Advanced Soil Moisture Predictive Methodology in the Maize Cultivation Region

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ABSTRACT

Soil moisture is a critical determinant of the maize crop health and productivity. With over 60% of India's maize cultivation concentrated in South Indian states, accurately forecasting soil moisture is essential for optimizing irrigation and enhancing agricultural output. This study introduces an Improved Hybrid Machine Learning (IHML) model that integrates and optimizes Machine Learning (ML) models to deliver superior predictive performance. By leveraging data from key maize-growing districts in South India, the IHML model demonstrates enhanced convergence rates and accuracy compared to traditional ML approaches. The research framework is grounded in comprehensive correlation evaluations, which inform parameter selection and model architecture. Extensive comparisons reveal that the IHML model significantly outperforms individual ML models in forecasting soil moisture with higher precision. These findings highlight the potential of IHML models to advance smart farming practices and enable precise irrigation management, paving the way for improved crop yield and sustainable agriculture.

Keywords-ensembe methods; error margin; moisture content; prediction; maize cultivation; temperature; rainfall; precipitation

I. INTRODUCTION

Soil moisture, defined as the water content in the surface layer of the soil, plays a critical role in the interaction between the soil and atmosphere, particularly through the process of evapotranspiration. This dynamic interaction significantly impacts agricultural practices, as soil moisture at different depths directly affects the crop growth and water distribution within hydrological cycles [1]. Surface moisture provides immediate support for crops, while deeper reserves sustain root systems during extended dry periods. Effective irrigation practices rely on accurate soil moisture monitoring to determine when water is needed, as plants draw from both the surface and subsoil reserves. Discrepancies in environmental factors, such as temperature and rainfall, can disrupt moisture levels, accentuating the need for precise management to maintain plant health and maximize crop yields [2]. Understanding the role of soil moisture in agriculture is essential for making informed decisions about water resource management, disaster preparedness, and drought mitigation [3]. Precise predictions of soil moisture trends can significantly enhance farming productivity by addressing the complex interactions between the physicochemical properties, ecological processes, and climatic conditions. Despite its importance, soil moisture is often overlooked in modeling efforts due to its intricate and dynamic behavior across time and space [4]. This research seeks to assess the effectiveness of various ML models in anticipating soil moisture and to enhance the accuracy of the factors influencing the moisture content in maize crop fields, thereby promoting enhanced agricultural practices and sustainability.

Recent advancements in soil moisture prediction at the soil, agricultural, and geographic levels have contributed to a more comprehensive understanding of the moisture content [5]. Research and technological progress have introduced a growing range of approaches for estimating soil moisture. Gradually, the scope of soil-scale studies has expanded beyond individual farms to encompass larger regional scales. Specifically, authors in [6] proposed an extrapolation method for forecasting the soil moisture concentration based on infused moisture content and evaporative coefficients, successfully predicting wetness levels at regional scales. Similarly, authors in [7] employed a Bayesian approach alongside artificial neural networks to model data retrieval from spatial datasets. These methods utilized moisture content as the output variable while examining confidence intervals and variances in two directions, providing insights into the strengths and limitations of various techniques under specific conditions. Indian researchers in [8] utilized artificial neural networks integrated with electromagnetic data to forecast soil moisture. By employing an X-band electromagnetic diffusion meter under diverse soil conditions, they adapted and retrained their neural models for various forecasting tasks, including the estimation of soil moisture levels. Researchers have compared various training techniques to identify the most effective methods for predicting soil moisture levels and surface roughness by analyzing discrepancies between the observed and predicted values. A range of predictive approaches was employed to achieve the desired estimates. Building on these efforts, authors in [9] developed an improved a micro-strip band resonant device for measuring the soil moisture. This device was tested across various soil types, with predictions having been made based on the response of incident waves in compost soil and sandy gravel at varying water content levels. Additionally, authors in [10] conducted research using a pedotransfer function to estimate the moisture levels in regional farmlands by analyzing the relationship between the fundamental soil parameters and their water-holding capacity. Forecasting procedures are expected to become more proactive, with many prediction activities being automated through frameworks or applications. However, current models often fail to autonomously retrieve essential data from meteorological frameworks as required for accurate predictions [11]. To address these limitations, the IHML methodology is proposed, offering a robust solution to improve data integration and enhance predictive accuracy. Recent advancements in soil moisture prediction highlight several methodological limitations. While some studies provide insights across diverse scales, they often lack integration at the micro-level, leading to gaps in its understanding. Specific approaches can successfully predict moisture but may fail to account for sudden environmental changes, limiting their real-world applicability. Many methodologies also rely heavily on specific conditions, restricting their generalizability. Although improvements in measurement techniques have been achieved, predictions often lack adaptability for real-time application. Furthermore, conventional methods largely rely on single data sources, missing the potential of advanced ML and multi-source data integration, which are essential for more robust and accurate soil moisture predictions.

II. METHODOLOGY

A. *Study Region (SR)*

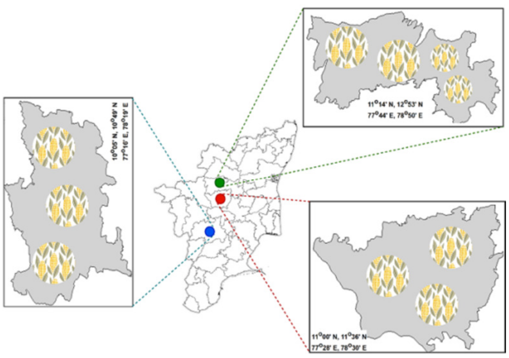

Fig. 1. Geographical representation of the three SRs.

This research was conducted in three key maize-growing districts, including Salem, Dindigul, and Namakkal, in the Indian state of Tamil Nadu [12-14]. Figure 1 depicts the geographical depiction of each SR.

B. *Dataset*

The Soil and Water Assessment Tool (SWAT) outputs, using the India Dataset are commonly employed to predict the soil moisture under various climatic scenarios [15]. This dataset is based on 20 days of trial data from 30 unique locations across three different SRs. As a result, the dataset comprises 600 data points that cover various key attributes, as listed in Table I. To prevent computation errors due to missing data, the datasets are normalized. The data are then split into training and testing sets in a 70:30 ratio to evaluate the performance of the ML models. To predict both the short- and long-term soil moisture for maize production, the selected ML models integrate prediction methodologies with empirical formulas.

TABLE I. BASE ATTRIBUTES OF THE DATASET

Attributes	Units
Volumetric Soil Moisture Content (VSMC)	m^3 water / m^3 soil
Air Temperature	K
Soil Temperature	℃
Precipitation	mm
Farmland Surface Temperature	K
Soil Depth	5-10 cm

C. *Optimal Soil Requirements*

Even though maize can be successfully grown in various soil types, the optimal soil conditions for cultivation are deeper, nutrient-rich, well-moisturized, and biologically fertile. The ideal soil for maize growth has a reasonably high moisture-holding capacity. However, because maize is highly susceptible to waterlogging, it is typically cultivated during the rainy monsoon season. Special care must be taken to ensure that excess precipitation remains on the surface for no more than five hours. Soils with relatively permeable subsoils, such as loamy soils, sedimentary loams, and clay-rich soils, are most suitable. The ideal soil would have a neutral pH range from 6.5 to 7.5, a cation-exchange capacity of approximately 20 milli-equivalents per 100 g, surface absorption from 70% to 90%, a density and porosity close to 1.3 g/cm^3, and a moisture-holding potential of about 16 cm per m of depth.

D. *Optimal Climatic Requirements*

Maize cultivation thrives in temperatures between 9 and 30 ℃. The number of leaves increases from emergence to tasseling as the crop adapts to its environment. The latency period for tasseling lengthens as the diurnal temperature range increases, when temperatures fluctuate between 0 and 17 ℃. Maize grows at its fastest rate when temperatures reach 30 ℃. A higher yield is likely if there is no frost during the grain-filling phase. Additionally, elevated levels of solar irradiance enhance maize photosynthesis, contributing to better growth and higher productivity.

E. *IHML Model*

The IHML approach incorporates two levels of predictive strategies. The base level consists of three advanced ML models, including Bidirectional-Gated Recurrent Unit (B-GRU), Support Vector Regression (SVR), and Multiple Linear Regression (MLR), whose predictions are addressed individually. The top level employs an assembling strategy that combines the outcome of the base level and produces the predictive result with optimal accuracy [16].

1) B-GRU Model

During training, the conventional Long-Short Term Memory (LSTM) model's variables are tuned to minimize loss, which represents the gap between the model's predictions and the actual soil moisture levels. However, the LSTM model only considers the accuracy of the predictions for the immediate sampling interval and does not account for the transitional temporal data after the feedback sampling interval [17]. As a result, it may fail to capture the complexity and uncertainty of the data and could potentially overfit the model. Figure 2 provides a conceptual illustration of the B-GRU model.

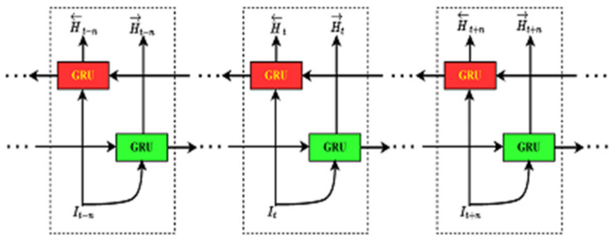

Fig. 2. Structure of the B-GRU model.

Bidirectionally models can integrate insights from both historical and future data into their present analysis. The B-GRU model employs two GRUs oriented in opposite directions [18]. The first processes the data sequentially from the beginning of the trend line, forward direction, while the other processes the data from the end of the sequence, backward direction. This bidirectional approach allows both past and future data to influence the current state. The B-GRU can be described as:

$$\overrightarrow{H}_t = F_{gru}\left[I_t, \overrightarrow{H}_{t-n}\right] \tag{1}$$

$$\overleftarrow{H}_t = B_{gru}\left[I_t, \overleftarrow{H}_{t+n}\right] \tag{2}$$

$$H_t = \left[\overrightarrow{H}_t \oplus \overleftarrow{H}_t\right] \tag{3}$$

where $\overrightarrow{H}_t$ denotes GRU's forward state, $\overleftarrow{H}_t$ represents GRU's backwards state, and $\oplus$ signifies the concatenation of two vectors.

The initial input sequence at time t consists of moisture data from n previous and subsequent recorded time points, represented as $I = [I_{t+n}, \dots, I_t, \dots, I_{t-n})]$. The B-GRU model processes this input sequence. The second-level B-GRU model determines the recurrence pattern based on the length of the input sequence. For this study the model performs $2n+1$ iterations over the recurrent time scales. Data transfer across these scales is maintained in the hidden unit H_t. The IHML linear layer inputs are directly connected to the output layers of the B-GRU model.

2) SVR Medel

The SVR model is derived from the core concepts of Support Vector Machines (SVM) [19, 20]. By employing a constant mapping linear model, SVM training enables a maximum-margin predictor to project the input parameters into high-dimensional data points. SVR extends this principle by using a radial-based linear model to generate the optimal hyperplane for regression. This approach mitigates issues, such as global maxima and local minima that often arise when optimizing training samples with limited features. Radial-based functions are considered effective because they are straightforward to implement and maintain, while also being capable of handling high-dimensional spaces with marginal isolation factors.

The SVR constructs its estimation by selecting a subset of sample points within a predefined error margin. These subsets, known as support vectors, represent the most influential data points for prediction. Given a set of samples $I = \{i_1, i_2, \dots, i_n\}$ and corresponding outcomes $J = \{j_1, j_2, \dots, j_n\}$, t he purpose of SVR is to determine the flattened version of the periodic function $f(x)$ that minimizes the error margin between the predicted and actual outputs in the test data.

3) MLR Model

The MLR is a widely used tool for predicting an outcome variable based on multiple independent predictor variables. The following formulation expresses the forecasts of k given the p predictor factors:

$$k = \left[\beta_0^{\omega_1} + \beta_{1p_i}^{\omega_1} + \beta_{2p_2}^{\omega_2} + \cdots + \beta_{np_n}^{\omega_n}\right] \tag{4}$$

where the regression-based beta coefficients (weights) are specified as β. The coefficient β_i indicates the average effect on k for a one-unit increase in p_i, assuming that all other variables remain constant. These coefficients enable the model to provide interpretable and actionable insights into the influence of individual predictors on the outcome.

4) Heterogeneous Ensemble

The heterogenous ensemble approach combines multiple ML models, each trained on the same dataset. This strategy is effective for datasets with limited size. The ensemble outcome is generated through a stacking process, where a meta-learner aggregates predictions from the integrated models. A meta-learner model is trained to synthesize the results of several predictive and regression methods. The training relies on the outputs of Base Learners (BLs), which are themselves trained using the entire training dataset.

Unlike boosting strategies, where models are trained sequentially to correct previous errors, the heterogeneous ensemble employs a concurrent training process for all BLs. For more complex models, the output from one layer serves as an input for the subsequent layers, creating a stacked architecture. This architecture builds an advanced, refined model by progressively leveraging simpler models as foundational components. The prediction error of such ensembles is consistently low, as each level enhances the predictive accuracy of the previous layer. The stacking process continues iteratively until an optimal forecast with minimal error is achieved. This hybrid approach, often referred to as a meta-model, generates predictions by aggregating the outputs of simpler models. By reducing both bias and variance, the method aims to develop a robust predictive model. The algorithmic procedures of this heterogeneous ensemble strategy are based on [21].

III. PERFORMANCE ANALYSIS AND DISCUSSIONS

The IHML model was trained on a standardized dataset generated via SWAT for around 20 input days. The predictions were made at two scales: a short-term scale of six hours and a long-term scale of two days. This setup enabled the model to predict the soil moisture with accuracy, two hours (short-term) and one day (long-term), in advance. The simulations were conducted using Python 3.6.5 on a PC with the following specifications: Intel i5-8600k processor, 16GB RAM, 250GB SSD, GeForce 1050Ti 4GB GPU, and 1TB HDD. The parameter settings for the IHML model were a learning rate of 0.01, ReLU activation function, 50 epochs, a dropout rate of 0.5, and a batch size of 5.

The primary objective of this investigation was to determine if the input time window could be reduced without compromising the predictive accuracy. The model was first trained using the generated datasets, and its performance was evaluated utilizing a testing dataset. The model effectiveness was assessed using three metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R^2). These metrics are mathematically defined as [22]:

$$RMSE = \sqrt{\sum_{v=1}^{O}[m_v - \hat{p}_v]^2 / O} \quad (5)$$

$$MAE = \frac{1}{O}\sqrt{\sum_{v=1}^{O}|m_v - \hat{p}_v|} \quad (6)$$

$$R^2 = 1 - \left[\sum_{v=1}^{O}[m_v - \hat{p}_v]^2 \Big/ \sum_{v=1}^{O}[m_v - \bar{p}_v]^2\right] \quad (7)$$

where O denotes the observation count, p represents the estimated values, $\hat{p}$ represents the predicted values, and $\bar{p}$ denotes the mean of the estimated value.

In this study, soil moisture levels in maize cultivation fields were treated as dependent variables, with the environmental, weather, soil composition, and depth factors acting as independent predictive variables. The IHML model, particularly effective for short-term forecasts, minimizes discrepancies between ther forecast and input times, enhancing soil moisture prediction capabilities across varying timeframes. The performance of multiple models was evaluated, with a focus on short-term predictions. The results, depicted in Figure 3, illustrate the superior accuracy of the IHML model in forecasting the soil moisture levels. Notably, MLR underperformed at a depth of 5–10 cm, while B-GRU and SVR demonstrated minimal error in their predictions following IHML integration.

Table II presents the results of an experiment comparing the performance of several ML methods based on three evaluation metrics: MEA, RMSE, and R^2. Among the tested models, the IHML and B-GRU approaches achieved optimal outcomes, with MAE values being under 4%. The RMSE for the predicted soil moisture levels across the four ML techniques ranged from 0.042 to 0.072 m^3m^{-3}. The IHML model demonstrated superior performance, achieving the highest R² value of 0.88 and the lowest RMSE value of 0.042. Following closely, the B-GRU and SVR models also performed commendably. Their respective RMSE values were 0.063 and 0.072, MAE values were 0.039 and 0.042, and R^2 were 0.82 and 0.71.

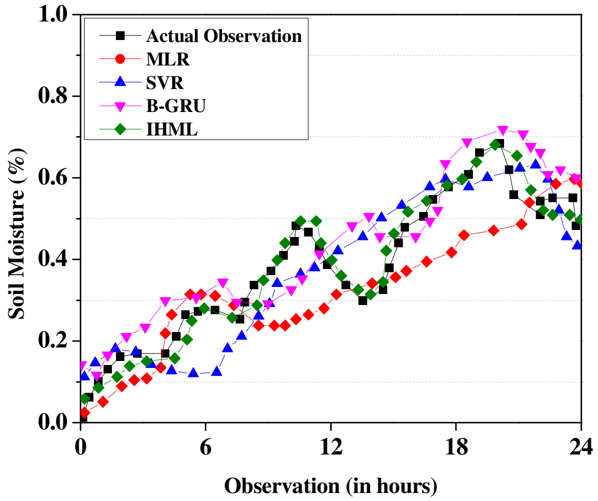

Fig. 3. Short-Term prediction of soil moisture.

TABLE II. PERFORMANCE COMPARISON OF SVR, MLR, B-GRU, AND IHML

Models	RMSE	R^2	MAE
SVR	0.072	0.71	0.042
MLR	0.052	0.65	0.062
B-GRU	0.063	0.82	0.039
IHML	0.042	0.88	0.033

The predictive models were evaluated over a 20-day period, with their predictions being daily assessed, as summarized in Table III. The IHML model consistently outperformed the other three models, exhibiting minimal error deviations. Given the significant variations in soil moisture across different climatic zones, the proposed model effectively mitigates these discrepancies by reanalyzing the output data of the base learners and adjusting the moisture content inputs for subsequent computations. For example, on day 5, the observed moisture was 31.91%. The IHML model had predicted a value of 29.69%, which was close enough to the observed value. Similarly, on Day 10, with an observed moisture of 16.45%, IHML had predicted 14.01% (close enough), while the remaining models had predicted: SVR (14.36%), MLR (16.78%), and B-GRU (13.28%). On Day 15, IHML's prediction of 19.09% aligned closely with the observed moisture of 19.19%, and was significantly better than the predictions of SVR (13.88%), MLR (13.23%), and B-GRU (16.04%). Finally, on Day 20, with an observed moisture of 32.72%, IHML had predicted 31.29%, again surpassing SVR (26.11%), MLR (26.44%), and B-GRU (26.35%). This adaptive approach improves the capability of the model to handle the soil moisture dynamics more efficiently.

TABLE III. DAILY OBSERVATIONS AND PREDICTIONS OF PRETICTIVE MODELS

Soil Moisture (%)					
Days	Observed	SVR	MLR	B-GRU	IHML
5	31.91	29.82	30.46	27.80	29.69
10	16.45	14.36	16.78	13.28	14.01
15	19.19	13.88	13.23	16.04	19.09
20	32.72	26.11	26.44	26.35	31.29

IV. CONCLUSION

This study successfully developed and evaluated predictive models for estimating the soil moisture in maize cultivation regions using climatic and vegetation indicators. Among the tested methods, the proposed Improved Hybrid Machine Learning (IHML) model demonstrated exceptional accuracy and reliability, outperforming traditional approaches, like Bidirectional-Gated Recurrent Unit (B-GRU), Support Vector Regression (SVR), and Multiple Linear Regression (MLR). Its ability to integrate short- and long-term predictions proved particularly valuable, making it a valuable tool for applications in agriculture and hydrology. The findings underscore the importance of the advanced machine learning techniques in addressing the complexities of soil moisture prediction, where temporal and environmental variability present significant challenges.

The study's outcomes hold practical significance for optimizing irrigation practices, improving fertilization strategies, and enhancing crop yield forecasting, thereby benefiting both farmers and environmental researchers. However, limitations remain, including reliance on historical datasets that may not capture sudden climatic anomalies and the potential variability of model performance across diverse regions.

Future research should address these gaps by incorporating real-time data inputs, exploring hybrid models for greater resilience, and expanding applications to broader agricultural and ecological contexts. Advanced methodologies for spatiotemporal mapping of soil moisture will further refine predictions, providing actionable insights for sustainable agriculture in diverse environments.

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