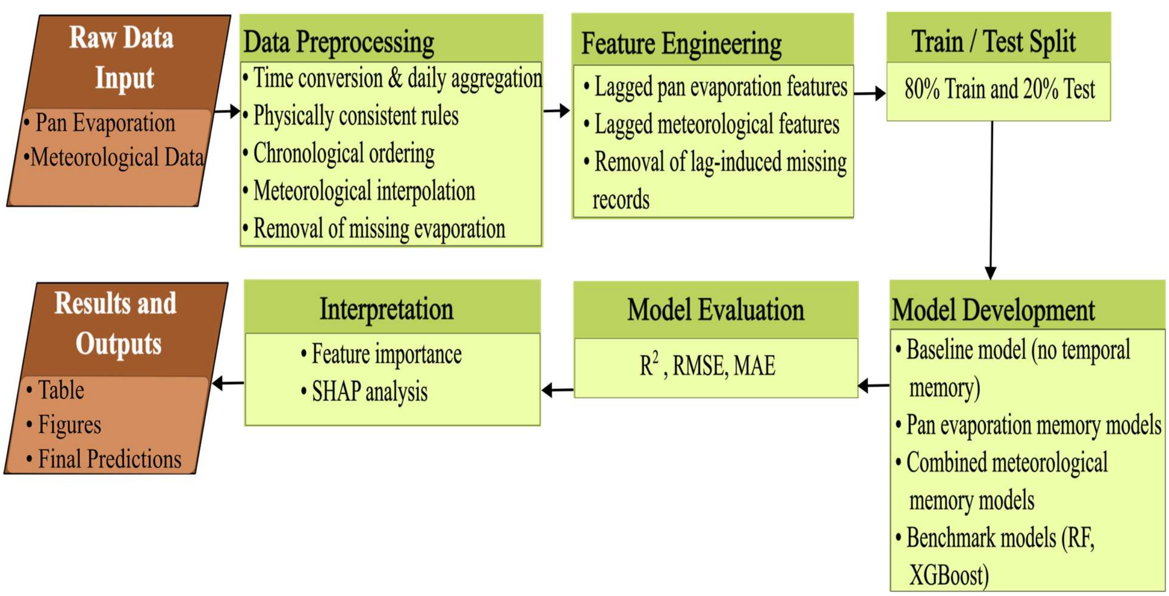

Fig. 1: Proposed machine learning framework for pan evaporation forecasting.

daily process simulation, daily mean values were considered appropriate for representing the integrated atmospheric conditions influencing evaporation.

This resulted in a time-series dataset that was appropriate for the analysis of temporal memory in evaporation processes. Data were ordered chronologically to preserve temporal dependence. Missing meteorological data were replaced using time-based linear interpolation, applied only to gaps of three days or fewer, which accounted for just 0.07% of the data. Remaining gaps were left unfilled, and the corresponding days were excluded from the dataset. The longest such gap was 151 days. Conversely, days with missing Ep values were completely removed so that they would not influence the target variable. Filling missing values using linear interpolation can slightly alter the temporal pattern of the data, which is why it was not applied to Ep. Other filling methods may produce slightly different results and can be explored in future work.

2.6. Feature Engineering

Feature engineering was performed to explicitly model the effects of temporal persistence and memory in the Ep process (Považanová et al. 2023). The lagged Ep features (Ep_lag_1, Ep_lag_3, Ep_lag_7, and Ep_lag_14) were created using fixed lag lengths of 1, 3, 7, and 14 days, representing short- and medium-term evaporation memory. Simultaneously, lagged forms of all the meteorological variables were created using identical lag lengths to represent the delayed atmospheric effects on evaporation. Feature creation was followed by the handling of missing values to obtain a complete and consistent set of features.

2.7. Data Splitting Strategy

To prevent information leakage and preserve the temporal structure of the data, the dataset was divided into training and testing sets based on chronological order. Eighty percent (80%) of the observations were used as the model training set, while the remaining 20% were used as the independent testing set. Random shuffling was not used to provide realistic model testing under forecasting conditions.

2.8. Model Development

2.8.1. Baseline Model (No Temporal Memory)

A baseline CatBoost regression model was developed using only current meteorological variables. Seasonal indicators and lagged inputs were excluded from this model. It serves as a reference to assess the impact of adding temporal features.

2.8.2. Ep Memory Models

The analysis started with a baseline model that used only meteorological variables. Past values of Ep (Ep_lag_1, Ep_lag_3, Ep_lag_7, and Ep_lag_14) were then added step by step to the model and compared with the baseline model. This was done to enable a systematic assessment of the effect of evaporation memory on the predictive performance of Ep. The lag that provided the best prediction accuracy on the test data was selected.

2.8.3. Combined Meteorological Memory Models

Once the best evaporation lag had been determined, lagged meteorological variables with the same lag length were added to the model. This configuration represents a combined temporal-memory model, capturing both surface persistence and delayed atmospheric effects. The CatBoost model that performed best in this setup was selected for further analysis.

2.8.4. Benchmark Models

RF and XGBoost regression models were trained using the same set of best-performing features to evaluate the robustness of the proposed framework. These benchmark models provide a comparative baseline against widely used ensemble learning techniques.

2.9. Model Evaluation

All models were evaluated on the independent testing dataset using three standard performance metrics: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). This multi-metric analysis provides a balanced assessment of model accuracy, error magnitude, and explanatory power.

2.10. Model Interpretation

To explain the impact of individual predictors and temporal memory elements, feature importance scores were obtained from the optimal CatBoost model. In addition, Shapley Additive Explanations (SHAP) were used to measure both the magnitude and direction of each feature's contribution to the model predictions. These analyses provide physical insight into evaporation persistence and the contribution of lagged meteorological factors.

3. RESULTS AND DISCUSSION

3.1. Baseline Model Performance

As shown in Table 1, the model achieved an R^2 of 0.615, suggesting that approximately 61.5% of the variability in daily evaporation is explained by same-day meteorological variables. An RMSE of 1.386 mm and an MAE of 1.093 mm reflect the average prediction errors. While the baseline model offers a reasonable initial estimate of daily evaporation, several limitations are evident.

Table 1: Prediction performance of the CatBoost baseline model.

Model	R^2	RMSE (mm)	MAE (mm)
CatBoost Baseline	0.615	1.386	1.093

Table 2: Model performance metrics for varying Ep lag days.

Ep_Lag_Days	R^2	RMSE (mm)	MAE (mm)
1	0.863	0.826	0.555
3	0.732	1.155	0.833
7	0.676	1.271	0.959
14	0.638	1.344	1.049

1. **Moderate predictability:** Approximately 38.5% of the variability in daily evaporation remains unexplained. This indicates that same-day meteorological variables cannot fully explain Ep.
2. **Lack of temporal persistence and motivation for memory-based modeling:** The short-term dependence of Ep is not captured by the baseline model. Therefore, it is necessary to add lagged Ep and meteorological variables. The remaining sections explain the effect of adding temporal memory.

3.2. Effect of Evaporation Memory

A series of CatBoost models was constructed, each incorporating a single lagged Ep term alongside all same-day meteorological variables. Lag durations of 1, 3, 7, and 14 days were evaluated. The performance metrics are summarized in Table 2, while Fig. 2 illustrates how prediction error varies with lag length. Incorporating Ep_lag_1 substantially improved model performance. Compared to the baseline model (RMSE = 1.386 mm), the RMSE dropped to 0.826 mm, and the model's explanatory power increased substantially (R^2 = 0.863), with the MAE decreasing to 0.555 mm.

This demonstrates that immediate temporal dependence accounts for a substantial portion of daily variation in Ep. Predictive accuracy declines as the lag length increases further. RMSE values rise to 1.155 mm, 1.271 mm, and 1.344 mm at lag lengths of 3, 7, and 14 days, respectively, accompanied by decreasing R^2 scores and increasing MAE. This trend suggests that information from longer lags becomes progressively less useful for representing current evaporation conditions.

Based on these findings, Ep_lag_1 was identified as the optimal temporal memory length for daily evaporation prediction at the study site and was consequently used for subsequent analyses involving meteorological memory and model benchmarking. When monsoon conditions change rapidly, evaporation does not respond immediately because it is a cumulative process over 24 hours that depends on heat storage in the pan water and atmospheric continuity. Therefore, previous-day evaporation (Ep_lag_1) provides substantial information about the current state. This explains why short-term persistence is stronger, while longer meteorological memory adds only minor incremental value.

The persistence of evaporation may vary across seasonal regimes, mainly during monsoon, post-monsoon, and dry seasons. In this study, the entire dataset from 2007–2021 was treated as a continuous time series to determine overall temporal memory characteristics. The dominance of Ep_lag_1 indicates an average annual behavior, but seasonal differences in persistence may exist. Future research should examine these variations under different regimes.

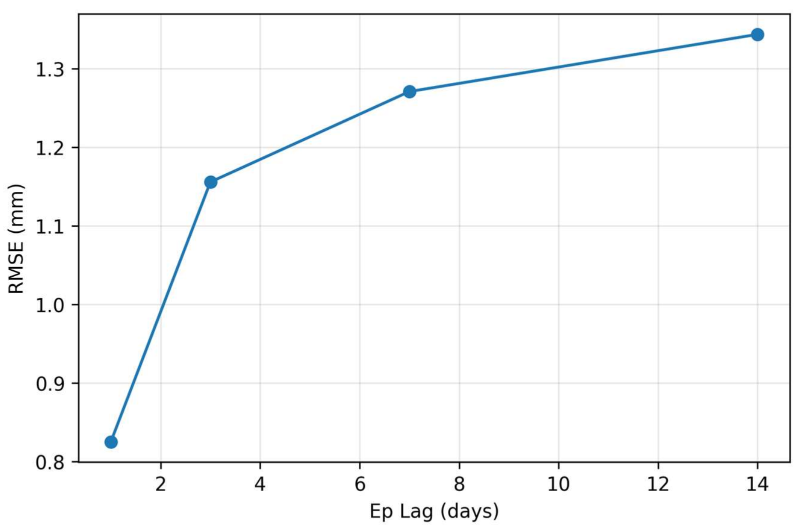

Fig. 2: Effect of Ep lag length on model performance, expressed in terms of RMSE (mm) for the testing dataset.

Table 3: Performance metrics of the Ep + Met memory configuration.

Configuration	R^2	RMSE (mm)	MAE (mm)
Ep + Met Memory	0.865	0.820	0.553

3.3. Effect of Meteorological Memory

After identifying Ep_lag_1 as the most effective predictor for evaporation, the influence of meteorological memory was evaluated by adding lagged meteorological variables alongside Ep_lag_1. This integrated approach was termed the Ep + Met Memory model. Its purpose was to determine whether past atmospheric conditions offer additional predictive value beyond evaporation persistence alone. The results are summarized in Table 3.

Compared with the evaporation-memory-only model, including lagged meteorological variables resulted in a modest but consistent improvement in predictive accuracy. The R^2 increased slightly to 0.865, while RMSE and MAE decreased marginally to 0.820 mm and 0.553 mm, respectively. This subtle enhancement indicates that much of the atmospheric persistence is already captured within the lagged evaporation signal.

3.4. Model Comparison

To evaluate the robustness of the proposed temporal memory framework, the highest-performing feature configuration was tested across three machine learning models: CatBoost, RF, and XGBoost. This configuration employed Ep_lag_1 alongside lagged meteorological variables. Table 4 presents the models' predictive performance on the test dataset. All three models demonstrated strong results, with R^2 values exceeding 0.86, indicating that daily Ep prediction can be notably enhanced by integrating temporal memory.

Table 4: Performance comparison of ML models using the proposed temporal memory feature configuration.

Model	R^2	RMSE (mm)	MAE (mm)
CatBoost	0.865	0.820	0.553
RF	0.863	0.826	0.546
XGBoost	0.860	0.835	0.556

The similar performance levels suggest that the improvements are primarily due to the memory-based feature design rather than model-specific characteristics. Among these, CatBoost achieved the lowest RMSE of 0.820 mm, reflecting a more precise capture of daily evaporation variability. RF showed a comparable R^2 value and a lower MAE, but a slightly higher RMSE, indicating reduced accuracy for larger prediction errors. XGBoost exhibited similar results but with marginally lower R^2 and higher error metrics, implying weaker generalization on this dataset.

3.5. Interpretability Results

Further interpretability analysis was carried out on the best-performing CatBoost configuration using feature importance and SHAP methods. The results are shown in Figs. 3–5. These figures help explain the effects of temporal and meteorological predictors on Ep estimates.

Fig. 3 displays a scatter plot comparing measured and forecasted daily Ep values within the test dataset. The forecasted data closely align with the 1:1 reference line, demonstrating strong agreement between observations and model predictions. Most points cluster near the diagonal, indicating the model effectively captures both low and high evaporation conditions. Slightly increased scatter at higher evaporation levels is observed but remains minor.

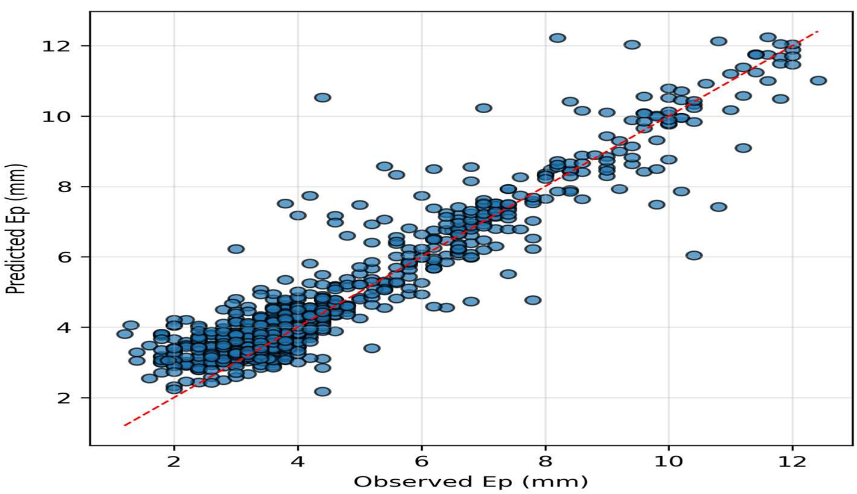

Fig. 3: Scatter plot of observed versus predicted daily Ep (mm) for the testing dataset.

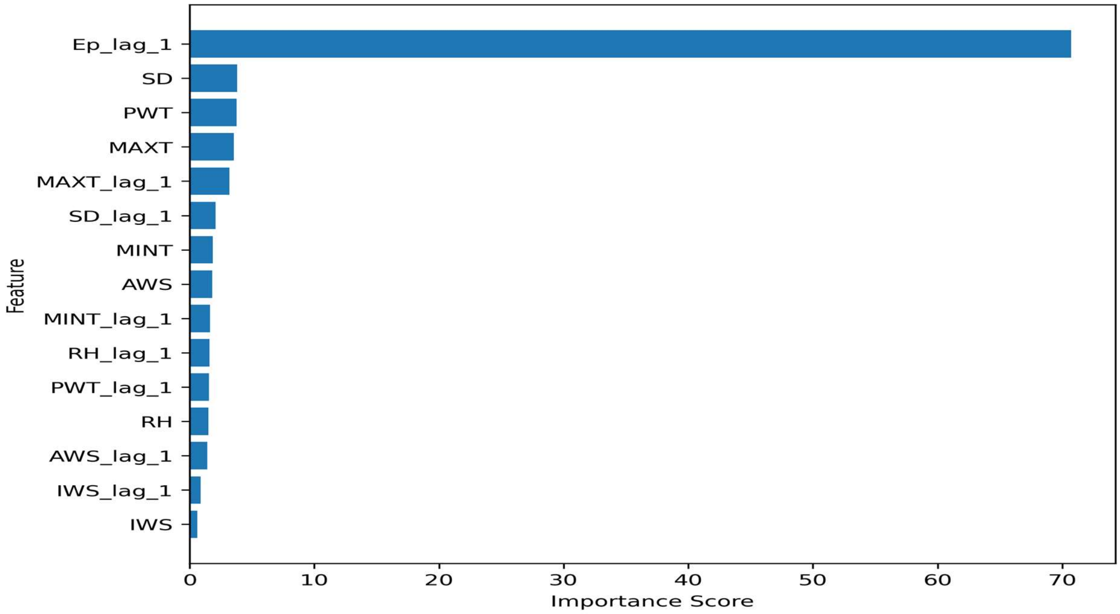

Fig. 4: Feature importance ranking of predictors obtained from the CatBoost model. Importance scores represent relative contribution to prediction.

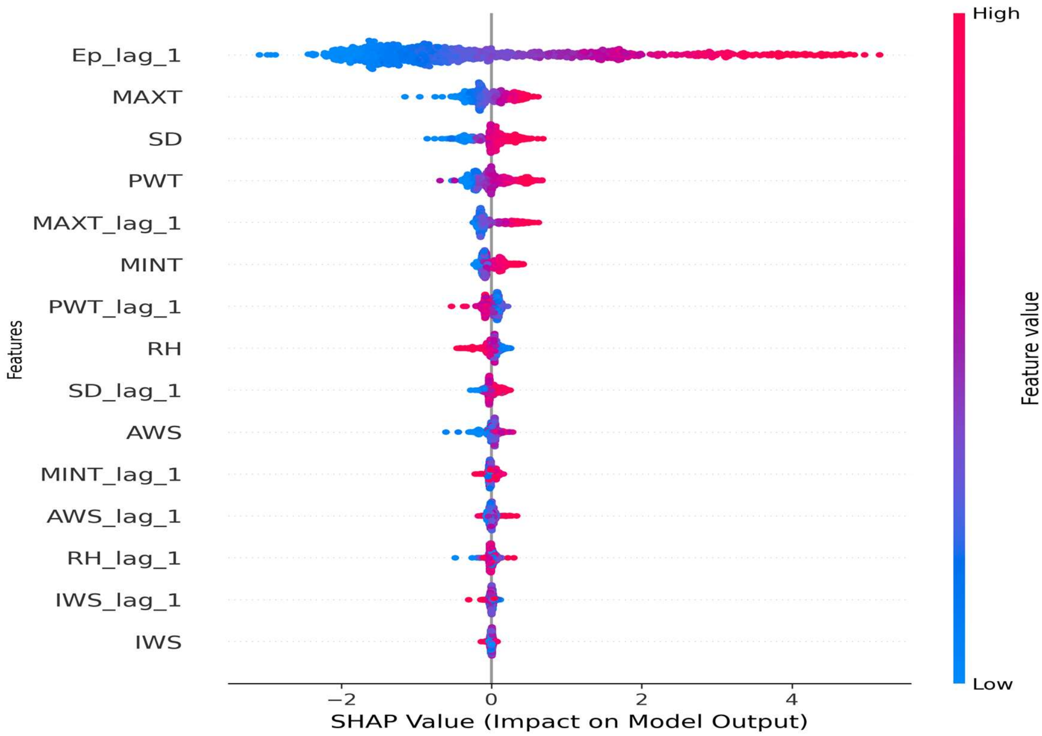

Fig. 5: SHAP summary plot showing the contribution of predictors to daily Ep estimation. Color indicates feature value (blue = low, red = high), and SHAP values represent impact on model output.

Overall, this suggests that incorporating temporal memory allows the model to accurately reflect daily variations in Ep.

Fig. 4 presents the feature importance ranking of the CatBoost model. The most influential predictor is Ep_lag_1, which is substantially more important than other meteorological variables. This highlights a strong short-term temporal dependence in daily Ep, likely due to atmospheric persistence and autocorrelation in cumulative pan evaporation measurements. The next most important features include SD, PWT, and MAXT, while lagged meteorological variables contribute minimally overall. This indicates that although short-term evaporation persistence dominates the temporal structure, meteorological factors still play a meaningful role in energy balance conditions.

Fig. 5 shows the SHAP summary plot, ranking features by their mean absolute SHAP values. Each point represents an observation, with positive SHAP values indicating increased contributions to evaporation and negative values indicating decreases. The most important predictor is Ep_lag_1; higher values lead to increased current evaporation, and vice versa. Since daily pan evaporation measures 24-hour accumulation and exhibits autocorrelation, the significance of Ep_lag_1 likely reflects statistical persistence, instrument memory, and atmospheric continuity. It is important to note that SHAP values indicate the contribution to prediction, not direct causality.

Higher MAXT, PWT, and SD values are associated with higher evaporation, consistent with physical expectations. The SHAP contributions of lagged meteorological variables are small, indicating limited residual influence from previous days. The SHAP values for RH and wind speed are lower in magnitude. The role of aerodynamic transport in evaporation is physically evident, but its additional predictive power is modest when Ep_lag_1 is included, as the previous day's evaporation already captures some effects of prior wind conditions.

4. CONCLUSIONS

This study investigated the influence of temporal memory on daily Ep by isolating the effects of evaporation persistence and meteorological memory. The results clearly indicate that daily Ep is predominantly influenced by short-term temporal persistence. Using a 1-day lag of evaporation (Ep_lag_1) yielded the highest predictive accuracy across all evaluated models. Incorporating longer evaporation lags reduced model performance, suggesting that daily evaporation is mainly affected by recent conditions rather than those from several days prior. Adding lagged meteorological variables provided only minor improvements, indicating that most meteorological information is captured in prior evaporation observations. Consequently, meteorological memory plays a secondary, corrective role, especially during periods of weather variability. Comparative analysis of CatBoost, RF, and XGBoost demonstrated that the observed improvements stem primarily from the proposed temporal memory–based feature design rather than model-specific characteristics. Among these, CatBoost exhibited the most balanced performance. Interpretability analyses, including feature importance and SHAP, supported the physical plausibility of the framework, with evaporation persistence identified as the most critical factor for predicting daily Ep. This research was conducted at a single station; future work should involve multi-station and multi-climate data, explore seasonal variations, and develop hybrid physical and machine-learning approaches. In summary, the proposed temporal memory model offers a logical, interpretable, and physically grounded approach to enhancing daily Ep forecasting.

5. ACKNOWLEDGMENTS

The authors gratefully acknowledge the Office of the Chief Engineer, Planning and Hydrology, Nashik, Water Resources Department, Government of Maharashtra, for providing the meteorological data used in this study. The data were utilized solely for academic and non-commercial research purposes.

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