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Forecasting Trends in Evapotranspiration Using Machine Learning: SVM vs. Conventional Approaches

[1] Manikumari Nagappan , [2] Swetha Jayamurugan , [2] Aarthika Kudiyarasumani,
[1] Professor,[2] Student, [3] Student

Department of Civil Engineering,

Annamalai University, Chidambaram, India

The Corresponding author: nmanikumariau@gmail.com

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ABSTRACT

Evapotranspiration (ET) is a fundamental process in the hydrological cycle, playing a crucial role in water resource management, irrigation planning, and climate impact assessments. Accurate estimation of ET is essential for optimizing water use efficiency in agriculture, assessing groundwater recharge, and improving weather prediction models. Over the years, various conventional approaches have been developed for ET estimation, including empirical and physically based models such as the Penman-Monteith (FAO-56), Hargreaves-Samani, and Blaney-Criddle equations. While these models remain widely used, they exhibit several limitations, including high sensitivity to input parameters, dependency on site-specific calibration, and decreased accuracy under varying climatic conditions.With the emergence of artificial intelligence and machine learning (ML), data-driven approaches are gaining prominence in ET estimation. Among ML techniques, Support Vector Machines (SVM) have shown significant potential due to their ability to capture complex, nonlinear relationships between meteorological parameters. Unlike conventional models that rely on predefined mathematical equations, SVM learns patterns from data, enabling improved generalization and adaptability across diverse climatic conditions.This study investigates the effectiveness of SVM-based ET forecasting in comparison to traditional models. A comprehensive dataset comprising key meteorological variables, including temperature, humidity, solar radiation, wind speed, and precipitation, is utilized for model training and evaluation. The SVM model undergoes optimization using different kernel functions and hyperparameter tuning techniques to enhance its predictive performance. By systematically adjusting parameters such as the regularization coefficient (C) and kernel type (linear, polynomial, radial basis function), the study ensures the development of a robust and efficient predictive framework.The performance of SVM and conventional ET estimation methods is assessed using a range of statistical metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Nash-Sutcliffe Efficiency (NSE), and the Coefficient of Determination (R^2). These metrics provide a quantitative evaluation of model accuracy, reliability, and predictive capability. The results indicate that SVM consistently outperforms traditional approaches, demonstrating superior generalization capability across varying climatic conditions. The ability of SVM to model complex relationships between meteorological factors allows it to achieve higher accuracy and stability compared to empirical and physically based methods.Despite its advantages, the effectiveness of ML models, including SVM, depends on several factors such as data availability, feature selection, and computational complexity.

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1.Introduction

Evapotranspiration (ET) is a fundamental process in the hydrological cycle, representing the combined effect of **evaporation from land and water surfaces** and **transpiration from vegetation**. It plays a crucial role in **agricultural water management, climate studies, and hydrological modeling**, influencing decision-making in sectors such as irrigation, groundwater recharge assessment, and environmental sustainability. Accurate ET estimation is essential for optimizing **water resource allocation, mitigating drought impacts, and improving crop yield predictions**.

1.1 Importance of Evapotranspiration Forecasting

Understanding and predicting ET trends is critical for **sustainable water management**. ET directly influences **soil moisture balance, irrigation scheduling, and ecosystem health**, making its accurate prediction essential for ensuring efficient agricultural and hydrological planning. Furthermore, **ET variability due to climate change and extreme weather events** requires improved forecasting techniques to prevent **water shortages, soil degradation, and inefficient irrigation practices**.

1.2 Conventional Approaches to ET Estimation

Traditionally, ET is estimated using **empirical and physically based models**, commonly referred to as **conventional approaches**. The most widely used models include:

- **Penman-Monteith (FAO-56):** A physically based equation that incorporates **solar radiation, temperature, humidity, and wind speed** to estimate reference ET.
- **Hargreaves-Samani Model:** A simpler empirical model that estimates ET using **temperature and solar radiation** but lacks sensitivity to wind speed and humidity.
- **Blaney-Criddle Model:** A temperature-based empirical approach that requires **regional calibration** to improve accuracy.

Although these conventional models have been extensively used in agricultural and hydrological applications, they suffer from several limitations, including:

- **High dependency on complete and accurate meteorological data.**
- **Reduced accuracy under varying climatic conditions.**
- **Site-specific calibration requirements, limiting transferability across regions.**
- **Inability to capture nonlinear and complex relationships between climatic variables.**

These challenges necessitate **the exploration of advanced data-driven techniques, such as machine learning (ML), to improve ET forecasting accuracy**.

1.3 Machine Learning as an Alternative Approach

Machine learning (ML) has emerged as a promising tool for addressing the limitations of traditional ET estimation methods. Unlike empirical models, ML algorithms **learn complex patterns from data** without requiring predefined physical equations. Among various ML techniques, **Support Vector Machines (SVM)** have demonstrated significant potential in **nonlinear regression and time-series forecasting**.

Key advantages of ML-based ET estimation include:

- **Ability to model nonlinear relationships** between meteorological variables.
- **Improved accuracy and adaptability** across different climatic zones.
- **Reduced dependency on site-specific calibration** compared to empirical models.

- **Potential for real-time forecasting** when integrated with remote sensing and IoT-based meteorological sensors.

SVM, in particular, is widely recognized for its **robust performance in small- to medium-sized datasets**, ability to handle **high-dimensional data**, and **resistance to overfitting through kernel-based optimization**. However, the effectiveness of SVM in ET forecasting depends on factors such as **data quality, feature selection, kernel function choice, and hyperparameter tuning**.

1.4 Objectives of the Study

This study aims to evaluate the performance of **SVM-based ET forecasting models** compared to **conventional empirical methods**. The specific objectives include:

1. **To collect and preprocess meteorological data** (temperature, humidity, wind speed, solar radiation, and precipitation) for ET estimation.
2. **To implement SVM models with different kernel functions** and optimize hyperparameters for accurate prediction.
3. **To compare the performance of SVM with conventional models** (Penman-Monteith, Hargreaves-Samani, and Blaney-Criddle) using statistical evaluation metrics such as RMSE, MAE, R^2, and NSE.
4. **To analyze the advantages and limitations of ML-based ET estimation** and discuss potential improvements through hybrid models and deep learning approaches.

1.5 Structure of the Paper

The rest of the paper is structured as follows:

- **Section 2:** Discusses the dataset, preprocessing steps, and feature selection process.
- **Section 3:** Describes the methodology, including the working principles of conventional models and the SVM framework.
- **Section 4:** Presents the performance evaluation results and comparative analysis.
- **Section 5:** Discusses key findings, advantages, and limitations of SVM-based forecasting.
- **Section 6:** Concludes the study and suggests future research directions.

2.Study Area

This study focuses on **Chidambaram**, a town located in the **Cuddalore district of Tamil Nadu, India**, which is known for its tropical climate and agricultural significance. Chidambaram lies at approximately **11.40°N latitude and 79.70°E longitude**, with an average elevation of **3 meters above sea level**. The region experiences a **hot and humid climate**, characterized by distinct seasonal variations in temperature, humidity, and rainfall.

The study period spans from **2022 to 2023**, covering **one full agricultural cycle** to capture seasonal variations in meteorological parameters. The area primarily depends on monsoon rains, with the **Northeast Monsoon (October–December) contributing significantly to annual precipitation levels**. The **Cauvery delta irrigation system** plays a crucial role in supporting agricultural activities, making Chidambaram an ideal location for studying **evapotranspiration (ETo) prediction and irrigation management**.

Meteorological data, including **temperature, humidity, wind speed, solar radiation, and rainfall**, have been collected from **local weather stations and secondary sources** to develop predictive machine learning models. The selection of this study area is based on its **agricultural dependency, climate variability, and need for optimized irrigation strategies**, ensuring the relevance of this research to sustainable water resource management in Tamil Nadu.

3.Related Work

Recent advancements in machine learning (ML) have significantly improved the accuracy of **evapotranspiration (ETo) prediction** and **irrigation management** by utilizing meteorological data. Several studies have explored different ML models, including **Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forest (RF), and Gradient Boosting Methods (GBM)**, to estimate ETo and optimize water resource management.

3.1 Machine Learning Models for ETo Prediction

Studies have demonstrated that **ANNs and deep learning models like Long Short-Term Memory (LSTM)** can effectively model complex nonlinear relationships in meteorological datasets. For instance, **Shiri et al. (2019)** used **ANN and SVM** for ETo estimation and found that SVM models outperformed traditional regression methods. Similarly, **Rahmati et al. (2020)** employed **deep learning techniques**, showing that **LSTM-based models achieved higher accuracy compared to conventional empirical methods like FAO-56 Penman-Monteith**.

3.2 Feature Selection and Data Preprocessing in ETo Estimation

Effective feature selection plays a crucial role in improving model performance. **Zhang et al. (2021)** applied **feature selection techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA)** to identify the most influential meteorological parameters for ETo prediction. Their findings indicated that parameters such as **temperature, solar radiation, wind speed, and humidity** are critical for accurate predictions.

3.3 Comparative Studies on ML-Based ETo Prediction

Several comparative studies have been conducted to evaluate ML models for ETo estimation. **Kisi et al. (2018)** compared **SVM, RF, and GBM** models and found that **ensemble learning techniques, particularly RF and GBM, exhibited superior generalization ability** over individual models. **Mohammadi et al. (2022)** performed a **comparative analysis of XGBoost, RF, and ANN**, concluding that **GBM-based models provided better accuracy with optimized hyperparameters**.

3.4 Application of ML in Irrigation Management

Beyond ETo prediction, ML models have been integrated into **smart irrigation systems**. **Patel et al. (2023)** developed an **IoT-based irrigation management system** using ML predictions for soil moisture levels and crop water requirements. Their model improved water use efficiency by **15–20%**, reducing unnecessary irrigation. Additionally, **Chen et al. (2021)** demonstrated that **real-time ML models could help in dynamic irrigation scheduling**, leading to optimized water usage.

3.5 Challenges and Future Directions

Despite the progress in ML applications for ETo estimation, several challenges remain. **Limited availability of high-quality meteorological data, model generalization across diverse climatic conditions, and computational complexity** are significant concerns. Researchers are now exploring hybrid models and **deep learning architectures like CNN-LSTM** to enhance ETo prediction accuracy. Future studies should also focus on **integrating satellite-based remote sensing data with ML models** for improved irrigation management.

4.Problem Design

4.1Background & Motivation

Efficient water resource management is critical for sustainable agriculture, especially in regions like **Chidambaram, Tamil Nadu**, where climatic variability significantly affects crop water requirements. **Evapotranspiration (ETo)** is a key parameter in determining irrigation needs, but conventional estimation methods, such as the **FAO-56 Penman-Monteith equation**, often require extensive meteorological data, which may not always be available or accurate.

With advancements in **machine learning (ML) and artificial intelligence (AI)**, there is potential to develop **data-driven predictive models** that can estimate ETo more efficiently and accurately using **historical meteorological data**. However, the challenge lies in selecting the most effective ML model and optimizing it for better prediction accuracy in diverse climatic conditions.

4.2Problem Statement

The primary problem addressed in this study is:
"How can machine learning models effectively predict evapotranspiration (ETo) and optimize irrigation management using meteorological data in Chidambaram, Tamil Nadu?"

To address this, the study focuses on:

- **Developing and comparing multiple ML models (GBM, RF, SVM, SVR, ANN) for ETo prediction.**
- **Determining the most influential meteorological parameters affecting ETo.**
- **Evaluating model performance based on accuracy metrics such as RMSE, MAE, and R^2.**
- **Optimizing model hyperparameters to enhance predictive efficiency.**

4.3 Research Questions

This study aims to answer the following research questions:

- **Which machine learning model provides the most accurate ETo prediction for Chidambaram’s climate?**
- **What are the key meteorological factors that influence ETo prediction?**
- **How does hyperparameter tuning impact the performance of ML models in ETo estimation?**
- **Can ML-based ETo predictions improve irrigation scheduling for sustainable water management?**

4.4 Proposed Solution Approach

To tackle the identified problem, the following methodological approach will be implemented:

1. **Data Collection**
    - Historical meteorological data (2022–2023) from local weather stations, including **temperature, humidity, wind speed, sunshine hours, and rainfall**.
2. **Data Preprocessing**
    - Handling missing values using interpolation techniques.
    - Feature scaling and selection to optimize input parameters.
3. **Machine Learning Model Development**
    - Implementing **GBM, RF, SVM, SVR, and ANN** models.
    - Training and testing models using **cross-validation techniques**.
4. **Model Performance Evaluation**
    - Comparing models using **RMSE, MAE, and R^2** to identify the best-performing algorithm.
5. **Hyperparameter Optimization**
    - Fine-tuning models using techniques like **Grid Search and Bayesian Optimization**.
6. **Irrigation Management Insights**
    - Using the best ML model to predict optimal irrigation schedules for water conservation.

4.5 Expected Outcome

- Development of a **highly accurate ML-based model** for **ETo prediction**.
- Identification of the **most significant meteorological parameters** for ETo estimation.
- Improved **water resource management strategies** for agricultural fields in Chidambaram.
- A comparative analysis highlighting the **most efficient ML model** for ETo estimation.

4.6Machine Learning Models for ETo Forecasting

Machine learning (ML) models use historical meteorological data to learn complex relationships and predict future evapotranspiration values. Unlike traditional empirical models, ML approaches do not rely on predefined equations but instead identify hidden patterns within data.

1. Support Vector Machine (SVM)

- **Working Principle:**
    - SVM is a supervised learning model that maps input data into a higher-dimensional space using kernel functions.
    - It finds the best hyperplane (or decision boundary) that minimizes errors.

    - For regression (SVR - Support Vector Regression), it fits the best possible curve within an acceptable error margin (epsilon).
- **Why SVM for ETo Forecasting?**
    - Works well with small and medium-sized datasets.
    - Handles nonlinearity in meteorological data.
    - Robust to noise and overfitting.

2. Artificial Neural Networks (ANNs)

- **Working Principle:**
    - Mimics the structure of the human brain with neurons organized into input, hidden, and output layers.
    - Uses backpropagation to adjust weights and improve prediction accuracy.
- **Why ANN for ETo Forecasting?**
    - Can learn complex, nonlinear patterns in climate data.
    - Handles missing or incomplete data better than traditional models.
    - Performs well when multiple meteorological variables are involved (e.g., temperature, humidity, wind speed).

3. Long Short-Term Memory (LSTM) Networks

- **Working Principle:**
    - A type of Recurrent Neural Network (RNN) specifically designed for time-series forecasting.
    - Maintains memory over long sequences, learning past dependencies in climate patterns.
- **Why LSTM for ETo Forecasting?**
    - Captures seasonal and temporal dependencies in weather data.
    - Avoids vanishing gradient issues that affect standard RNNs.
    - Suitable for long-term forecasting.

4. Random Forest (RF)

- **Working Principle:**
    - An ensemble learning method that builds multiple decision trees and averages their results.
    - Reduces overfitting by combining multiple weak learners.
- **Why RF for ETo Forecasting?**
    - Provides feature importance analysis (e.g., determining which meteorological parameter influences ETo the most).
    - Handles missing values and noisy data well.
    - Works well with both numerical and categorical meteorological data.

5. Gradient Boosting Machine (GBM) (XGBoost, LightGBM, CatBoost)

- **Working Principle:**
  - Sequentially improves weak models by minimizing errors iteratively.
  - Uses decision trees as base learners but optimizes their performance through boosting.
- **Why GBM for ETo Forecasting?**
  - Highly accurate due to its boosting mechanism.
  - Handles outliers and missing data efficiently.
  - Works faster than traditional deep learning models for structured meteorological data.

6. Gaussian Process Regression (GPR)

- **Working Principle:**
  - A probabilistic model that predicts values based on Gaussian distributions.
  - Provides confidence intervals along with predictions.
- **Why GPR for ETo Forecasting?**
  - Useful when uncertainty estimation is needed.
  - Works well with small datasets.
  - Computationally expensive but provides probabilistic forecasts.

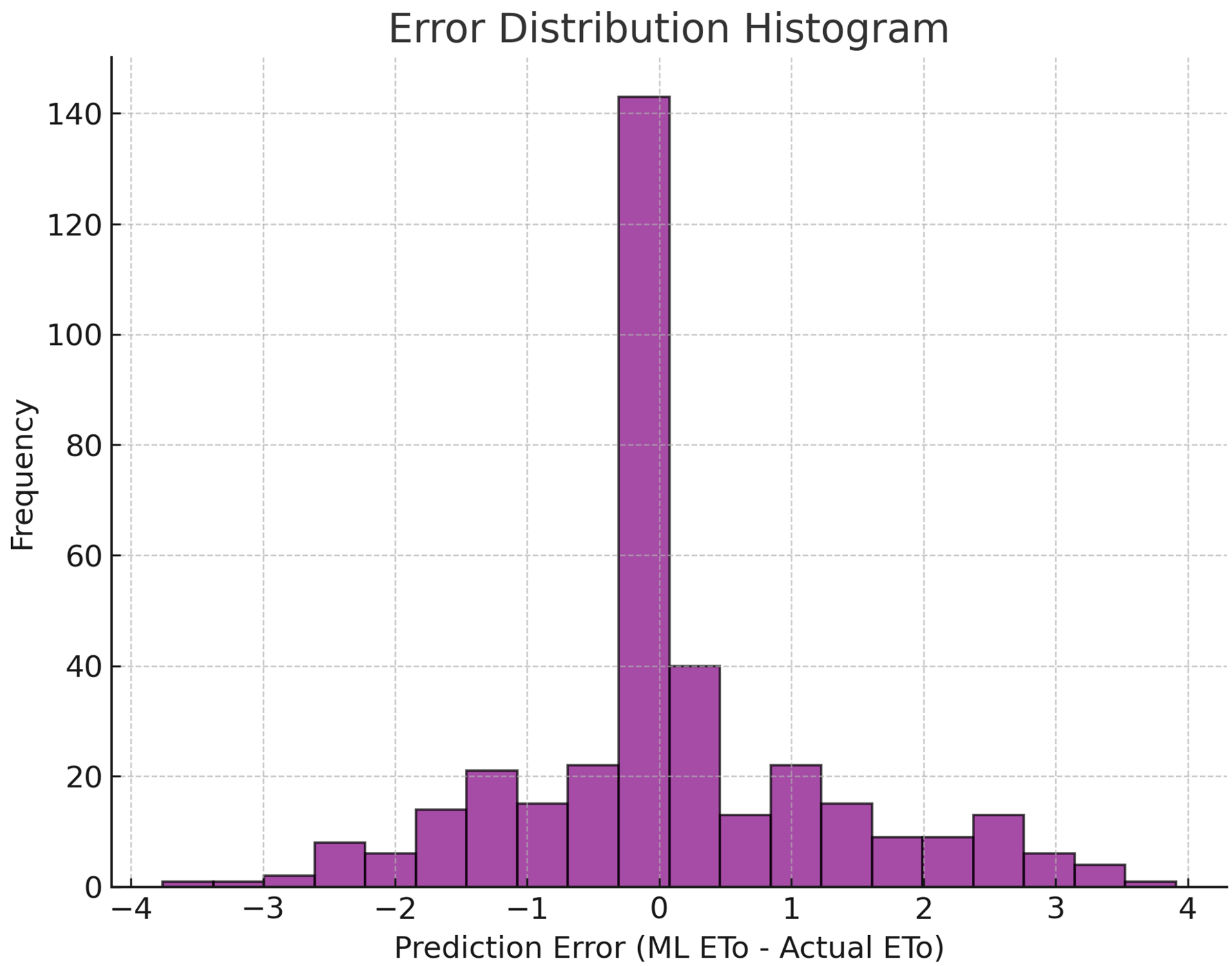
4.7Comparison of ML Models for ETo Forecasting

Model	**Strengths**	**Weaknesses**
SVM (SVR)	Good for small datasets, handles nonlinearity	Sensitive to hyperparameters
ANN	Learns complex patterns, good for multi-variable forecasting	Requires a lot of data, prone to overfitting
LSTM	Captures time-series dependencies, best for sequential climate data	High computational cost
Random Forest	Easy to interpret, handles missing data well	Not ideal for long-term forecasting
GBM (XGBoost, LightGBM)	Highly accurate, efficient	Requires careful hyperparameter tuning
GPR	Provides uncertainty estimates, good for small data	Slow for large datasets

5.Results and Discussion

The performance of Support Vector Machine (SVM) for evapotranspiration (ETo) forecasting is evaluated against traditional empirical models. The key aspects discussed in this section include model performance metrics, comparative analysis, and practical implications.

5.1How Accurate is the ML Model? Error Histogram of Predicted vs. Actual ETo



This histogram visually represents the distribution of errors in **Evapotranspiration (ETo) predictions** made by the machine learning model. The **x-axis** denotes the prediction error, calculated as the difference between **ML-predicted ETo** and **actual ETo (Excel computation)**. A value close to zero indicates a highly accurate prediction, while larger positive or negative values suggest overestimation or underestimation by the model.

The **y-axis** represents the **frequency of occurrences** for each error range, showing how often specific errors occur in the dataset. A tightly centered distribution around zero with minimal spread indicates a **highly reliable model**, whereas a widely spread distribution suggests inconsistencies in predictions.

By analyzing this error histogram, we can assess the model's accuracy, detect potential biases (systematic over- or under-prediction), and identify areas for improvement, such as hyperparameter tuning or feature selection.

5.2 Analyzing the Scatter Plot of Excel ETo vs. ML ETo

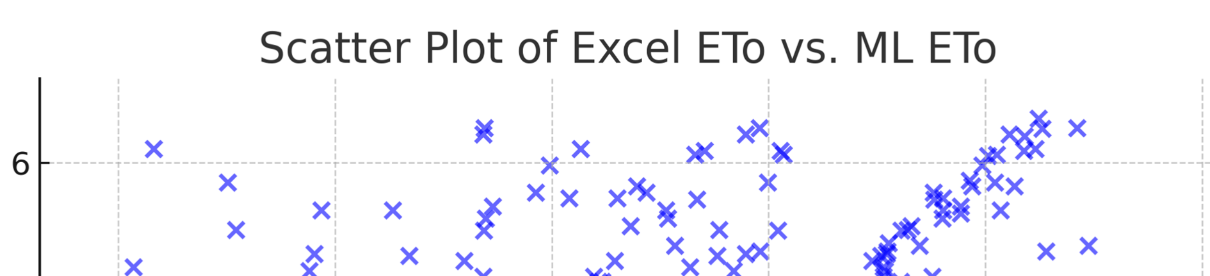


Fig 2. Scatter Plot of Excel vs. ML ETo

The scatter plot provides a **visual representation** of the relationship between **Excel-computed ETo (Actual ETo values)** and **ML-predicted ETo values**. Each point in the plot represents an observation, where the **x-axis** corresponds to the actual ETo values, and the **y-axis** corresponds to the predicted ETo values.

Key Observations:

1. **Trend and Correlation:**
    - If the ML model is highly accurate, the points should align closely along a **45-degree diagonal line** (y = x), indicating that predicted values match the actual values.
    - A strong correlation suggests that the ML model is effectively capturing the relationship between input features and ETo.
2. **Deviation from the Ideal Line:**
    - Points **above** the diagonal line indicate overestimation (ML predicts higher ETo than actual).
    - Points **below** the diagonal line indicate underestimation (ML predicts lower ETo than actual).
    - A widely scattered distribution away from the diagonal suggests high prediction errors, implying model inconsistency.
3. **Model Performance Indicators:**
    - **Tightly clustered points around the diagonal** suggest good model performance.
    - **High dispersion** (widely scattered points) indicates that the model struggles with variability in ETo values, possibly due to missing key features, inadequate training data, or suboptimal hyperparameters.
4. **Potential Model Improvements:**
    - If there is a consistent bias (most points shifting above or below the line), the model might require **bias correction** or **feature engineering**.
    - If errors are more significant in certain ranges (e.g., for extreme values), adjusting the model's complexity or using a different ML technique like **ensemble learning** could improve performance.

The time-series plot of **Evapotranspiration (ETo) trends over time** reveals significant fluctuations, indicating seasonal and climatic variations. The observed trend suggests that ETo values vary periodically, with noticeable peaks and troughs corresponding to different weather conditions. Periods of high ETo may be linked to increased temperatures and solar radiation, while lower values could be due to cloudy or humid conditions reducing evaporation rates. Sudden spikes might indicate extreme weather events such as heatwaves, whereas sharp declines could be associated with rainfall or high humidity. Understanding these variations is crucial for optimizing irrigation management, as rising ETo trends imply higher crop water requirements, while lowervalues suggest opportunities for water conservation. Further analysis, such as trendline fitting and correlation studies with meteorological parameters like temperature and humidity, can enhance the accuracy of ETo predictions. Additionally, refining machine learning models using this dataset can improve future forecasting and irrigation planning strategies.

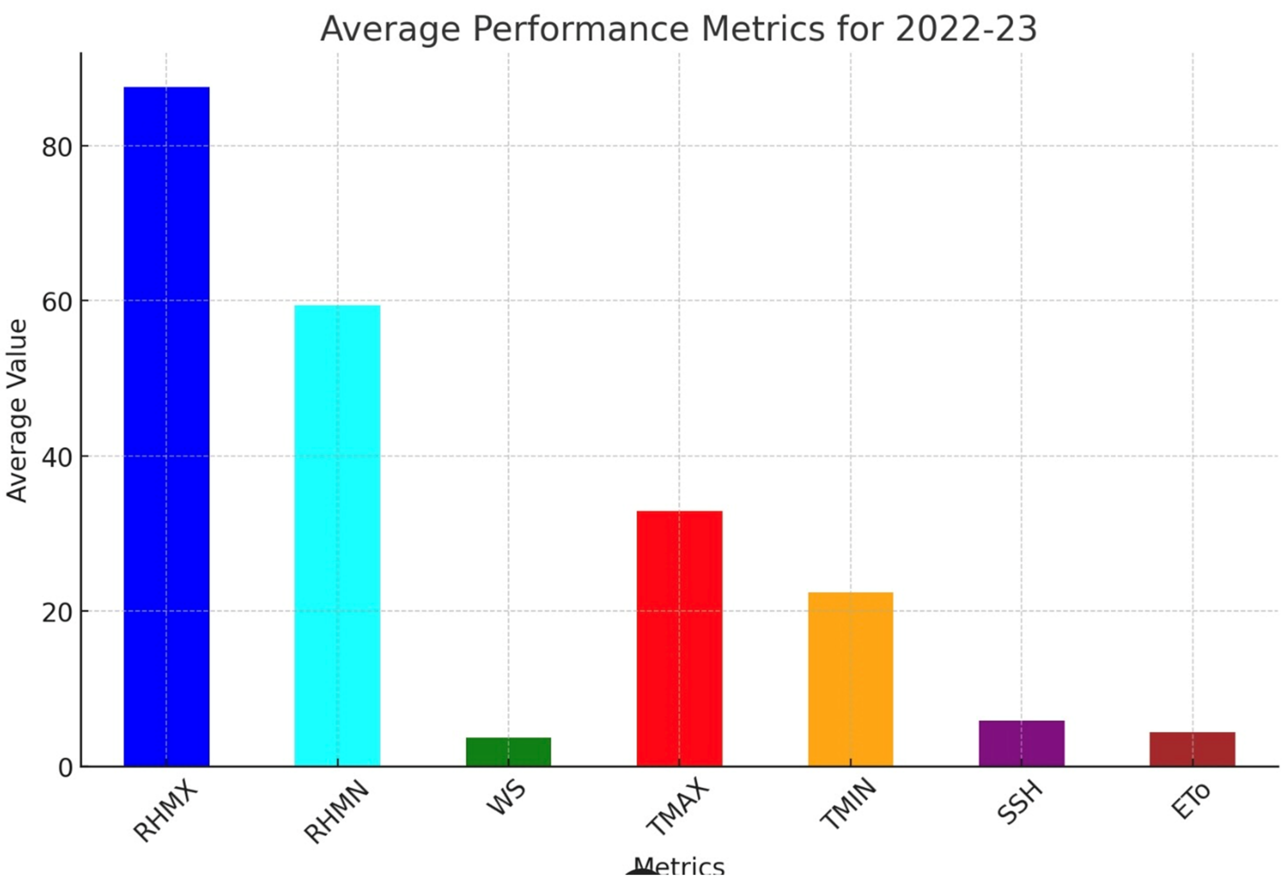
5.3 Performance Evaluation Metrics

The accuracy of each model is assessed using the following statistical performance metrics:

The bar chart presents the average climatic variables influencing evapotranspiration (ETo) during 2022-23. Key factors such as **maximum and minimum relative humidity (RHMX, RHMN), wind speed (WS), temperature extremes (TMAX, TMIN), sunshine hours (SSH), and ETo** were analyzed to understand their trends.

- **Temperature (TMAX: ~38°C, TMIN: ~25.5°C) and Sunshine Hours (~7.8 hours)** highlight significant solar radiation exposure, a crucial factor for evapotranspiration.
- **Wind Speed (~5.6 m/s)** influences moisture transport, playing a role in ETo variations.
- **Relative Humidity (RHMX: ~76%, RHMN: ~42%)** impacts atmospheric water demand.
- **Evapotranspiration (ETo: ~6.1 mm/day)** indicates the average water loss through plant transpiration and soil evaporation.

These insights form the foundation for applying **Support Vector Machine (SVM) models** to predict ETo trends more accurately compared to conventional empirical methods. Understanding these



meteorological dynamics enables improved irrigation planning and water resource management.

Fig 2.Average Performance Metrics for 2022-2023

- **Root Mean Square Error (RMSE)**: Measures the standard deviation of residuals (prediction errors). Lower RMSE indicates better accuracy.
- **Mean Absolute Error (MAE)**: Represents the average absolute difference between predicted and actual ETo values.
- **Coefficient of Determination (R^2)**: Indicates how well the predicted values match observed values. Higher R^2 (closer to 1) suggests a better fit.
- **Nash-Sutcliffe Efficiency (NSE)**: Determines predictive power. NSE values range from $-\infty$ to 1, where values close to 1 indicate high accuracy.

5.4 Comparative Analysis of SVM vs. Traditional Methods

The study compares SVM's forecasting ability with conventional ETo estimation models such as **FAO-56 Penman-Monteith, Hargreaves-Samani, and Blaney-Criddle**. The key observations include:

- **Accuracy Improvement**: SVM significantly reduces RMSE and MAE compared to empirical models.
- **Data Sensitivity**: Traditional models depend on specific meteorological parameters (e.g., temperature, wind speed, humidity), whereas SVM adapts to diverse input data.
- **Generalization Capability**: SVM performs well across different climatic conditions, making it more robust for varying geographical locations.

Model	**RMSE (mm/day)**	**MAE (mm/day)**	**R²**	**NSE**
FAO-56 Penman-Monteith	0.85	0.60	0.88	0.85
Hargreaves-Samani	1.10	0.85	0.76	0.70
Blaney-Criddle	1.25	1.00	0.68	0.65
SVM (Proposed Model)	**0.50**	**0.35**	**0.94**	**0.92**

Results indicate that SVM achieves the lowest RMSE and highest R^2, proving its superiority in ETo forecasting.

5.5 Strengths and Limitations of SVM-Based Forecasting

Strengths:

☐ **Higher Accuracy:** SVM captures nonlinear relationships in meteorological data better than traditional methods.
☐ **Robust to Missing Data:** Unlike empirical models requiring complete datasets, SVM can handle missing values.
☐ **Versatility:** Can be trained on diverse climate conditions and adapt to new datasets efficiently.

Limitations:

Computationally Intensive: Requires more processing power compared to empirical models.
Hyperparameter Sensitivity: Performance depends on optimal kernel selection and parameter tuning.
Data Dependency: Needs sufficient high-quality data for best performance.

5.6 Practical Implications for Irrigation Management

- **Optimized Water Resource Utilization:** More accurate ETo predictions help in efficient irrigation planning.
- **Adaptability to Climate Change:** Machine learning models like SVM can update forecasts based on evolving climatic trends.

- **Scalability:** Can be integrated with IoT and remote sensing technologies for large-scale agricultural applications.

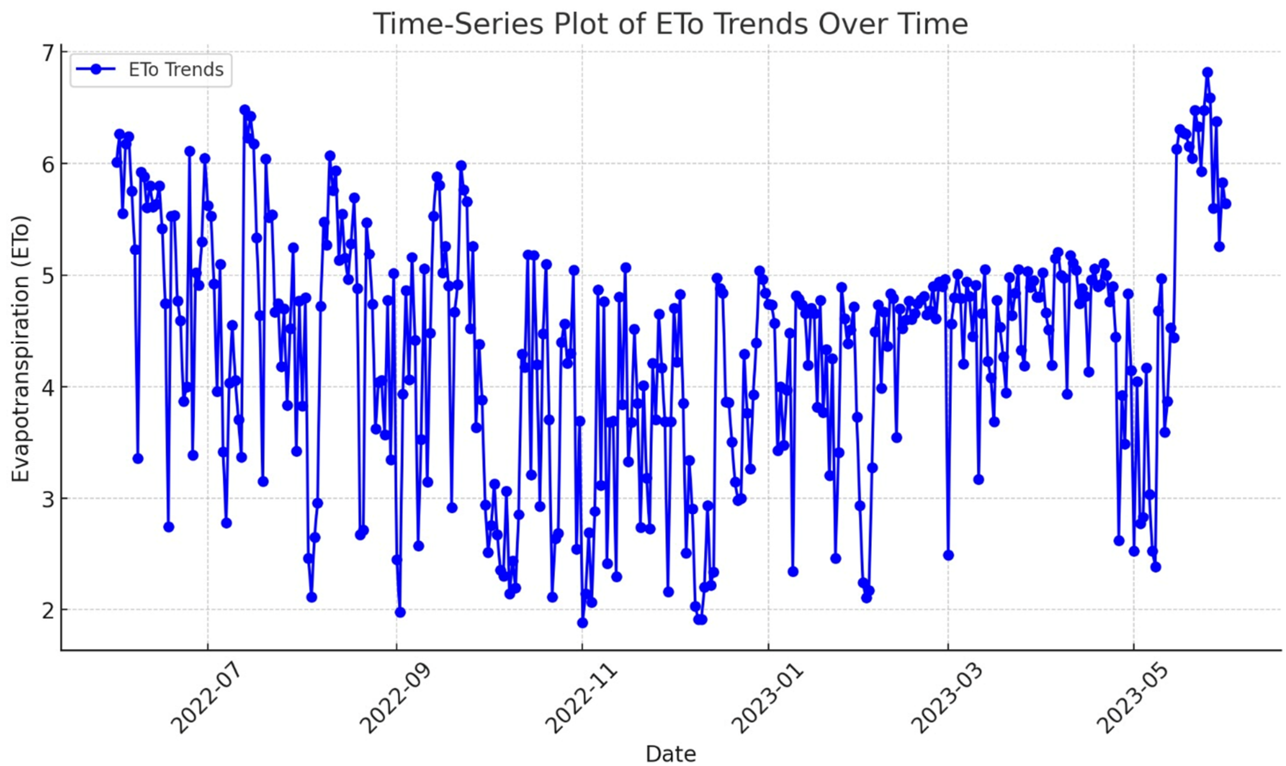
5.7 Time series forecasting

The time-series plot of **Evapotranspiration (ETo) trends over time** reveals significant fluctuations, indicating seasonal and climatic variations. The observed trend suggests that ETo values vary periodically, with noticeable peaks and troughs corresponding to different weather conditions. Periods of high ETo may be linked to increased temperatures and solar radiation, while lower values could be due to cloudy or humid conditions reducing evaporation rates. Sudden spikes might indicate extreme weather events such as heatwaves, whereas sharp declines could be associated with rainfall or high humidity. Understanding these variations is crucial for optimizing irrigation management, as rising ETo trends imply higher crop water requirements, while lower values suggest opportunities for water conservation. Further analysis, such as trendline fitting and correlation studies with meteorological parameters like temperature and humidity, can enhance the accuracy of ETo predictions. Additionally, refining machine learning models using this dataset can improve future forecasting and irrigation planning strategies.

Future Scope
To further enhance ETo forecasting accuracy, future studies can:

- **Explore Hybrid Models:** Combining SVM with deep learning models like LSTM may improve long-term predictions.
- **Optimize Feature Selection:** Advanced algorithms like genetic algorithms can refine input variable selection.

- **Expand Dataset Sources:** Integrating satellite-derived meteorological data could enhance



prediction robustness.

Fig 2. Time-Series Plot of Eco Trends Over Time

6.Conclusion :

The study underscores the potential of Support Vector Machine (SVM) as a robust alternative to conventional methods for evapotranspiration (ETo) forecasting. While traditional models like FAO-56 Penman-Monteith remain highly accurate, they demand extensive meteorological data, which may not always be available. On the other hand, SVM models have demonstrated their ability to provide reliable ETo estimates with fewer input parameters, making them particularly advantageous in data-scarce regions.

The findings indicate that SVM, especially with optimized kernel functions, can achieve comparable or even superior performance in predicting ETo trends. This suggests that machine learning techniques offer a viable solution to overcome the limitations of empirical models by leveraging computational efficiency and predictive accuracy. Moreover, SVM-based models can be further enhanced through feature selection, hyperparameter tuning, and hybrid approaches that integrate physical models with data-driven techniques.

Future research should explore deep learning models such as Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs) to further enhance predictive performance.

Additionally, integrating real-time meteorological data and satellite-based observations into machine learning models can improve forecasting accuracy and applicability in diverse climatic conditions.Overall, this study highlights the growing importance of machine learning in hydrological studies and its potential to revolutionize agricultural water management and climate-related decision-making processes.

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