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Advanced Soil Moisture Predictive Methodology in the Maize Cultivation Region using Hybrid Machine Learning Algorithms

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Abstract—The moisture level in the soil in which maize is grown is crucial to the plant's health and production. And over 60% of India's maize cultivation comes from the states of South India. Therefore, forecasting the soil moisture of maize will emerge as a crucial factor for regulating the cultivation of maize crops with optimal irrigation. In light of this, this research provides a unique Improved Hybridized Machine Learning (IHML) model, which combines and optimizes several ML models (base learners-BL). The convergence rate of all the considered BL approaches and the preciseness of the proposed approach significantly enhances the process of determining the appropriate parameters to attain the desirable outcome. Consequently, IHML contributes to an improvement in the accuracy of the overall forecast. This research collects data from districts in South India that are primarily committed to maize agriculture to develop a model. The correlation evaluations served as the basis for the model's framework and the parameter selection. This research compares the outcomes of BL models to the IHML model in depth to ensure the model's accuracy. Results reveal that the IHML performs exceptionally well in forecasting soil moisture, comprising Correlation Coefficient (R^2) of 0.9762, Root Mean Square Error (RMSE) of 0.293, and Mean Absolute Error (MAE) of 0.731 at a depth of 10 cm. Conceptual IHML models could be used to make smart farming and precise irrigation much better.

Keywords- Ensembling Strategy, Error Margin, Moisture Content, Prediction, Maize Cultivation, Temperature, Rainfall, Precipitation.

I. INTRODUCTION

The term "soil moisture" indicates the quantity of water in the soil's surface layer, which exchanges energy with the air via evapotranspiration. The moisture content at a depth of 10 cm underneath the soil's surface is the hydration composition that represents the surface moisture. In comparison, the moisture content at the level of the crops' root system (at 200 cm) represents the subsoil moisture. In farmlands, the moisture content concentration in the soil significantly impacts how water is distributed among the significant aspects of its hydrological processes. Crops need soil as a growing substrate [36]. It protects the crop's base and absorbs and retains moisture. One typical form of agricultural irrigation is to water after the soil has lost a significant moisture amount. Variations in temperature, rainfall, as well as other environmental conditions, have a more substantial detrimental influence on soil moisture. Soil moisture is mainly viewed as the quantity of water present as the subsoil moisture at the root systems of crops, which is the principal means through which vegetation gets its water requirement [31]. Suitable moisture range aids plant growth in every soil condition since crops can in-take and use water more efficiently. Thus, the entire development of crops relies on soil moisture. Ecological moisture deficits reflect their effect on carbon sequestration, which indirectly lowers GDP [21, 29]. A crop root system draws water from the subsoil as it expands. Soil moisture declines when plants utilize it, signalling the need for hydration to prevent oxidative stress. The crop would focus on using the available moisture until the most petite range of moisture is in the soil, beyond which they may die, thus signalling the need for irrigation [41].

A. Significance of Soil Moisture in Farming

Besides being crucial to crop development, soil moisture is still an essential component of the natural ecosystem in processes that span the compost, the vegetation, and the environment [37, 38]. Unfortunately, the overall condition of subsurface water supplies is deteriorating because of the enhanced interruption from anthropogenic sources, and the degree of soil exploitation is far above what is sustainable [26]. As the water table continues to fall, both soil moisture content and sustainable groundwater retention capabilities decrease. Insufficient precipitation, notably in arid regions, prevents soil

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moisture from being replenished promptly, therefore hindering the steady development of vegetation [52].

The timely implementation of a suitable supply of water resources is of primary interest in such a context. Water usage from moisture content and crop yields are both intimately related to soil moisture levels. In light of its implications, farmers may employ it to make knowledgeable decisions concerning disaster preparation [23], water distribution, and drought mitigation [62]. To efficiently handle farming water supplies and encourage productivity improvements, the precise prediction of recurring trends in the soil water-dependent variable is crucial. Soil moisture may only be present in trace amounts at any location, yet it has a massive impact on,

- a vast array of physicochemical, ecological, and environmental phenomena;
- patterns of heat exchange between the farm substrate and the environment; and precipitation, rainfall, and runoff
- dry spell
- the atmosphere's composition, salinity, and concentration of harmful compounds;
- composition and density of the subsoil;
- The soil's moisture content and readiness to retain heat.

This factor protects against corrosion and establishes whether or not farmland is fit for agronomic operations. Soil moisture monitoring becomes more critical in light of such scenarios. A *dry spell* is a condition that reduces the soil's water content. The drought has exacerbated cultivation catastrophes [9]. Whenever soil moisture is inadequate to provide the required amount of water for crops, a dryness spell/drought is presumed to have ensued, negatively impacting crop productivity [46]. Soil dryness usually follows a sustained period of drought in the atmosphere. Additionally, surface soil concentrations might reach lethal heights.

B. Impact of Soil Moisture on Plant Growth

Crops' health is inextricably associated with the availability and quality of water and oxygen that their roots can use. It's an indicator of the farmland's immune function, not just the level of the water in a specific area. The influence of moisture in the soil on crop production and harvest is crucial. Variables, including weather, vegetation, and terrain, all have a role in this performance indicator. Primary soil properties for the cultivation of maize crops are depicted in Figure 1.

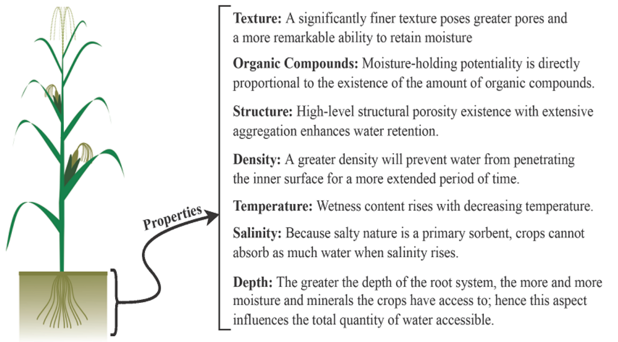

Figure 1. Primary Soil Properties

Before the actual plantation, it is crucial to assess the soil moisture in the farmland. The ideal quantity varies significantly from one crop variety and one geographical location to the next. In this way, maize is negatively impacted by too much moisture. Increased demands in recent decades have been addressed by a confluence of technical advancements, productivity gains, and acreage expansion, leading to dramatic growth in global maize output. Maize (corn) is a widely grown cereal grain, animal feed, and commercial commodity due to its adaptability and high productivity. The grain produced by such a crop is a high-quality, potent food source for all domesticated bird species and animals. The maize crop is usually grown for its edible kernels. Its grain produces several foods, including cereal, cornstarch, flakes, and more. In addition, maize grain is used as a source of ethanol, essential sugars, and starch. A variety of products, including parchment, adhesives, pigments, and artificial resins, are derived by utilizing both the husks and stalks of the harvested crops. Growing maize is crucial for several other reasons, including the economy and the efficiency of various government agencies. Maize fields may make more efficient use of personnel and farming implements since they are planted and reaped longer throughout any applicable season than most other springtime crop varieties.

India is the world's seventh-largest producer of maize (corn) and has the fourth-largest area dedicated to cultivating the crop. In India, the acreage planted with maize hit 9,200,000 hectares in the 2018-2019 crop years (Economics and Statistics Directorate, Ministry of Agriculture, Government of India, 2019). From a productivity level of 17,300,000 metric tonnes in 1950–51 to an expected 27,800,000 metric tonnes in 2019–20, India has seen a steep growth in maize output of about sixteen-fold which is evident in the statistical report exhibited in Figure 2 (FAOSTAT, 2020). And it is projected to rise further in the coming farming years. During that duration, average production went from 547 to 2965 kilograms/hectare, around a 5.42-fold rise, but the land area rose by just around three-fold. India accounts for about half of global production, yet its average crop production is comparable to several top-producing nations.

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Maize is India's highly prolific staple crop as well as a critical source of feed; therefore, it also helps satisfy people's nutritional requirements. For optimal crop growth, producers choose to plant in soils with substantial mineral content, a balanced acidity, and a significant moisture-holding capacity.

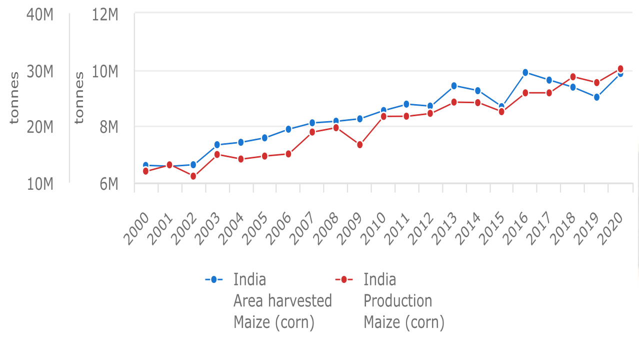

Figure 2. India's Maize (corn) Yield/Production Statistics (2000-2020)

India's main growing periods for maize are the winter (Rabi) and rainy (Kharif) seasons. The proportion of land used for growing maize during the kharif season is roughly 83 per cent, with the rabi season accounting for the remaining 17 per cent. Seventy per cent or more of the Kharif cornfield acreage is cultivated throughout the rain-fed period and environment, where several biological and environmental stressors are present. Low yields during the rainy season (2706 metric tonnes) may be attributed to the environment's susceptibility to stress, compared to the higher yields during the winter season (4436 metric tons), cultivated in a more stable environment. The nation's springtime maize crop acreage in the northwest region (western parts of Uttar Pradesh, Haryana, and Punjab) has been expanding rapidly. Admittedly, there is no reliable information on spring maize cultivation and output. Its exact cultivation area is unknown, although rough calculations estimate it at approximately 150,000 hectares. In terms of land use and production, maize has the fastest-expanding market share. From the year 2010, India's maize yield has increased at a rate of more than 50 kilograms/hectare annually, making it the most productive food commodity in the country.

Karnataka and Madhya Pradesh have the most significant areas of maize cultivation in India, at about 13 and 12 per cent, trailed by Kerala, Telangana, and Tamil Nadu, which are statistically reported in figures 3a and 3b. Currently, Andhra Pradesh is found to be the most productive region in the country. As much as 12 tonnes per hectare output has been recorded in districts including West Godavari, Krishna, etc.

Maize requires a substantial amount of water throughout its entire growing cycle. However, maize's availability of actual water across each phase is hampered by various growth phases, seasonal weather, degree of saturation (moisture), and other variables [43]. This has significantly contributed to a reduction in maize production [42]. Therefore, as a corollary, a reliable method of determining soil moisture level has emerged as a critical priority.

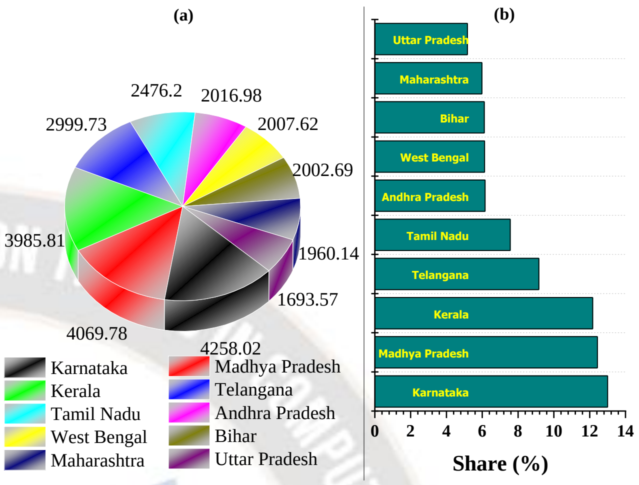

Figure 3. (a) Maize Production (in tonnes), (b) Production Contribution of each state

Many scientists have spent the past few decades developing testable theories that rely on regulating principles that incorporate the intricate hydrological cycle necessary to forecast soil moisture [50]. [40] also related the soil quality of cornfields with the crop water requirements. The assessment of topsoil moisture is helpful in many contexts, including the planning of irrigation, the prediction of farm productivity, the notification of dryness, and the forecasting of precipitation. This research examines the connection between significant Relative Production Indicators (RPIs) and soil moisture's ability to hasten socioeconomic development and ensure food sustainability. Since Tamil Nadu is responsible for around eight per cent of India's overall output, we chose three significant regions as prominent Study Regions (SRs) for the research investigations. The preferred SRs are Salem, Dindigul, and Namakkal districts.

Machine Learning (ML) methodologies have recently garnered popularity due to their ability to alleviate problems inherent in more conventional and parametric frameworks. As [3] proposed, ML methods can interpret and predict complicated non-linear mappings of the dispersed dataset without requiring any previous information. Beyond that, it helps combine inputs with unclear definitions and uncertain likelihood distributions. Unfortunately, ML algorithms provide no insight into the correlation effects of various indicators and require a large number of information units to construct models. Since conventional assumptions about data properties do not constrain ML models, they are more effective in addressing and constructing complicated connections (non-linear,

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heterogeneous, and non-monotonic relationships characteristic of the environment and ecosystem).

Forecasting the moisture in the soil using prior moisture records has been implemented by utilizing advanced computational models [58], Support Vector Machines (SVM) [24], and quadratic extrapolation [25] in the hydrological sector. However, using those existing ML algorithms, farm diversification of maize types in terrain with cold soil categories and seasonally flooded geological content is understudied. This study contributes to filling up those blanks. This research focused on evaluating the advanced ML models' ability to forecast soil moisture in cornfields using data from formally evaluated documents and data observations that are generated using meteorological tools under various climatic conditions and crop management.

To resolve such concerns, we looked at a multi-layer predictive hybrid strategy, where the bottom layer consists of individual predictive methods for enhancing soil moisture estimation and prediction. The preferred base learners are the Bi-directional Gated Recurrent Unit (B-GRU) [10], Multi-Linear Regression (MLR) [56], and Support Vector Regression (SVR) [22]. The data generative approach was employed to generate a dataset for 20 random days based on primary attributes of soil moisture in the depth of 5-10 centimeters and climatic conditions of three distinct SRs. To account for the transitional temporal data, a B-GRU was included as one of the BLs in the baseline layer rather than a conventional LSTM framework. Therefore, considering system transitional temporal data, the predictive abilities of the proposed model are increased by minimizing the variance between the actual and predictive transitional temporal data. To refine the accuracy level of each BS, a completely linked layer was implemented, which comprises an ensembling strategy in the top layer. The base layer's resultant data and the initial soil moisture variables were used as input feed for the top layer. Last, this layer provided the anticipated soil moisture with significant accuracy. The IHML is developed with two-level concepts to avoid overfitting issues, and the preceding model's distortion is corrected.

C. Motivation

The implications of soil moisture, a key parameter in acreage hydrologic processes, span fields as diverse as agribusiness, ecosystem function and facilities, biodiversity, environmental health, the forecasting and tracking of hydrological cycle hazards, research of adaptation strategies, water management, cultivation and inundation general liability, crop waterlogging, and many others. Because it controls acreage interaction, soil moisture directly impacts climate and weather. SM affects soil hydration gradients and maintains the balance between the two types of inbound solar radiation by controlling the sensible to latent heat ratio [18]. Although its effects are far-reaching, soil moisture is not often used as a modelling variable because of its complex temporal and geographical behaviour in the actual context and the limitations of objective assessment or other estimations in the large-scale temporal and spatial depiction of the soil moisture. With the help of a process known as "carbon sequestration," soil may act as either a source or a sink for CO_2 in the atmosphere. Therefore, accurate soil moisture estimations are typically crucial elements in several climatic transition models to better comprehend the process of climatic change through time and to help develop effective abatement, adaptation, and development programmes.

D. Research Objectives

The priorities of this article were to

- examine the efficacy of various ML techniques in predicting soil moisture and
- use advanced ML methods to improve the accuracy of the predictor factors that influences the moisture content of maize crop fields.

E. Structure of the Article

This research study's layout constitutes several sections that include several sections. Section 1 elaborates on the essential contents with precise objectives; Section 2 delineates and overviews the existing methodologies in the anticipation of soil moisture in maize crop areas; Section 3 defines the datasets with various contexts and the core concept of the presented IHML method; Section 4 defines the observed empirical outcome and analyses it with standard performance metrics, and Section 5 provides the generic conclusion terms of the investigation and an outline of future work.

II. RELATED WORK

Recently, soil level, agricultural level, and geographic level predictions have contributed to a complete understanding of moisture content. Research and technological advancements have resulted in a growing number of approaches to estimating soil moisture. Slowly but surely, the soil scale is expanding the study scale beyond the size of farming. Scott et al. [49] established an extrapolation approach for forecasting soil moisture concentration using the two factors of infused moisture content and evaporative coefficients. They were successful in forecasting soil wetness levels at regional scales. In [44], a Bayesian approach was utilized and an artificial neural network approach to model data retrieval from spatial data. The moisture content was used as an actual output, and the confidence intervals of moisture levels and variance in two directions were examined to learn the benefits and drawbacks of various approaches and relevant situations.

Indian researchers Pandey et al. [45] used an artificial neural system in conjunction with electromagnetic information to

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perform several forecasting tasks, including estimating the soil's moisture levels. To accomplish the adaptation and retraining of the neural networking model, electromagnetic data transmission and reception using an X-band electromagnetic diffusion meter under diverse soil conditions were used. To determine which training techniques were most effective for predicting soil moisture levels and surface roughness, the researchers associated the incongruity amongst the detected and anticipated values. They used a variety of methods to predict the desired estimates.

Then et al. [53] developed a better micro-strip band resonant device for measuring soil moisture, conducted experiments in various soil types, and made predictions based on the changing incident wave of compost soil and sandy gravel at varying water contents. Finally, Holland, and Biswas [27] conducted research using a pedotransfer formula to construct and estimate the moisture level of regional farmland based on studies investigating the relationship between fundamental soil parameters and water-holding capacity.

Jin, Luo, and Miu [35] established a BP neural network approach for anticipating the winter wheat's soil moisture in the Xuzhou farming climate examining station in the district of Huaibei, Jiangsu province. Also, in this investigation, 51 ten-day experimented information was gathered at the time of the experimental station of two nearer medium drought years. The implementation of the soil moisture anticipation is accomplished via training, final checking, and fitting. Hui, Yue, and Jun [28] performed the soil moisture anticipation by the utilization of support vector regression machineries depending on bacterial forage optimizing model that gave assistance for farming production.

By constructing a forecasting model in China's new Daxing town's Lu Cheng locations. In [60], the authors were able to forecast the soil moisture at various depths. By examining the predicted significance of the framework with the known information, the researcher confirmed the forecasting concept might also encompass the moisture of different soil types. Chen et al. [6] investigated the prediction strategy of tobacco plants' prolonged soil water concentration in the mountainous region (Liangshan Kuaili-peaks), and they presented the neural network approach based on Radial Basis Functions (RBFs) and Principal Component Analysis (PCAs). The algorithm, built on top of a conventional neural network, used PCA to boost its operational effectiveness and accuracy. With the use of a multi-weighted neural network, the authors [33] has developed a multi-step forecasting model for moisture content prediction utilized as a premise for formulating trained decisions when choosing drip irrigation. In addition, Ji, Li, and Zhang [32] provides a short-term projection of moisture content in farming fields, demonstrating the viability of creating a time-series framework via a grayscale correlation matrix to estimate the moisture concentration in a short-term mode.

Using factual data collected in the western part of Colorado City, Aboitiz et al. [1] developed a forecasting model based on specific timeframes that, once fitted and calibrated, could forecast the content of the soil water in that region. The predictive validity of the approach and erroneous statistics can be used to influence the development of irrigation schemes that completely account for the potential risk of yield losses in the face of constrained resources (such as time, finances, and manpower). As per ERS-1 Spectral analysis, Weimann et al. [55] calculate the amount of soil moisture, especially in the moistened erosional region of eastern Germany. Satellite measurements enable an extra potent forecasting strategy for the local estimation of soil moisture levels since it properly determines the facts of water holding capacity.

Elmaloglou, and Malamos [16] conducted a simulated investigation of grassy soil moisture in Belgium's blue area by using the single-dimensional method SWAP93. Smax, a new parameter added by the methodology, initially increases with z-depth. Also, the research demonstrated that the assessed value was lesser with a depth below 30 cm due to the prevalence of relatively close perforations, which led to the moisture content. This happens because the soil moistness inaccuracy is less the deeper one digs. Evapotranspiration and wetness index, as well as the degree of saturation and distinctive geographical factors, were investigated by the authors [51], who then constructed a generic process.

With data collected over several years of monitoring the farm fields, Yamaguchi et al. [59] developed two approaches to forecast moisture content: a hydrogeological framework and a statistical approach. Both models were shown to be very accurate and stable. Jiang et al. examined the viability of using a multilayer network to predict moisture levels. They simulated a computational model using inputs from Maryland University, the US Meteorological Department, and the International Centre for Ecological Information. Then, Jiang, and Cotton [34] checked for consistency between the simulated and facts. The findings exhibited a high degree of consistency between the geographical average moisture content values, arguing the merits of provincial forecasting of moisture levels.

In [17], the authors characterized the relationship involving the flow separation and the ambience of the topsoil throughout the Subarabaskar watershed in Canada via primary energy equilibrium and the hydrological cycle. The experimental conduction is carried out with concern for both moisture and resource balance aspects. The data-driven framework that uses synthetic neural networks to approximate the diverse soil moisture progression has been widely studied for its potential

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utility in a variety of contexts, including the simulation of annual precipitation, heating rate, gross radio waves, and the heat and magnetization of the soil's porosity-based relative humidity. In the absence of time-dependent climatic factors, ambient heat is the primary impactful conditional variable in defining moisture levels. The strong association amongst the thermo-soil aspects and the moisture condition is emphasized. In addition, the surface of the soil is the crucial core aspect in determining how much moisture is in the topsoil.

Cafarelli et al. [5] improved the model's predictive performance by including the control variable in the predictor, leading to a valuable forecast for farmland in the southeastern part of Italy. Soil moisture is sometimes predicted with reasonable accuracy by employing the Hydrus-1D concept, as shown by the work of the authors [7]. Their simulations focused on the rapid water movement in two subbasins (Krui and Stanley).

Liu et al. [39] made predictions about prospective soil moisture variations based on the estimated criteria of future climatic components. For this forecast, researchers used the Priestley-Taylor framework, the dual crop predictor correlation, and the notion of wetness in the topsoil balance. A representation to achieve water holding capacity is also introduced that is premised on the geo-location of adaptation of feature variables, the adoption of RS as well as GIS satellite knowledge, and the acquisition of data for crop type, slope, vegetative saturation, and soil characteristics in the Beijing region.

Alun et al. [4] used Beijing's Tongzhou zone as their field survey. Also, they used a quartet of geospatial analytic techniques—the complete usage proximity methodology, Normal Kriging, co-Kriging, and probabilistic computation approach to examine the moisture content of soil at varying depths. It also offers a solid foundation for geospatial predictive assessment of provincial water content by evaluating the pros and cons of various approaches and the contexts under which they are used. Zhang, Li, and Jiao [61] developed a method for tracking and predicting the soil's moisture content on crop fields in the Liaoning region using VC++ as well as Fortran. The regions of Hunan and Hubei in China were also chosen for this study. Finally, based on atmospheric factors and associated geographical location data, Wang et al. [54] successfully predicted and simulated crop water loss.

Additionally, the forecasting procedure will be more proactive, with many of the predicting activities being carried out autonomously by the framework or application. By connecting to a meteorological framework, for various instances, the existing models may not automatically invoke the necessary data following the requirement of activity. Thus, we propose an IHML methodology to overcome the specified issue.

III. METHODOLOGY

A. Study Region

This research was undertaken in three maize-growing districts (Salem, Dindigul, and Namakkal districts) in the Indian state of Tamil Nadu. A geographical depiction of each SR is displayed in Figure 4.

Over the last nineteen years, the average yearly rainfall in the SR of Salem has been recorded at about 997.9 millimeters at an estimated elevation of 278 meters. A typical annual rainfall totals 40.1 millimeters. Salem, on average, has a high temperature of 34 degrees Celsius and a low temperature of 22.4 degrees Celsius. Red calcareous sedimentary soil covers 247,391 hectares in the district, making up the most significant percentage of any soil variant. The red, non-calcareous soil covers around 50,212 hectares. With brownish, non-calcareous soil, this area encompasses 38,267 hectares. The contribution of mixed soil is 21776 hectares in area. Approximately 34250.46 hectares are deeply committed to cultivating maize, with an annualized rate of 340,577 metric tonnes, representing 10 per cent of the total of the district's overall production to the state (District Diagnostic Report, 2020a).

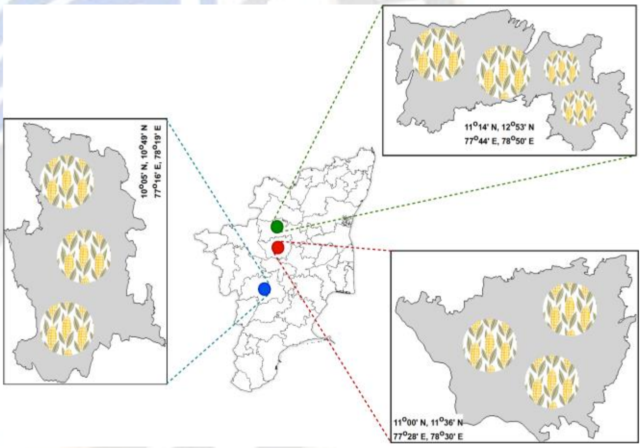

Figure 4. Geographical Area Representing Three Study Regions

The average altitude of the Dindigul district is 265 meters (869 feet). Red granular loam, red soil, and clayey soil are the major prevalent soil varieties in the area. Rice, maize, legumes, sugarcane, cotton, etc., are some of the primary crops cultivated in the Dindigul district, with a net acreage of 626,513 acres. Peak precipitation occurs throughout the North-East Monsoon (417.9 millimeters), which accounts for most of the district's annual rainfall (836 millimeters). The average yearly yield of corn in the region is approximately 1985 kilograms per hectare (District Diagnostic Report, 2020b).

The total yearly precipitation in Namakkal districts averages 716.54 millimeters. The Northeastern rainy monsoon brings heavy rainfall to this region. Red soil is the dominant factor in

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this area, accounting for 77 per cent of the soil type. The pH level is between 5.2 and 8.7 per cent. Thus, Namakkal's annual maize acreage, yield, and productivity continue to upswing at 6.30 per cent, 5.40 per cent and 12.05 per cent, respectively (District Diagnostic Report, 2020c).

B. Dataset

TABLE I. BASE ATTRIBUTES OF THE DATASETS

Attributes	Units
Volumetric Soil Moisture Content (VSMC)	m^3/ m^3 (water/soil)
Air Temperature	Kelvin (ºK)
Soil Temperature	Celsius (ºC)
Precipitation	Millimeters
Farmland Surface Temperature	Kelvin (ºK)
Soil Depth	5-10 Centimeters

For various climatic scenarios, SWAT (India Dataset | SWAT | Soil & Water Assessment Tool, n.d.) outputs are often used to predict soil moisture. The dataset is constructed based on the results of 20 days of SWAT trialling data from 30 unique locations across three different SRs. Thus, the dataset comprises 600 data points that concern various vital attributes listed in Table 1. The resulting datasets are normalized to prevent computation errors caused by missing data. Following that, the data is split 70:30 between training and testing sets to assess the ML models. To anticipate both long- and short-term soil moisture for the production of maize, the relevant ML models integrate prediction methodologies with empirical formulas.

C. Optimal Soil Requirement

While the optimal soil conditions for cultivating maize are deeper, more nutritious, well-moisturized, and rich in biological content, maize may be successfully cultivated in such a far-reaching condition of the soil. The ideal soil condition for crop growth is one with reasonably high moisture-holding potential. Because the crop is very vulnerable to waterlogging, it is mainly cultivated during the rainy monsoon period. Special attention needs to be paid to ensure that over-precipitation does not remain on the surface for five hours. The relatively permeable subsoil, such as those found in loamy soils, sediment loams, and turbid clay soils, is appropriate. This means that the soil type would have a neutral pH of 6.5 to 7.5, a tradeable potential of approximately 20 milli-equivalents per 100 grams, a surface absorption of 70 to 90%, a density and porosity of almost 1.3 gram per cubic centimetre, and a moisture-holding potentiality of about 16 centimeters per meter of depth.

D. Optimal Climatic Requirement

Temperatures between 9 and 30 degrees Celsius are ideal for maize cultivation. The total number of leaves rises from appearance to tasselling as the crop adapts to its environment. Tassel latency lengthens when the range of diurnal temperatures from 0 to 17 degrees Celsius increases. At 30 degrees Celsius, maize grows at its fastest pace. The harvest will be greater if there is no frigid weather during the grain-filling phase. In addition, elevated levels of solar irradiance will increase corn photosynthesis.

E. IHML Model

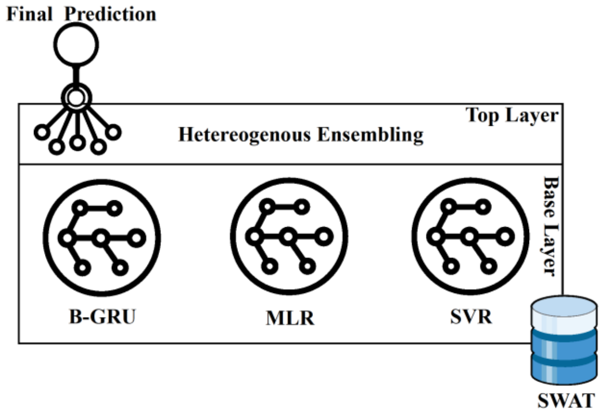

Figure 5. Structure of IHML

The IHML approach includes two levels of predictive strategy which is depicted in Figure 5, where the base level comprises three advanced ML models (B-GRU, SVR, and MLR) whose prediction is addressed individually. The top-level employs an ensembling strategy which combines the outcome of the base level and produces the predictive result [47] with optimal accuracy.

1) B-GRU

During training, the conventional LSTM model's variables were tuned to reduce a loss (the gap between the model's predictions and the actual soil moisture levels). However, since the LSTM concept only considers the precision of its predictions for the immediate sampling interval and does not focus on the transitional temporal data after the feedback sampling interval [19], it may be unable to account for the complexity and uncertainty of the information and may even overfit the model.

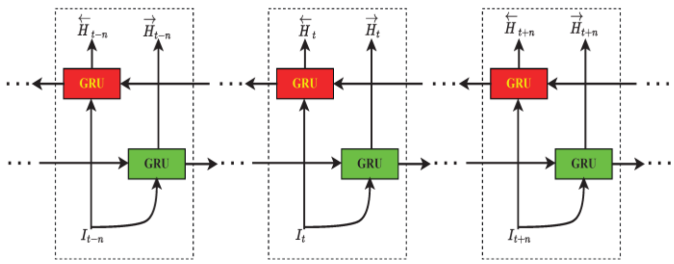

Figure 6. Structure of B-GRU

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Bidirectionally structured models may incorporate insights from both historical and future data into their present analysis. Figure 6 is a conceptual illustration of the B-GRU concept. The condition of two GRUs facing in oppositional directions is employed to establish the B-GRU model [57]. One GRU works forward, commencing at the beginning of the trend line (data sequences), and the other works backwards, beginning at the end of the sequence. This allows contextual future and previous data to influence current conditions. The B-GRU can be described in the following way:

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

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

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

where, $\vec{H}_t$ denotes the forward state of GRU, $\overleftarrow{H}_t$ represents the backward state of GRU, and $\oplus$ signifies the concatenation of two vectors.

This model's initial level consists of numerous inputs fed at varying times, *t*, with 'n' previous and subsequent recorded moisture data as $I = [I_{t+n}+, \ldots, + I_t, + \ldots, + I_{t-n}]$. This sequence is processed by the B-GRU network. The B-GRU model represents the second level. The ultimate pattern determined from the input sequence length specifies how often the B-GRU model will repeat its temporal phases. Our work uses $2n+1$ iterations for its recurring time scales. The transfer of data over recurrent time scales is usually maintained in the hidden unit H_t. IHML linear layer inputs are directly coupled to the B-GRU model's layer outputs.

2) SVR

The core concepts of SVM are used in SVR [8, 15]. Employing a constant mapping linear model, SVM training makes it easier for a maximum-marginal predictor to project input parameters over high-dimensional data points. SVR uses a radial-based linear model to produce the optimal hyperplane, which can be exploited for prediction via regression, avoiding global maxima as well as local minima difficulties caused as a result of using limited features during the optimization of the training sample. Since they are easy to implement and maintain and also can handle high-dimensional spaces with marginal isolation factors, radial-based functions have been deemed effective.

To construct an estimation technique among predictor parameters and informative factors, the SVR uses a selection of sample points determined by a preset sampling error margin. These smaller portions of the data points (subsets) are denoted to as support vectors. Assume we have a set of samples $I = \{i_1, i_2, \ldots i_n\}$ and a set of intended outcomes $J = \{j_1, j_2, \ldots j_n\}$. The SVR purpose is to discover the flattened version of the periodic function, $f(x)$ that minimizes the error margin amongst the trialed and actual output of the testing data.

3) MLR

MLR is a valuable tool that forecasts an outcome data point from a set of predictive parameters that includes more than two independent predictive variables. The following formulation expresses the forecasts of 'k' given the "p" predictor factors.

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

Regression-based beta coefficients/weights are specified as β. The estimates of the correlation between the dependent variables and the result 'β_i' could be defined as the mean implications on k with an increment in p_i, provided that all other variables are held constant throughout the analysis.

4) Heterogeneous Ensemble

The heterogeneity ensemble approach combines several learners or ML models, all of which are trained using the same dataset. This strategy is effective for limited data sets. The ensemble method's outcome is reached by stacking computation via meta-leaner across all the integrated models' predictions.

A meta-learner model is constructed and used to aggregate the results of several executed predictor and regression methods. The meta-learner predictive process relies on training using the results of the BLs, which are, in turn, trained using the whole training samples. In contrast to boosting strategies, a concurrent learning and training process is applied to each BL. For more complex models, the output from one layer is given to the next level as training data parameters, resulting in a stack in which the advanced, refined model is constructed and thoroughly trained than its simpler counterparts. The prediction error of such models is always low since they are built on the foundation of more basic models. The stack will continue to grow as long as the optimal forecast is made with the least amount of error. This hybrid process, or meta-model, makes its forecast by aggregating the predictions of many simpler models. With this method, the goal is to create a model with reduced bias. The algorithmic procedures of heterogeneity are derived from the work of [48].

IV. PERFORMANCE ANALYSIS AND DISCUSSIONS

The IHML model was trained using a common dataset generated via SWAT for around 20 input days, with a scale factor of six hours (short-term) and two days (long-term). This was done to make an accurate prediction of the moisture, with a scale factor of two hours (short-term) and one day (long-term) ahead.

The investigation's goal was to determine whether the data input time window could be shortened without impacting accuracy. First, the model was created and trained using the generated datasets, and then its accuracy and efficiency were determined using the testing dataset. The efficacy of several approaches was assessed by computing their output for RMSE,

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MAE, and R^2 and the formulations are expressed in equations (5), (6), and (7), respectively [2].

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

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

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

where '*O*' denotes observation count, p represents the estimated values, p̂ represents the predicted values, and p̄ denotes the estimated mean value. The soil moisture level in the maize cultivation area was designated as the reliant factor, while all other variables were designated as predictive variables.

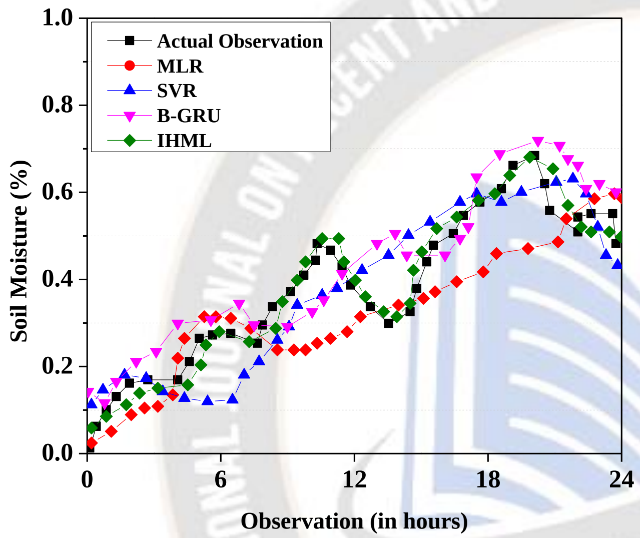

Figure 7. Short-Term Prediction of Soil Moisture

Environment, weather, soil composition, and depth all have a role in the quantity of moisture in the farmland. Therefore, we used the IHML model, which excelled at short-term forecasts, to lessen the discrepancy between the forecast and input times and improve the soil moisture predicting capability at varying timeframes. Short-term measurements for all four models are shown in Figure 7, demonstrating that the proposed IHML accurately forecasts soil moisture levels. However, MLR performed poorly at a depth of 5–10 cm, whereas B-GRU and SVR showed the least error in their moisture content predictions after IHML.

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

Table 2 displays the results of an experiment in which several ML methods were subjected to MAE, RMSE, and R^2 tests. In particular, optimal outcomes have been attained by IHML and B-GRU models exhibiting less than 4 per cent of MAE values. Using four distinct ML techniques, we get an RMSE for projected soil moisture levels ranging from 0.042 to 0.072 m^3m^3. The IHML model fared better than the other approaches because of its more substantial R^2 value (0.88) and lesser RMSE value (0.042). Following the performance of the IHML model, both B-GRU and SVR succeeded commendably, as shown by their corresponding values of RMSE (0.063 and 0.072), MAE (0.039 and 0.042), and R^2 (0.82 and 0.71).

Four ML models' testing outcomes are shown as box plots illustrating the variation in soil moisture (m^3m^3) between observations and predictions. The box plots the estimated records between the 10th - 95th percentiles with the Inter-Quartile Range (IQR) (Q3-25th to Q1-75th percentiles). The box's solid (black and red) line denotes the median level (50th percentile). In contrast, the box's horizontal stripe denotes the average soil moisture scores measured throughout the testing period. Figure 8 shows a box plot of the experimental dataset's observed and estimated median moisture content values as well as percentiles.

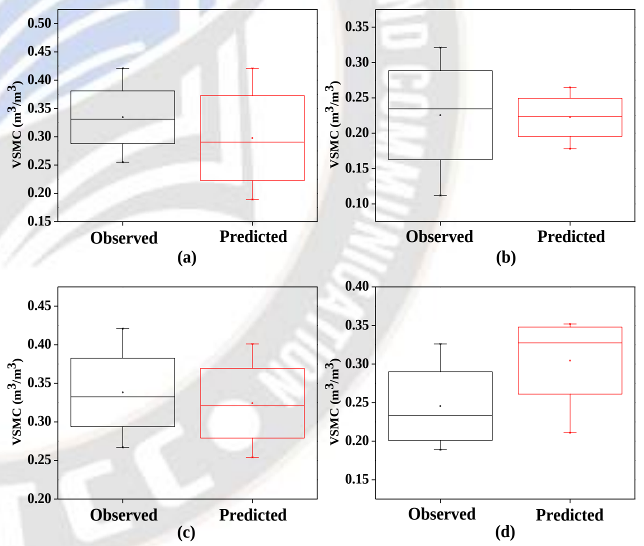

Figure 8. Four models, (a) SVR, (b) MLR, (c) IHML, and (d) B-GRU are shown in a box plot exhibiting their soil moisture estimations throughout the testing phase

The solid marker in the middle of every box illustrates the average value of the data gathered throughout the testing period. In contrast to previous ML algorithms, the IHML model demonstrated that the predicted soil moisture average best reflected the observed moisture content average. The IHML model included influential components of all the soil variants in SR and climatic factors. As a result, it was able to come up with more accurate forecasts than the other estimates, which is

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evident in Figure 8. A greater correlation was found among the distributive patterns of soil moisture data whenever IHML was applied. The lowest RMSE, as well as MAE, was achieved by the IHML approach, trailed by the B-GRU and SVR models in expressing the association among soil moisture in each SRs and VSMC as documented for every relevant meteorological SR, precipitation, rainfall, and certain other soil factors. We saw no evidence of fields drying to the point of moisture stress among the maize crops, which would have affected crop metabolism and vegetative development. This could be because there is still enough water available in the soil below the surface to saturate the root zone, as well as groundwater, is relatively shallow below the level. Vegetation index values are probably less prone to fluctuate due to such context.

Figure 9 displays the results of several models' soil moisture predictions throughout the experimental period. Predictions of soil moisture were recorded satisfactorily in scatter plots by the IHML, B-GRU, and SVR models. Almost all data points clustered near the bisector axis, indicating that the IHML model approximated the moisture content range observed. Only a small fraction of the spots in the test were located distant from the axis, which is indicative of inaccurate estimations. Predictions of moisture content using the B-GRU and SVR models had indicative slope measures of 0.67 and 0.63, correspondingly implying that both models accurately represented soil moisture next to IHML. On the other hand, MLR performed 0.58 worse on the experimental records regarding dispersion. Overall, the findings indicated that building another meta-learner off the outputs of the trained models without validation may realistically result in a stronger impact on R^2, which is a radical departure from the original setting.

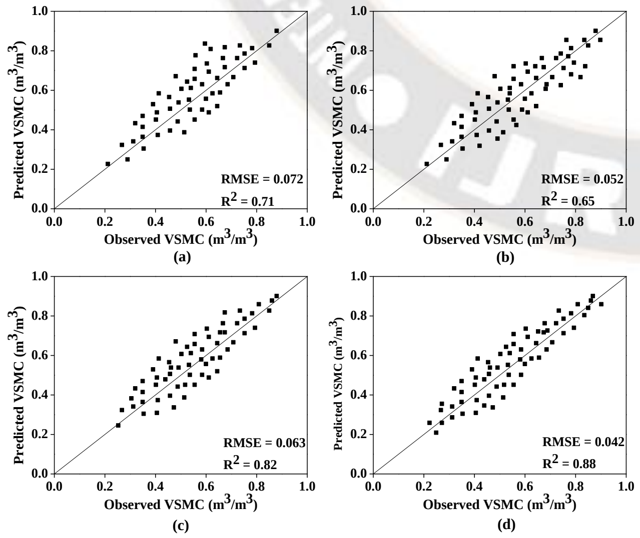

Figure 9. Four models, (a) SVR, (b) MLR, (c) B-GRU, and (d) IHML are tested, and their predicted VSMC is demonstrated against the observed VSMC in a scatter plot

Table 3 displays the outcomes of investigations of IHML model errors across the three SRs. All the investigated SRs have a mean absolute inaccuracy of 0.033, and their combined predicted score is slightly below the actual value. As shown in Figure 9, rainfall decreased from the first to the twentieth day in all three SRs, while the measured moisture content remained relatively substantial and was significantly impacted. The forecasts are more appropriately represented only after the 15th day, which exhibits the correlation between moisture content and rainfall. This is because precipitation-related factors primarily determine soil moisture. This is predictable because evaporation and rainfall directly affect the humidity content. The inconsistent correlation amongst humidity content and rainfall will likely prevent conventional ML models from providing reliable forecasts, particularly during wetter seasons.

At the Dindigul site, the surface soil moisture is found to exhibit many peaks and persisted during the observation period. Besides, these peaks are generally trailed by heavy rainfall. In the meantime, identical rainfall could have diverse values of the soil moisture. These circumstances cannot be taken well by the overall anticipative approaches. But, at the Salem site, the identical wet condition of the soil humidity in the first 10 days and dry condition of the soil humidity from the last 10 days can be captured well comparatively via IHML. During this time, the soil moisture of the mean in the training phase had an identical trend in the testing phase.

TABLE III. MULTI-REGION PREDICTION ERROR ANALYSIS OF THE IHML MODEL

SR	Estimation	Values
Salem	MAE	0.035
	RMSE	0.041
	R^2	0.87
Dindigul	MAE	0.031
	RMSE	0.044
	R^2	0.9
Namakkal	MAE	0.033
	RMSE	0.046
	R^2	0.85

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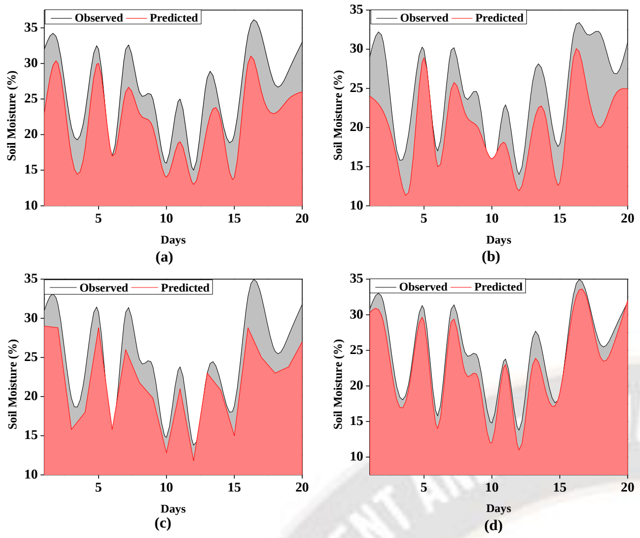

Figure 10. Daily remarks and anticipations of predictive methods a) SVR, (b) MLR, (c) B-GRU, and (d) IHML in the testing phase at three SRs

Predictive models are evaluated, and their predictions are assessed daily (20 days), as seen in Figure 10. IHML model excels the other three models with minimal error deviations. Because moisture in soil dynamics varies significantly across climatic zones, the proposed model shows that such deterioration issues can be mitigated by reevaluating the BL's output data and the actual moisture content inputs in the subsequent level of computations. A daily mean was calculated by aggregating the data collected every hour. The likelihood that a given instance will be included in a machine's training phase is proportional to the accuracy of its predecessors' predictions about that instance. To do this, it keeps track of variables throughout the training phase. It increases them according to the error gap that may be existing between the observed and expected values concerning the relying variables. To put it another way, the method keeps tabs on all the erroneously estimated specifications. It gives them a higher chance of being included in the following random subset, emancipating the base learner to focus on more complex scenarios.

V. CONCLUSION

Using readily accessible variables like climatic elements and vegetation indicators of maize crops, the considered models aim to create reliable, accurate estimations of moisture content in the cultivated soil. Producers and hydrological scientists may use this data to make better decisions regarding irrigation and fertilization, for instance, and to better predict future harvests. This effort has also provided an opportunity to learn about and practise several empirical modelling approaches and the mathematics that underpin them.

From multi-linear regression to more specialized methods, including IHML, this study gives a comprehensive overview of the most popular and widely-used multivariate techniques. The findings are quite promising and interesting. Tables 2 and 3 summarize RMSE, R^2, and MAE for the testing dataset in all the incorporated models examined in the current study. IHML was shown to be the most influential predictor in this research, with acceptable training as well as validation errors. The proposed IHML had the best training effects against the inaccuracies of other approaches, but overall, assessment errors aren't in the least bit adequate. In addition, B-GRU and SVR models produced generally acceptable outcomes next to IHML. In addition, we intend to use more advanced techniques in the upcoming research to create spatiotemporal representations of the predicted moisture content data.

REFERENCES

[1] Aboitiz, M., Labadie, J. W., & Heermann, D. F. (1986). Stochastic Soil Moisture Estimation and Forecasting for Irrigated Fields. Water Resources Research, 22(2), 180–190. Portico. https://doi.org/10.1029/wr022i002p00180

[2] Acharya, U., Daigh, A. L. M., & Oduor, P. G. (2021). Machine Learning for Predicting Field Soil Moisture Using Soil, Crop, and Nearby Weather Station Data in the Red River Valley of the North. Soil Systems, 5(4), 57. https://doi.org/10.3390/soilsystems5040057

[3] Ali, I., Greifeneder, F., Stamenkovic, J., Neumann, M., & Notarnicola, C. (2015). Review of Machine Learning Approaches for Biomass and Soil Moisture Retrievals from Remote Sensing Data. Remote Sensing, 7(12), 16398–16421. https://doi.org/10.3390/rs71215841

[4] Alun, L., Weizhong, Y., & Juan, L. (2012). Spatial analysis methods and application of regional soil moisture. Chin. Agric. Sci. Bull., 2012(21), 60.

[5] Cafarelli, B., Castrignanò, A., De Benedetto, D., Palumbo, A. D., & Buttafuoco, G. (2014). A linear mixed effect (LME) model for soil water content estimation based on geophysical sensing: a comparison of an LME model and kriging with external drift. Environmental Earth Sciences, 73(5), 1951–1960. https://doi.org/10.1007/s12665-014-3543-8

[6] Chen, C., Tan, J., Yin, J., Zhang, F., & Yao, J. (2010). Prediction model for soil moisture in tobacco fields based on PCA and RBF neural network. Transactions of the Chinese Society of Agricultural Engineering, 26(8), 85-90.

[7] Chen, M., Willgoose, G. R., & Saco, P. M. (2012). Spatial prediction of temporal soil moisture dynamics using HYDRUS-1D. Hydrological Processes, 28(2), 171–185. https://doi.org/10.1002/hyp.9518

[8] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297. https://doi.org/10.1007/bf00994018

[9] Daryanto, S., Wang, L., & Jacinthe, P.-A. (2016). Global Synthesis of Drought Effects on Maize and Wheat Production. PLOS ONE, 11(5), e0156362. https://doi.org/10.1371/journal.pone.0156362

[10] Deng, Y., Jia, H., Li, P., Tong, X., Qiu, X., & Li, F. (2019). A Deep Learning Methodology Based on Bidirectional Gated Recurrent Unit for Wind Power Prediction. 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA). https://doi.org/10.1109/iciea.2019.8834205

[11] Directorate of Economics and Statistics, Ministry of Agriculture, Government of India. (2019). Dacnet.nic.in. https://eands.dacnet.nic.in/

[12] District Diagnostic Report. (2020a, July). https://tnrtp.org. https://tnrtp.org/wp-content/uploads/2020/07/SALEM-FINAL.pdf

[13] District Diagnostic Report. (2020b, July). https://tnrtp.org/wp-content/uploads/2020/07/DINDIGUL-FINAL.pdf

[14] District Diagnostic Report. (2020c, July). https://tnrtp.org/wp-content/uploads/2020/07/NAMAKKAL-FINAL.pdf

[15] Drucker, H., Donghui Wu, & Vapnik, V. N. (1999). Support vector machines for spam categorization. IEEE Transactions on Neural Networks, 10(5), 1048–1054. https://doi.org/10.1109/72.788645

[16] Elmaloglou, St., & Malamos, N. (2000). Simulation of soil moisture content of a prairie field with SWAP93. Agricultural Water Management, 43(2), 139–149. https://doi.org/10.1016/s0378-3774(99)00054-2

[17] Elshorbagy, A., & Parasuraman, K. (2008). On the relevance of using artificial neural networks for estimating soil moisture content. Journal of Hydrology, 362(1-2), 1–18. https://doi.org/10.1016/j.jhydrol.2008.08.012

[18] Engman, E. T. (1997). Potential for remotely sensed soil moisture data in hydrologic modeling. Earth Surface Remote Sensing. https://doi.org/10.1117/12.298142

[19] Fang, K., & Shen, C. (2020). Near-Real-Time Forecast of Satellite-Based Soil Moisture Using Long Short-Term Memory with an Adaptive Data Integration Kernel. Journal of Hydrometeorology, 21(3), 399–413. https://doi.org/10.1175/jhm-d-19-0169.1

[20] FAOSTAT. (2020). www.fao.org. https://www.fao.org/faostat/en/#data/QCL/visualize

[21] Farmer, J. A., Baricuatro, J. H., & Campbell, C. T. (2013). Correction to "Ag Adsorption on Reduced CeO2(111) Thin Films." The Journal of Physical Chemistry C, 117(51), 27167–27167. https://doi.org/10.1021/jp411745x

[22] Fearn, T. (2004). Support Vector Machines I: The Support Vector Classifier. NIR News, 15(5), 14–15. https://doi.org/10.1255/nirn.788

[23] Feki, M., Ravazzani, G., Ceppi, A., Milleo, G., & Mancini, M. (2018). Impact of Infiltration Process Modeling on Soil Water Content Simulations for Irrigation Management. Water, 10(7), 850. https://doi.org/10.3390/w10070850

[24] Gill, M. K., Asefa, T., Kemblowski, M. W., & McKee, M. (2006). Soil Moisture Prediction Using Support Vector Machines. Journal of the American Water Resources Association, 42(4), 1033–1046. https://doi.org/10.1111/j.1752-1688.2006.tb04512.x

[25] Gorthi, S., & Dou, H. (2011). Prediction Models for the Estimation of Soil Moisture Content. Volume 3: 2011 ASME/IEEE International Conference on Mechatronic and Embedded Systems and Applications, Parts A and B. https://doi.org/10.1115/detc2011-48259

[26] Hashemy Shahdany, S. M., Firoozfar, A., Maestre, J. M., Mallakpour, I., Taghvaeian, S., & Karimi, P. (2018). Operational performance improvements in irrigation canals to overcome groundwater overexploitation. Agricultural Water Management, 204, 234–246. https://doi.org/10.1016/j.agwat.2018.04.014

[27] Holland, J. E., & Biswas, A. (2015). Predicting the mobile water content of vineyard soils in New South Wales, Australia. Agricultural Water Management, 148, 34–42. https://doi.org/10.1016/j.agwat.2014.09.018

[28] Hui, D., Yue, Z., Jun, Z., (2016). Application of support vector regression machines in soil moisture prediction based on bacteria foraging optimization algorithm. Bull. Soil Water Conserv. 36(6), 131–135.

[29] Humphrey, V., Zscheischler, J., Ciais, P., Gudmundsson, L., Sitch, S., & Seneviratne, S. I. (2018). Sensitivity of atmospheric CO2 growth rate to observed changes in terrestrial water storage. Nature, 560(7720), 628–631. https://doi.org/10.1038/s41586-018-0424-4

[30] India Dataset | SWAT | Soil & Water Assessment Tool. (n.d.). Swat.tamu.edu. Retrieved November 23, 2022, from https://swat.tamu.edu/data/india-dataset/

[31] Jensen, M. E., and Allen, R. G., eds. (2016). Evaporation, evapotranspiration, and irrigation water requirements. ASCE manual of practice #70, 2nd Ed., ASCE, Reston, VA.https://doi.org/10.1061/9780784414057

[32] Ji, R., Li, X., & Zhang, S. (2016). Short-term prediction of soil moisture in field based on GM (1, 1) model group. Transactions of The Chinese Society of Agricultural Machinery, 401-407.

[33] Ji, R., Zhang, S., Zheng, L., & Liu, Q. (2017). Prediction of soil moisture based on multilayer neural network with multi-valued neurons. Transactions of the Chinese Society of Agricultural Engineering, 33(1), 126-131.

[34] Jiang, H., & Cotton, W. R. (2004). Soil moisture estimation using an artificial neural network: a feasibility study. Canadian Journal of Remote Sensing, 30(5), 827–839. https://doi.org/10.5589/m04-041

[35] Jin, L., Luo, Y., Miu, Q., (1998). Study of artificial neural network prediction model of soil moisture in farmland. Acta Pedol. Sin. 35(1), 25–32.

[36] K. M., K. R., & G. R., A. R. (2020). Neuro-Fuzzy-Based Smart Irrigation System and Multimodal Image Analysis in Static-Clustered Wireless Sensor Network for Marigold Crops. Deep Neural Networks for Multimodal Imaging and Biomedical Applications, 237–255. https://doi.org/10.4018/978-1-7998-3591-2.ch015

[37] Li, X., Huo, Z., & Xu, B. (2017). Optimal Allocation Method of Irrigation Water from River and Lake by Considering the Field Water Cycle Process. Water, 9(12), 911. https://doi.org/10.3390/w9120911

[38] Liao, R., Yang, P., Wang, Z., Wu, W., & Ren, S. (2018). Development of a Soil Water Movement Model for the Superabsorbent Polymer Application. Soil Science Society of America Journal, 82(2), 436–446. Portico. https://doi.org/10.2136/sssaj2017.05.0164

[39] Liu, H. B., Wu, W., & Wei, C. F. (2003). Study of soil water forecast with neural network. Journal of Soil and Water Conservation, 5, 59-62.

[40] Machado, S., Bynum, E. D., Archer, T. L., Lascano, R. J., Wilson, L. T., Bordovsky, J., ... & Xu, W. (2000). Spatial and temporal variability of corn grain yield: Site-specific relationships of biotic and abiotic factors. Precision agriculture, 2(4), 359-376. https://doi.org/10.1023/a:1012352032031

[41] Martin, E. (n.d.). Methods of Determining When to Irrigate Cooperative Extension Extension Irrigation Specialist. Retrieved November 22, 2022, from https://cals.arizona.edu/extension/ornamentalhort/waterquality/irrigation_when.pdf

[42] Moraru, P. I., & Rusu, T. (2012). Effect of tillage systems on soil moisture, soil temperature, soil respiration and production of wheat, maize and soybean crops. Journal of Food, Agriculture & Environment, 10(2 Part 1), 445-448.

[43] Narasimhan, B., & Srinivasan, R. (2005). Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. Agricultural and Forest Meteorology, 133(1-4), 69–88. https://doi.org/10.1016/j.agrformet.2005.07.012

[44] Notarnicola, C., Angiulli, M., & Posa, F. (2008). Soil moisture retrieval from remotely sensed data: Neural network approach versus Bayesian method. IEEE Transactions on Geoscience and Remote Sensing, 46(2), 547–557. https://doi.org/10.1109/tgrs.2007.909951

[45] Pandey, A., Jha, S. K., Srivastava, J. K., & Prasad, R. (2010). Artificial neural network for the estimation of soil moisture and surface roughness. Russian Agricultural Sciences, 36(6), 428–432. https://doi.org/10.3103/s106836741006011x

[46] Pandey, S., Bhandari, H., Ding, S., Prapertchob, P., Sharan, R., Naik, D., Taunk, S. K., & Sastri, A. (2007). Coping with drought in rice farming in Asia: insights from a cross-country comparative study. Agricultural Economics, 37, 213–224. https://doi.org/10.1111/j.1574-0862.2007.00246.x

[47] Pandiyan, S., M., A., R., M., K.M., K. R., & G.R., A. R. (2020). Heterogeneous Internet of things organization Predictive Analysis Platform for Apple Leaf Diseases Recognition. Computer Communications, 154, 99–110. https://doi.org/10.1016/j.comcom.2020.02.054

[48] Sabzevari, M., Martínez-Muñoz, G., & Suárez, A. (2021). Building heterogeneous ensembles by pooling homogeneous ensembles. International Journal of Machine Learning and Cybernetics, 13(2), 551–558. https://doi.org/10.1007/s13042-021-01442-1

[49] Scott, C. A., Bastiaanssen, W. G. M., & Ahmad, M.-D. (2003). Mapping Root Zone Soil Moisture Using Remotely Sensed Optical Imagery. Journal of Irrigation and Drainage Engineering, 129(5), 326–335. https://doi.org/10.1061/(asce)0733-9437(2003)129:5(326)

[50] Shoaib, M., Shamseldin, A. Y., Melville, B. W., & Khan, M. M. (2016). A comparison between wavelet based static and dynamic neural network approaches for runoff prediction. Journal of Hydrology, 535, 211–225. https://doi.org/10.1016/j.jhydrol.2016.01.076

[51] Sulebak, J. R., Tallaksen, L. M., & Erichsen, B. (2000). Estimation of areal soil moisture by use of terrain data. Geografiska Annaler: Series A, Physical Geography, 82(1), 89–105. https://doi.org/10.1111/j.0435-3676.2000.00009.x

[52] Sun, Z., Zhang, Y., Zhang, Z., Gao, Y., Yang, Y., Han, M., & Wang, Z. (2019). Significance of disposable presowing irrigation in wheat in increasing water use efficiency and maintaining high yield under winter wheat-summer maize rotation in the North China Plain. Agricultural Water Management, 225, 105766. https://doi.org/10.1016/j.agwat.2019.105766

[53] Then, Y. L., You, K. Y., Dimon, M. N., & Lee, C. Y. (2016). A modified microstrip ring resonator sensor with lumped element modeling for soil moisture and dielectric predictions measurement. Measurement, 94, 119–125. https://doi.org/10.1016/j.measurement.2016.07.046

[54] Wang, S., Fu, Z., Chen, H., Nie, Y., & Wang, K. (2015). Using Gene-Expression Programming method and geographical location information to simulate evapotranspiration in Hunan and Hubei Provinces. Zhongguo Shengtai Nongye Xuebao/Chinese Journal of Eco-Agriculture, 23(4), 490-496.

[55] Weimann, A., Von Schonermark, M., Schumann, A., Jorn, P., & Gunther, R. (1998). Soil moisture estimation with ERS-1 SAR data in the East-German loess soil area. International Journal of Remote Sensing, 19(2), 237–243. https://doi.org/10.1080/014311698216224

[56] Wu, J. (2014). Study Applicable for Multi-Linear Regression Analysis and Logistic Regression Analysis. The Open Electrical & Electronic Engineering Journal, 8(1), 782–786. https://doi.org/10.2174/1874129001408010782

[57] Xiong, C., Merity, S., & Socher, R. (2016, June). Dynamic memory networks for visual and textual question answering. In International conference on machine learning (pp. 2397-2406). PMLR.

[58] Xu Qiao, Feng Yang, & Xianlei Xu. (2014). The prediction method of soil moisture content based on multiple regression and RBF neural network. Proceedings of the 15th International Conference on Ground Penetrating Radar. https://doi.org/10.1109/icgpr.2014.6970402

[59] Yamaguchi, Y., & Shinoda, M. (2002). Soil Moisture Modeling Based on Multiyear Observations in the Sahel. Journal of Applied Meteorology, 41(11), 1140–1146. https://doi.org/2.0.co;2">10.1175/1520-0450(2002)041<1140:smmbom>2.0.co;2

[60] Yang, S., Wang, Y., Guo, Z., (2006). Study of ARIMA model on soil moisture content prediction. Agric. Res. Arid Areas 24(2), 114–118.

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[61] Zhang, X., Li, R., Jiao, M., (2016) Research and development of soil moisture monitoring and forecasting system in farmland. Trans. Chin. Soc. Agric. Eng. 32(18), 140–146.

[62] Zhu, Q., Luo, Y., Xu, Y.-P., Tian, Y., & Yang, T. (2019). Satellite Soil Moisture for Agricultural Drought Monitoring: Assessment of SMAP-Derived Soil Water Deficit Index in Xiang River Basin, China. Remote Sensing, 11(3), 362. https://doi.org/10.3390/rs11030362