

*Original Research*

# Modeling Temporal Persistence in Daily Pan Evaporation Using Interpretable Machine Learning

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**Abstract:** Accurate prediction of daily pan evaporation (Ep) is critical for irrigation management and water resource planning, yet remains challenging due to strong temporal variability and persistence. The majority of available models are based mainly on the contemporaneous meteorological variables and do not take into account inherent memory of evaporation. This paper systematically explores the impact of the temporal memory on daily Ep by explicitly separating the evaporation persistence and meteorological memory through a machine learning framework. A Categorical Boosting (CatBoost) model was used to analyze multiple year data of 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 days time scale. 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. The feature importance and SHAP analysis offered interpretability. The findings indicate that the addition of a lag of 1 day pan evaporation significantly enhances predictive performance with RMSE dropping to 0.83mm. This enhancement indicates a presence of high 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 has the most balanced performance among the models that are evaluated. Overall, the findings confirm that short-term evaporation persistence dominates temporal dependence in daily Ep, with meteorological memory playing a secondary role, 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 has an important role in the scheduling of irrigation, management of reservoirs, and water management in agriculture (Martínez Alvarez

et al. 2008). Effective water resource planning requires accurate estimation of daily evaporation because water losses by evaporation directly affect the availability of water and crop production. Besides, the evaporation is closely associated with climate change and global warming, since it accounts for a substantial portion of global precipitation redistribution (Zhou et al. 2021). Therefore, the accurate estimation and prediction of evaporation is an important issue yet to be resolved in the hydrology and water resources engineering field. The pan evaporation ( $E_p$ ) is one of the most common and practical techniques of evaluating evaporative demand among all existing options (Wang et al. 2023). Direct measurement of  $E_p$  is feasible with a simple evaporation pan, which makes it especially useful in data-scare areas where radiation and other measurements of the energy balance are inaccessible. It has been adopted widely as a proxy measure of atmospheric evaporative demand due to its simplicity, low cost and a small amount of data needed. However, pan measurements are influenced by pan siting, maintenance problems, exposure to the environment and scale differences between pan and natural water bodies which may cause uncertainty in the daily evaporation records (Du et al. 2023).

Naturally, it is difficult to determine the daily  $E_p$  as the process of evaporation is too complicated and nonlinear (Goyal et al. 2014). The rates of evaporation are controlled by a variety of interacting meteorological factors, which comprise air temperature, relative humidity (RH), wind speed, and solar radiation, which may vary at a high rate on a daily scale (Taheri et al. 2025). Such sudden changes, added to the presence of seasonality, geographical position, and local climatic conditions complicate the daily evaporation forecasting especially (Ghafouri-Azar and Lee 2023). The  $E_p$  has been determined traditionally with the help of empirical and physically developed models, including the Penman, Hargreaves Samani, and FAO 56 Penman Monteith approaches (Ruiz-Ortega et al. 2024). These models are physically interpretable (their calculations are based on physical principles) and are computationally efficient. However, they rely on simplifying assumptions about atmospheric processes. They also need the correct and full meteorological data (e.g. temperature, radiation, humidity, and the speed of the wind) and inaccurate meteorological data can severely impact the estimates of the evaporation (Irizarry-Ortiz and Harmsen 2023). Their performance is moderate when compared to seasonal or monthly estimation but at the daily scale, performance is poor because of their inability to respond to the short-term variability and nonlinear interactions (Moratiel et al. 2020). Moreover, such models are very sensitive to the quality of data and even minute mistakes in the measurements of the wind speed or humidity can result in large estimation uncertainties. In addition, empirical models are often site-specific and must be re-calibrated when used in other climatic areas which restricts their usefulness (Xu and Singh 2002).

Evaporation has also been estimated using statistical and time-series methods, such as multiple linear regression, and autoregressive methods. Even though 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 still falls short in representing the daily evaporation dynamics in weather conditions which change rapidly (Almedej 2016).

Machine learning (ML) methods have become strong alternatives to predict evaporation in recent years because they can learn complicated nonlinear mappings based on data (Al Sudani and Salem 2022). Artificial neural networks, support vector regression, random forests (RF), and gradient boosting algorithms are some of the techniques that have proven to have high predictive accuracy in comparison to the traditional empirical and statistical models (Fan et al. 2021). Nevertheless, numerous studies that have been conducted on ML-based models are largely focused on prediction accuracy but little consideration is given to the time dependence of the evaporation process. Many research uses past meteorological variables or previous day evaporation values for predicting evaporation. However, these inputs are often included without a careful or systematic evaluation of contribution of individual variable and without proper evaluation of lag duration (Phesa et al. 2024).

Ensemble tree-based algorithms like RF, Extreme Gradient Boosting (XGBoost), and Categorical Boosting (CatBoost) have become popular because they have high predictive results, can learn the nonlinear interactions, and are less susceptible to multicollinearity and missing factors (Agrawal et al. 2022). Even though these models are accurate, they are usually assumed to be black-box predictors. Because of this they are not extensively used to study the temporal dynamics of evaporation, especially the relative role of evaporation persistence as compared to previous meteorological situations.

Despite the state of art in the development of empirical and ML methods to estimate the  $E_p$ , the time-varying characteristics of the daily evaporation are under-researched. Specifically, it is unclear whether the present evaporation is controlled primarily by their own temporal persistence or it is controlled by preceding meteorological conditions. The inclusion of lagged information is often done ad hoc without much systematic consideration of optimum lag lengths (Phesa et al. 2024). This absence of systematic analysis limits the interpretability of models and physical knowledge as the vast majority of studies focus on the predictive power and not on temporal insight.

To fill these gaps, the current research paper suggests a systematic temporal-memory model to make daily  $E_p$  prediction based on ensemble ML models, such as RF, XGBoost, and CatBoost. The framework critically analyzes various lag lengths and empirically separates evaporation persistence and meteorological persistence. Furthermore, explainable machine-learning techniques are also used to measure the contributions of the previous evaporation and antecedent meteorological variables (Linardatos et al. 2021). The objective of this approach is to estimate better the day-to-day evaporation, as well as giving a better understanding of the temporal dynamics of evaporation. Fig. 1 shows the overall methodology and Section 4 describes it.

## 2. STUDY AREA AND DATA

### 2.1. Study Location and Climatic Characteristics

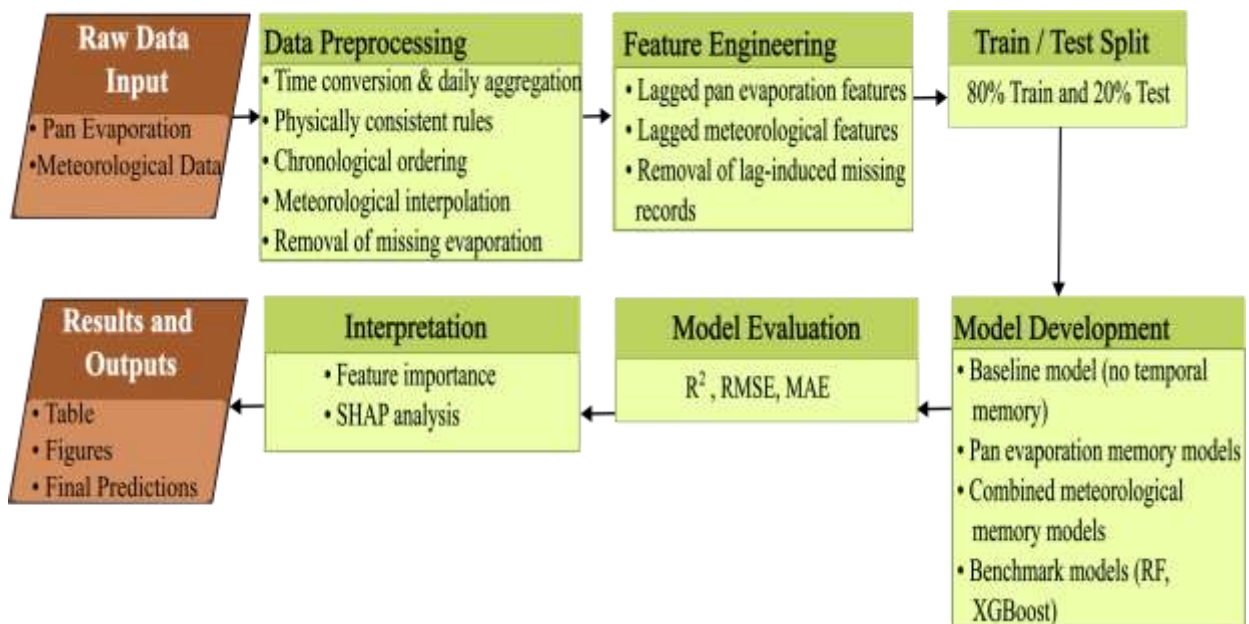
The meteorological data that was used in this study were acquired at the station of Samangaon (19.34° N, 75.15° E) which is in Maharashtra in India. The climate of Samangaon is semi-arid to sub-humid, with discrete

wet and dry seasons, that have a strong impact on the dynamics of the daily evaporation. The station is part of the network maintained by the Office of the Chief Engineer, Planning and Hydrology, Nashik, Maharashtra. The access to data was provided on an academic-use agreement and the data is not publicly accessible. The measurements of evaporation were recorded using a standard pan mounted at the meteorological station. The pan was put in an open-field environment, and the siting was done per the traditional guidelines. It is on a flat area and well exposed to the sun and the cycle of natural winds. Such arrangement reduces the 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) and SD and RH. Each variable has two entries per day except sunshine duration (SD). One of these values is associated with time 8.30AM, and the other is associated with time 5.30PM. The data is available from year 2007 to 2021.

## 3. METHODOLOGY



**Fig. 1:** Proposed Machine Learning Framework for Pan Evaporation Forecasting.

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

### 3.1. Raw Data Input

The meteorological dataset was comprised of Ep, AWS, IWS, MAXT, MINT, PWT, SD, and RH on a daily basis. The data were also received in spreadsheet form and later handled as discussed in the next section.

### 3.2. Data Preprocessing

The data were preprocessed to provide temporal consistency, physical realism and appropriateness to be used in ML analysis (Maharana et al. 2022). The column having measurement timestamps were first changed into standard datetime format and calendar dates were obtained. SD was originally measured hourly. To make the dataset consistent, SD observations were aggregated to single daily value by summing all measurements recorded within each calendar day. Other features were recorded twice daily. To carry out the analysis, these twice-daily values were then reduced to single daily values with physically meaningful rules: Ep values were summed over the day. MAXT and MINT were considered as extreme day-to-day variables. The daily MAXT was determined as the larger of the two values of MAXT, and the daily MINT was determined as the smaller of the two values of MINT. While 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-daily process simulation, daily mean values were considered appropriate to represent the integrated atmospheric conditions influencing evaporation. This process resulted in a strictly daily dataset that could be used to investigate the effects of temporal memories in evaporation. The resulting daily data set was organized in order of strict chronology in order to maintain temporal dependence. The meteorological variables had missing values that were replaced using time-based linear interpolation. Conversely, days with missing values of Ep were eliminated totally so that they would not influence the target variable. Filling missing values using linear interpolation can slightly change the time pattern of the data. It was used only for short gaps and not for Ep. Other filling methods may give slightly different results and can be explored in future work.

### 3.3. Feature Engineering

The feature engineering was done to explicitly model the effects of temporal persistence and memory in 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 a fixed lag length of 1, 3, 7, and 14 days, which reflect short, and medium term evaporation memory. Simultaneously, lagged forms of all the meteorological variables were formed with the identical lag lengths to represent the delayed atmospheric effects on evaporation. The feature creation was followed by handling missing values in order to have a full and consistent set of features.

### 3.4. Data Splitting Strategy

To prevent information leakage and preserve the temporal structure of the data, the dataset was split into training and testing sets, based on the chronological splitting. The 80 percent of the observations were to be used as the model training set, and the remaining 20 percent were to be used as the independent testing set. Random shuffling was not used so that it could offer realistic model testing in the forecasting conditions.

### 3.5. Model Development

#### 3.5.1. Baseline Model (No Temporal Memory)

A baseline CatBoost regression model was built with contemporary meteorological variables only. In this model seasonal indicators and lagged inputs were not included. This model is used to check the effect of addition of temporal features.

#### 3.5.2. Ep Memory Models

We started with a baseline model that used only meteorological variables. Then, past values of Ep (Ep\_lag\_1, Ep\_lag\_3, Ep\_lag\_7, and Ep\_lag\_14) were added step by step to the model and compared with baseline model. This was done to enable a systematic assessment of evaporation memory on predictive performance of Ep. The lag that gave the best prediction accuracy on the testing data was selected.

### 3.5.3. Combined Meteorological Memory Models

Once the best evaporation lag had been determined, lagged meteorological variables of 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 performs best in this setup was chosen for further analysis.

### 3.5.4. Benchmark Models

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

## 3.6. Model Evaluation

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

## 3.7 Model Interpretation

To explain the impact of individual predictors and temporal memory elements, feature importance scores were obtained based on optimal CatBoost model. Also, Shapley Additive Explanations (SHAP) was used to measure both the size and the direction of the contribution of each feature to the model predictions. These studies give physical understanding of the persistence of evaporation and the contribution of lagged meteorological causes.

## 4. RESULTS AND DISCUSSION

### 4.1. Baseline model performance

**Table 1:** Prediction performance of the CatBoost baseline model.

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

The model achieved a  $R^2$  of 0.615. It says that approximately 61% of the variance in daily Ep is captured by Same-day meteorological variables. RMSE of 1.386 mm and MAE of 1.093 mm indicate the average magnitude of prediction errors. Even though the baseline model offers a decent initial estimate of the daily evaporation, there are a number of limitations that can be observed:

1. Moderate predictability: There is almost 39% variability on the daily evaporation that cannot be explained. It shows that same-day meteorological variable cannot be fully used to describe Ep.
2. Lack of temporal persistence and motivation for memory-based modeling: Short term dependence of Ep is not captured by baseline model. So it is required to add lagged Ep and meteorological variable.

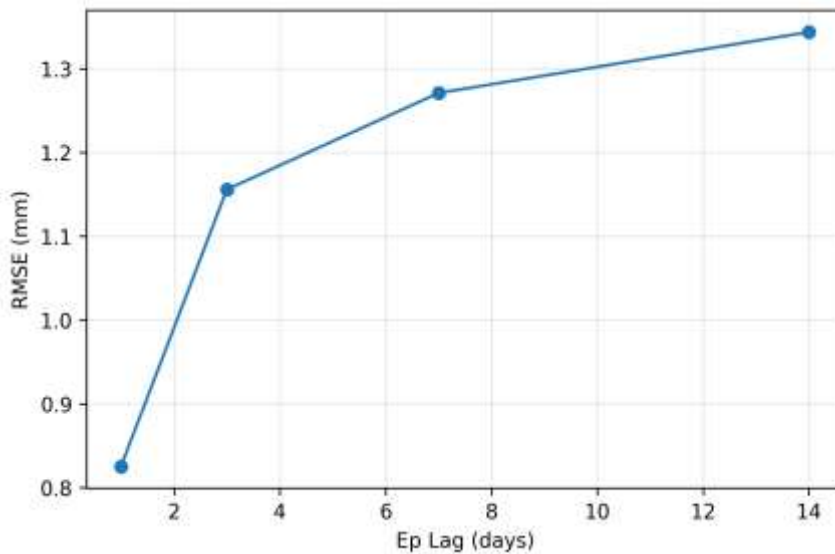
The remaining sections explain the effect of adding temporal memory.

## 4.2. Effect of Evaporation Memory

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

Ep_Lag_Days	R <sup>2</sup>	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

A series of CatBoost models were developed. In each model, a single lagged Ep term was added while preserving all same-day meteorological variables. Lag lengths were considered to be 1, 3, 7 and 14 days and the respective performance measures are summarized in Table 2 while the variation in prediction error with lag length is illustrated in Fig. 2. The addition of Ep\_lag\_1 leads to a significant improvement of the model performance. Relative to the baseline model (RMSE = 1.386 mm), the value of RMSE is reduced to 0.826 mm, accompanied by a significant increase in the explanatory power ( $R^2 = 0.863$ ) as well as a decrease in MAE to 0.555 mm. This proves that immediate temporal dependence is capturing a large percentage



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

of the variation of Ep on a daily basis. Predictive performance starts to decline with further increase in lag length. RMSE rises to 1.155 mm, 1.271 mm and 1.344 mm at lag lengths of 3, 7 and 14 days respectively, with decreasing  $R^2$  and increasing MAE. This tendency shows that information recorded in longer lags becomes successively less valuable to present evaporation conditions. Based on these results, Ep\_lag\_1 was identified as the optimal temporal memory length for daily evaporation prediction at the study site and was consequently adopted for subsequent analyses involving meteorological memory and model benchmarking. When the monsoon conditions vary within a short time, the evaporation does not react immediately since it is the cumulative process (24 hours) based on the heat storage of the pan water and the continuity of the atmosphere. Thus, the previous-day evaporation Ep\_lag\_1 automatically provides a lot of information on the present state. This is the reason why

short-term persistence is stronger, and longer meteorological memory provides only a minor incremental value. The persistence of evaporation may differ between regimes of seasons. This difference is mainly noticeable in monsoon, post-monsoon seasons and dry seasons. In this study the entire data 2007- 2021 was considered as a continuous time series. The aim was to determine the general temporal memory features. The dominance of  $Ep\_lag1$  is thus an indicator of an annual average behavior. There may still be some seasonal differences in persistence. In future research, such variations must be addressed individually under different regimes.

### 4.3. Effect of meteorological memory

**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

After determining  $Ep\_lag\_1$  as best feature for predicting evaporation, the role of meteorological memory was assessed by incorporating lagged meteorological variables in addition to  $Ep\_lag\_1$ . This combined configuration is referred to as the Ep + Met Memory model. It was used to assess whether antecedent atmospheric conditions provide additional predictive information beyond evaporation persistence alone. The corresponding performance is shown in Table 3. When lagged meteorological variables are included and compared to the evaporation-memory-only model, a negligible but systematic increase in the predictive variables is observed. The  $R^2$  rises slightly to 0.865, and RMSE and MAE also reduce slightly to 0.820 mm and 0.553 mm, respectively. Physically, this modest gain suggests that much of the atmospheric persistence is implicitly embedded in the lagged evaporation signal.

### 4.4. Model comparison

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

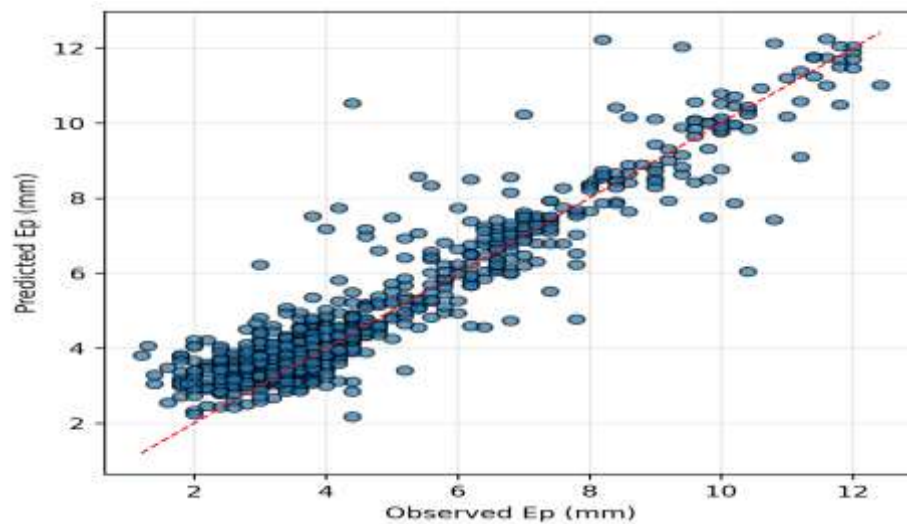
Model	$R^2$	RMSE (mm)	MAE (mm)
CatBoost	0.865	0.820	0.553
RF	0.863	0.826	0.546
XGBoost	0.860	0.835	0.556

In order to check the robustness of the proposed temporal memory framework, the best performing feature configuration was applied to three ML models: CatBoost, RF, and XGBoost. In this configuration we used the  $Ep\_lag\_1$  with lagged meteorological variables. Table 4 shows the predictive performance of the models on the test dataset. All the three models shown good performance. The  $R^2$  value is more 0.86 for all the three models. This proves that daily Ep can be improved significantly by adding temporal memory. The similar performance across the models indicates that the observed improvement is mainly due to the proposed memory-based feature design rather than by model-specific effects.

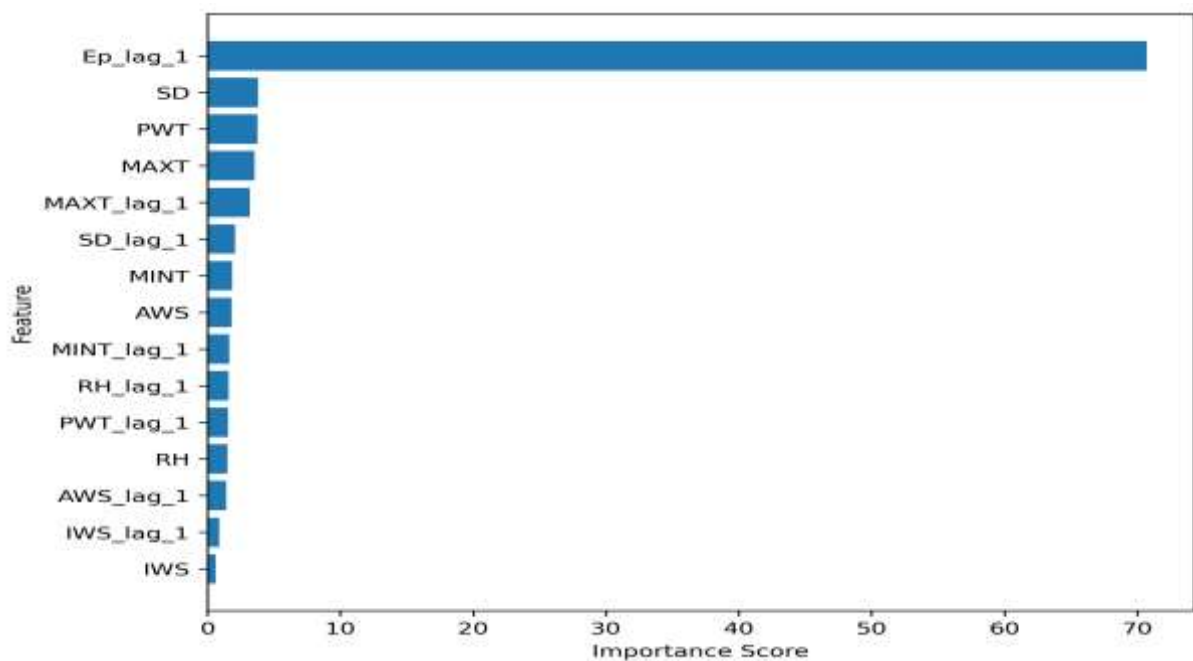
CatBoost has the lowest RMSE (0.820 mm) among the considered models. It means that it is more accurate in reflecting the variability of daily evaporation. RF also performs at a similar level, having the same  $R^2$  value and a smaller MAE. Nevertheless, it has a slightly larger RMSE, indicating lower accuracy in responding to larger prediction errors. XGBoost is also similar in terms of performance but has a slightly lower  $R^2$  and higher error values meaning that it is relatively weakly generalized in this data.

#### 4.5. Interpretability results

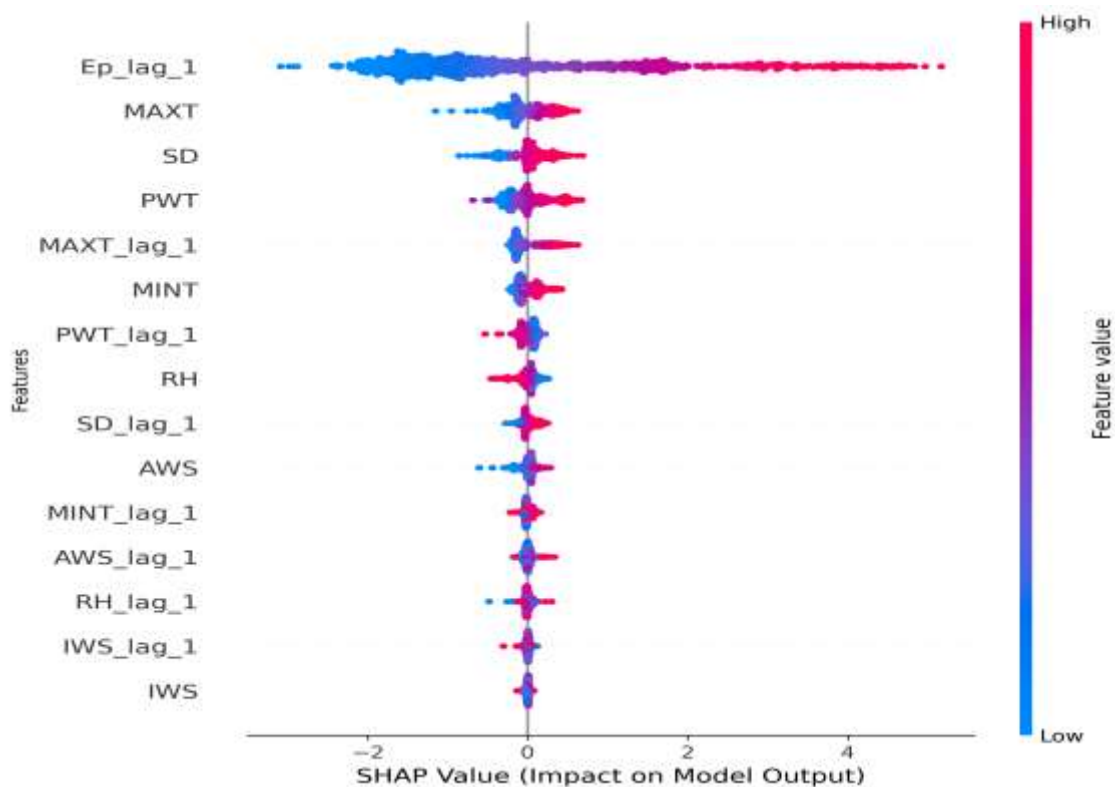
Further interpretability analysis was carried out on the best-performing CatBoost configuration. Feature importance and SHAP methods were used. Its results are shown in the figure 3-5. These figures help to understand the effect of temporal and meteorological predictors on Ep estimates.



**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.

Fig. 3 indicates the scatter plot of measured versus forecasted daily Ep of test dataset. The forecasted values are close to the 1:1 reference line which shows that there is a good consistency between observations and model predictions. Majority of the points are concentrated close to the diagonal and this indicates that the model is effective in representing low and high evaporation conditions. A little more dispersion at higher evaporation values is seen but minor. In general, this finding supports the fact that the temporal memory inclusion enables the model to reflect day-to-day variances in Ep.

Fig. 4 shows the feature importance ranking of the CatBoost model. The most significant predictor is Ep\_lag\_1, which is significantly greater than the importance of all meteorological variables. This shows that there is a high short-term temporal dependence in daily Ep, which can be a combination of atmospheric persistence and intrinsic autocorrelation in the cumulative pan evaporation measurements. The second level of importance includes SD, PWT, and MAXT. Conversely, lagged meteorological variables add very little to the total significance. This implies that although short-term evaporation persistence will dominate the temporal structure, meteorological variables still have a physically significant effect on setting the conditions of the energy balance.

Fig. 5 shows SHAP summary plot. The features are ranked based on mean absolute SHAP values. Every point corresponds to an observation. We can observe positive as well as negative SHAP values. The observation with positive SHAP values indicate increasing contributions to evaporation while observations with negative SHAP values indicate decreasing contributions to evaporation. The strongest predictor is Ep\_lag\_1. An increase in the values of Ep\_lag\_1 leads to a rise in current evaporation and vice versa. Daily pan evaporation is a cumulative 24-hour measure and inherently exhibits autocorrelation. Thus, the importance of Ep\_lag\_1 may reflect statistical persistence and instrument memory as well as

atmospheric continuity. SHAP values represent predictive contribution rather than direct causality. An increase in MAXT, PWT and SD boost evaporation as expected physically. The lagged meteorological variables have small, although significant, effects, implying a poor residual memory of the previous days. The magnitudes of SHAP of RH and wind speed are lower. The physical significance of aerodynamic transport in evaporation is observed. Although, it has an extra predictive contribution which is not very strong when it contains `Ep_lag_1`. The reason is that even evaporation of the previous day already reflects some of the previous wind effect..

## 5. CONCLUSIONS

This study examined the effects of temporal memory on the daily  $E_p$  by isolating the evaporation persistence effect and the meteorological memory. The findings clearly shows that daily  $E_p$  is mostly affected by short-term temporal persistence. The best predictive performance was achieved by use of a 1 day lag of evaporation (`Ep_lag_1`) in all the evaluated models. The addition of longer evaporation lags decreased model accuracy. This implies that evaporation per day is primarily affected by the rather recent past conditions, rather than conditions many days ago. Only minor gains were achieved with the addition of lagged meteorological variables. This implies that most of the relevant information about atmosphere is getting captured in prior evaporation observations. Meteorological memory hence has a secondary, corrective role, mainly during periods of changing weather conditions. Comparative analysis involving CatBoost, RF, and XGBoost has proven that the observed improvements are due to primarily the proposed temporal memory-based feature design rather than model-specific characteristics. CatBoost had the most balanced performance among these models. Analysis of interpretability by feature importance and SHAP also supported the physical consistency of the framework, with the persistence of evaporation being the most important factor of daily evaporation predictability.

This study is done on only one station and therefore future researches need to broaden to multi-station and multi-climate data, examine seasonal changes and develop hybrid physical ML methods. In summary the suggested temporal memory model is a logical, interpretable, and physically realistic way of enhancing daily  $E_p$  forecasting.

**Author Contributions:** Conceptualization, J.K. and S.S.; methodology, J.K.; software, J.K.; validation, J.K. and S.S.; formal analysis, J.K.; investigation, J.K.; data curation, J.K.; writing—original draft preparation, J.K.; writing—review and editing, J.K. and S.S.; visualization, J.K.; supervision, S.S.; project administration, S.S. All authors have read and agreed to the published version of the manuscript.

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