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Soil moisture forecasting from sensors-based soil moisture, weather and irrigation observations: A systematic review

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ABSTRACT

Agriculture is one of the most essential industries since it provides food for the entire population worldwide. Maintaining limited water resources is a challenging problem in this field, as growing healthy vegetables and fruits require consistent plants watering. To automatize this maintenance, software companies started developing solutions utilizing artificial intelligence tools to forecast soil moisture levels from past observations of soil humidity, weather and irrigation, measured by different sensors. This forecast is useful for irrigation decisions support and crop growth monitoring. Even though such solutions are widely developed, still, a transparent, unified methodology how forecasting models for irrigation management from sensors should be designed and evaluated is still missing. In this paper, we provide such methodology from analysis of state-of-the-art scientific articles presenting forecasting methods for soil moisture from sensor data. This review tackles several research question of how to forecast future soil moisture level from sensor-based past observations of soil moisture, weather and irrigation information. Furthermore, we follow the standard Preferred Reporting Items for Systematic Reviews and Meta-Analyses procedures for literature search analysis in computer science. As a result of literature search, we summarized 60 scientific articles presenting soil moisture forecast published from 2014 to 2024. In conclusion, we present the main challenges in forecasting soil moisture and suggest how they can be addressed.

1. Introduction

Agriculture plays a significant role in the Gross Domestic Product worldwide since it is the population's primary food source. A large amount of water is needed to nourish the conditions for healthy plant growth. Water management is complex since weather variables are hardly unpredictable (for instance, rain, temperature, solar radiation, wind, etc.) [76,12]. At the same time, this weather-related information can be modelled and measured automatically with Internet-of-things (IoT) devices placed in the soil. As examples, there exist Artificial Intelligence (AI) solutions for soil moisture (SM) measurements with different types of IoT sensors [26,86]. Recently, some IoT edge-based innovative systems were developed for vegetable cultivation [39] and irrigation scheduling [88]. Some collected sensor-based SM measurements were recently publicised by investigators online [84]. With such data availability, other scientists started investigating software solutions offering step-ahead predictions/forecasts for time-series data in the agricultural domain [20,21]. Many of these solutions utilise field-installed IoT sensors, measuring soil water levels within their location. The low cost and affordability of these sensors made it possible to measure the water level of the land automatically [58]. Even though many articles have been published in this domain, a unified framework on how such AI solutions should be developed and deployed still needs to be retained. A recently published review surveys main SM prediction techniques and recaps the primary data and methods used for future soil moisture forecast [61]. Still, this survey aims to cover additional agricultural-related problems, such as:

1. sensor types being used for SM measurements,
2. weather variables assessed for forecasting,
3. irrigation information integration,
4. feature types to be generated from sensor-based measurement,
5. evaluation of the forecasting models.

To provide a unified methodology for SM forecast development from sensor data, in this literature survey, we examined different developed software solutions based on a systematic review technique by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) [59,42]. Following the PRISMA guidelines, we define the main research questions this survey aims to solve in this work. Fur-

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Table 1
Research Questions definition.

RQ id	RQ definition
RQ №1	How to forecast future soil moisture level from sensors-based past observations of soil moisture, weather and irrigation information?
RQ №2	What type of sensors can be used for SM forecasting?
RQ №3	What type of methods/models can be implemented for SM forecasting?
RQ №4	What type of features can be generated to train the forecasting models?
RQ №5	How were the models evaluated?
RQ №6	For what purposes the forecasting models were used?

Table 2
Digital Library Sources, Related Search String and Imported Studies Outcome. An asterisk (*) was used as a wildcard to broaden the search for words starting or ending with a keyword.

Digital Source	Search Text
ACM Digital Library	[Title: soil] AND [Title: moisture] AND [[Title: forecast*] OR [Title: predict*] OR [Title: estimat*]] AND [E-Publication Date: (02/01/2014 TO 02/29/2024)]
IEEE Digital Library	(((“Document Title”: “soil moisture” AND ((“Document Title”: “forecast*”) OR (“Document Title”: “predict*”) OR (“Document Title”: “estimat*”))))) 2014 - 2024
ISI Web of Science	(TI = (soil moisture forecast*) OR TI = (soil moisture estimat*) OR TI = (soil moisture predict*)) Timespan: 2014-02-19 to 2024-02-19 (Publication Date) Languages: English, Research Areas: Remote Sensing or Computer Science
Scopus	TITLE (soil) AND TITLE (moisture) AND (TITLE (predict*) OR TITLE (estimat*) OR TITLE (forecast*)) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA, “COMP”) OR LIMIT-TO (SUBJAREA, “ENGI”)) AND (LIMIT-TO (LANGUAGE, “English”))
Springer Link	‘SOIL AND MOISTURE’ where title contains “SOIL AND MOISTURE FORECAST*” OR “SOIL AND MOISTURE PREDICT*” OR “SOIL AND MOISTURE ESTIMAT*” within English Computer Science 2014-2024

thermore, we provide the search resources and strings used for this purpose. In addition, we describe the outcome of the literature analysis and suggest future directions. This survey aims to help computer scientists apply specific methodologies for developing forecasting systems for the SM based on the past observation of sensors' data and weather- and irrigation-related information.

2. Research questions

To better describe the problem of SM forecast, we pose several research questions (RQs). These RQs are posted in Table 1.

These questions are further answered below in Section 5.

3. Search procedure

3.1. Conducting search

We follow the search procedure defined by the PRISMA 2020 statement [59], a standard procedure for performing literature surveys. Following this guideline, for the literature sources, we employed five databases, those are: 1) ACM Digital Library [1]; 2) IEEE Digital Library [2]; 3) ISI Web of Science [3]; 4) Scopus [4]; 5) Springer Link.[5]

The search was performed using relevant search terms formed by two groups of keywords related to (i) ‘soil moisture’ and (ii) ‘forecasting’. The search was conducted on February 19, 2024, and included a filter to select studies which were published in English after 2014 in computer science, engineering or remote sensing domains. The search strategy included the query on the study title based on the defined string: **‘soil AND moisture AND (prediction OR estimation OR forecasting)’**. Search strings for each of the sources are given in Table 2. Wildcards (*) are used to broaden the search for words starting or ending with the keyword.

The amount of imported papers per data source is indicated below:

1. ACM Digital Library - 45;
2. IEEE Digital Library - 281;
3. ISI Web of Science - 486;
4. Scopus - 472;
5. Springer Link - 873.

After the papers were searched in each data source by the search string, they were uploaded to the web platform Parsifal [6] - a dedicated software tool for literature review. It is an instrument that supports researchers in performing systematic literature reviews. In this platform, we further marked papers as selected or rejected based on the below criteria.

3.2. Selection criteria

To be included in the literature review, the study needed a sensor as the primary source to forecast the value. In addition, the studies allowed the use of weather and irrigation-related features as dependent variables on the sensors. To shorten the search outcome, we also excluded all the papers utilizing satellite-based sensing, thus focusing only on the documents where the data was collected with the earth-located sensors. All inclusion and exclusion criteria are described in Table 3.

The statistics of selection procedure outcome per digital source are shown in Fig. 1(a). This figure indicates that most articles have been found by Springer Link search, while only 2% of papers were selected further for a quality assessment instrument. On the other hand, the ACM Digital Library search resulted in 45 articles, where 9% have been selected as being accepted.

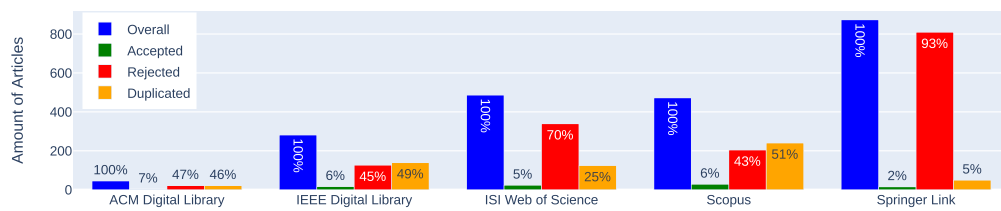
3.3. Quality assessment instrument

After the papers were selected, they were further analyzed for quality purposes. The Parsifal.al platform allows quality scores for each of the collected papers to be defined based on the defined questions. The quality assessment checklist qualifies papers with some issues with their content for rejection. We included several questions and their related an-

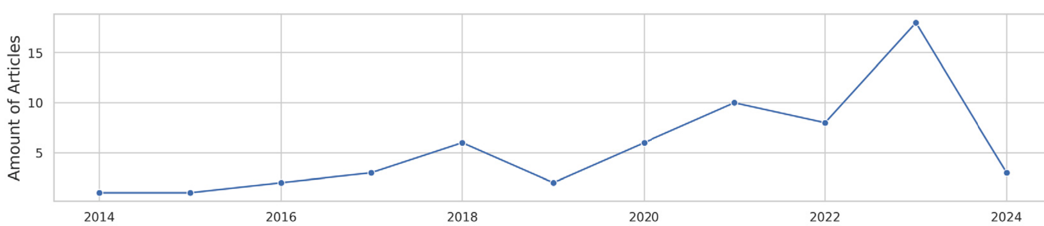
[1] http://portal.acm.org.
[2] http://ieeexplore.ieee.org.
[3] http://www.isiknowledge.com.
[4] http://www.scopus.com.
[5] http://link.springer.com.
[6] https://parsif.al/.

Table 3
Inclusion and Exclusion Criteria for studies.

	Inclusion Criteria	Exclusion Criteria
1	paper applied methodology on the real data set	paper did not report an evaluation of the method
2	paper is about forecasting soil moisture from time series	paper is not about forecasting future soil moisture value
3	paper is about soil moisture prediction for irrigation	paper is not related to the irrigation
4	paper reported the metrics on the data set	paper is not related to the soil moisture values
5	paper was published in the conference	paper did not apply the method on climatic data
6	paper was published in the journal	paper was not published in the computer science domain
7	paper used data collected with earth-located sensors	paper used satellite-based sensing



(a) Accepted Articles per Digital Data Source.



(b) Accepted Articles per Digital Data Source.

Fig. 1. Statistics for PRISMA search outcome.

swers with the score per answer. This quality checklist was formed from six questions posed below.

Quality Assessment Questions Checklist:

1. Was this paper published in the computer science domain?
2. Did this paper use climatic features to predict soil moisture?
3. Is this paper related to the earth- and sensor-based measured values?
4. Is the data set of their results available?
5. Did this paper present metrics for their methodology?
6. Is this paper about forecasting soil moisture from time series?

Possible Answers and their Scores:

- yes (+1)
- not known (0)
- no (-1)
- not only climatic (-2)

4. Search results

The selection process described above led to the inclusion of 60 papers. The search results are shown in Fig. 6. The distribution of the accepted articles per year, as depicted in Fig. 1(b), reveals a notable surge in the number of papers published in this domain, peaking in 2023. This increase underscores the escalating interest and research activity in the field.

The articles were further analyzed to understand which countries the collected data sets are coming from. All related countries and amount of publications mentioned in these countries are shown in Fig. 2. This figure shows that the primary data sources for the SM forecast are from China (16 papers), the United States of America and India (10 papers each). These countries probably have good investment support from the government, thus, the research for smart agriculture is expanding dramatically. Surprisingly, four scientific articles utilized data sources from the small country of Mongolia, the same as those found in Australia, although Australia is more prosperous regarding research funding. Some countries are missing in this map: for instance, Italy, although the primary investment source in this country is agriculture [14].

5. Main findings

To better understand the SM forecast domain, it's essential to summarize the main findings from the studies retrieved. This section provides some aspects of the SM forecasting field, including sensor types, forecasting methods, feature generation, and evaluation metrics. This knowledge is further summarized in Appendix (Table 6), with information about the articles' publication year, and related aspects.

5.1. General pipeline for SM forecasting

The **RQ№1** addresses a general design methodology for SM forecasting modelling. One of the known pipelines can be given as follows (adopted from [16]):

1. Smart irrigation system with strategic placement of sensors;
2. Data collection & processing;
3. Variability analysis & grouping data over time domain;
4. Developing spatiotemporal machine learning models.

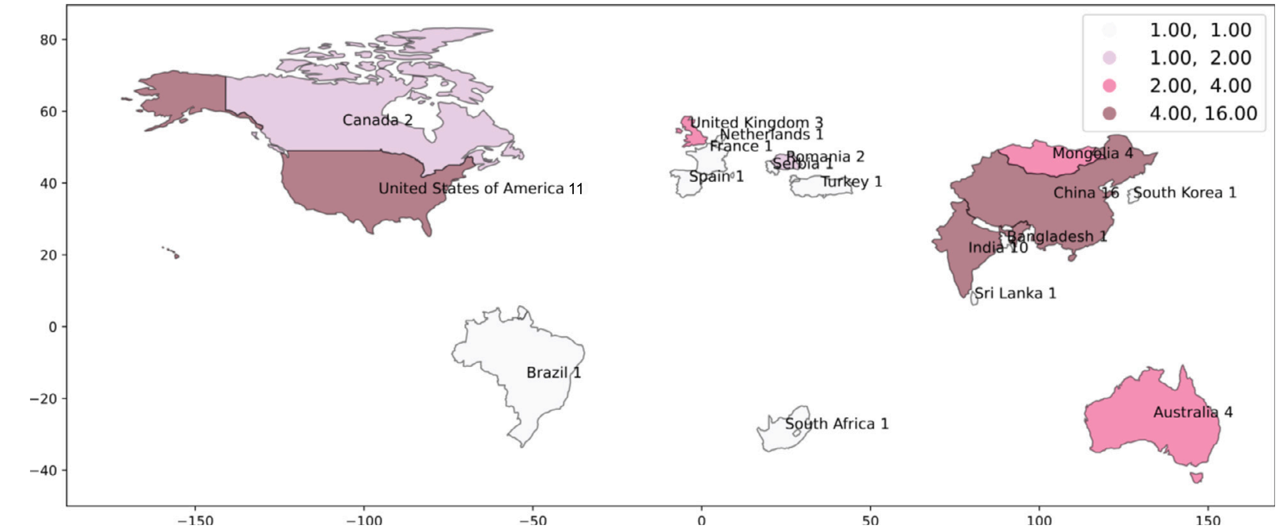


Fig. 2. Data sets distribution by countries.

Table 4
Sensors for soil moisture measurement grouped by their types (extended from [26,86]).

Group	Sensors Types	Sensors Names
Volumetric water content sensors (VWM)	Capacitance	Spectrum SMEC300, SM100; Sentek Enviroscan, Diviner 2000; METER 5TE, 5TN
	Time Domain Reflectometry (TDR)	Acclima true TDR 315, 315L, 310 S; Spectrum Field Scout TDR; CS 655, 650 tec
	Frequency Domain Reflectometry (FDR)	SM3002B
	Neutron probe	CPN-Instrotek; Troxller; CNC503A [6]
	Resistive-based	VH400
Soil water tension sensors	Tensiometers	Irrometer tensiometers, etc.
	Granular matrix sensors	Irrometer watermark sensors, etc.
Satellite-based sensing	Cosmic-ray neutron sensing	Hydroinnova CRS-1000
	Satellite	Soil Moisture Active Passive

Some other researchers developed a parallel definition for the forecasting pipeline, e.g., in [81]:

i. Data preprocessing;
ii. Smooth non-white noise sequence;
iii. Calculate autocorrelation function and partial autocorrelation;
iv. Model recognition;
v. Estimate the value of the unknown parameter in the model;
vi. Model inspection (if failed, then return to the step №4);
vii. Predict the future movement of the series.

5.2. Sensors for soil moisture estimation

Recent AI forecasting solutions made it possible to predict future sensor values from past observations, especially if the sensors are of good quality and the data coming from sensors is well processed. Unfortunately, most of the sensors have problems with their installation and deployment, and some researchers have tried to investigate this problem. This section briefly introduces different sensors used for forecasting and answers the **RQ№2**.

The sensors for soil moisture measurements can be divided into three types depending on the technology they measure: 1) volumetric water content (VWM); 2) soil tension when placed in the soil profile; 3) satellite-based sensing (adopted from [26,86,80,1]). The granularity of the sensors' types and their examples are shown in Table 4.

Each of the sensors' categories has some advantages and limitations. VWM includes several other sub-categories: capacitance, Time Domain Reflectometry (TDR), Frequency Domain Reflectometry (FDR), Neutron probe, and Resistive-based. The capacitance sensors measure the impedance or the capacitance of a buried probe or planar structure, which depends directly on the permittivity of the soil [40] (Fig. 3d). TDR measures the travel time of a reflected wave of electrical energy along a transmission line [16] (Fig. 3c). FDR use the soil as a capacitor to measure the maximum resonant frequency in the electrical circuit and relate the resonant frequency to water content [15] (Fig. 3b). The neutron probe method uses the characteristic property of hydrogen nuclei in water molecules to scatter and to slow down neutrons [40] (Fig. 3f). The resistive-based sensor measures the current which goes through the soil, and then it measures the resistance value to measure the moisture level [63] (Fig. 3a). Some attempts have been made to compare specific types of sensors [75]. Recently researchers compared capacitance and resistive-based sensors and showed that the resistive one is less sensitive than the capacitance [18]. Still, the comparison of sensors should be investigated further.

Examples of soil water tension sensors are tensiometers and granular matrix sensors. A tensiometer is a device that mimics the operation of a plant's root, measuring the ease with which a plant can absorb water up from the soil [40] (Fig. 3e). Granular matrix sensors employ a porous material like a gypsum block or a granular matrix with embedded electrodes. Satellite-based sensing is a sensor that measures soil moisture from a far distance with the help of a satellite.

5.3. Forecasting methods

The **RQ№3** addresses different forecasting models which can be implemented for SM prediction. Most forecasting models are supervised machine learning ones and can be divided into three main categories: (i) regression-based, (ii) classification-based, and (iii) simulation and modelling. The model's division is outlined in Table 5.

(a) VWM Resistive-Based Sensor VH400 (Prakash and Sahu, 2020).

(b) VWM FDR ECH2O EC-5 (Carranza et al., 2021b).

(c) VWM TDR MP406 (Chandrappa et al., 2023).

(d) VWM Capacitance sensor WaterScout SM 100 (Singh et al., 2020).

(e) Tensiometer `https://www.irrometer.com`.

(f) Satellite-based Cosmic-ray neutron Sensor Hydroinnova CRS-1000 (Adeyemi et al., 2018).

Fig. 3. Sensors used for soil moisture forecasting.

5.3.1 **Regression-based Methods.** This model type solves the forecasting problem with a sliding window algorithm applied to time-series data, further generating features for each window and applying regression-based machine learning models for predicting a continuous number of sensor values.

5.3.2 **Classification-based models.** Typically, they measure whether someone should irrigate in the following days. A particular study focuses on classification-based solutions, including models such as ResNet50 (a 50-layer Convolutional Neural Network), DT (Decision Tree), KNN (K-Nearest Neighbours), Logistic Regression, Naive Bayes, RF (Random Forest), and SVM (Support Vector Machines) [12].

5.3.3 **Simulation and Modelling.** This type of SM forecast is presented by statistical analysis and correlation examination performed between soil moisture and other variables, for instance, precipitation [69]. In addition, the effects of anthropogenic forcing (e.g., greenhouse gases, anthropogenic aerosols, and land use change) largely affect the prediction trend and should also be considered [65].

Modelling represents soil moisture prediction problems from the factors directly influencing the wetness (rain, humidity, wind, etc.). For instance, modelling formulation is shown as the following (adopted from [32]):

$$W = k\frac{P - E}{-W_f} + b + \varepsilon \tag{1}$$

where W - soil moisture water, W_f - evaporation, P - precipitation, E_f - latent heat flux (Energy Flux); k and b are coefficients learned per sensor.

Furthermore, regression- and classification-based model division is further distinguished into several groups based on their algorithm behind. These groups are defined as follows:

i. *Bayesian Theory*: the models utilizing Bayes Theory.
ii. *Parametric Regression*: the models presenting forecast problem as linear dependant task.
iii. *Regularization*: the models utilizing penalty and regularization as their main contribution.
iv. *Optimization*: the main feature of the models is how they perform optimization.
v. *Dimensionality reduction*: these models utilize the dimensionality reduction method for regression tasks.
vi. *Ensemble Learning*: these models combine multiple models, utilizing advantages and decreasing the weaknesses of each of them.
vii. *Non-parametric Regression*: data-driven approaches which model dependency with the target value with some function. Some representatives include different types of Convolutional Neural Networks (CNN).

5.4. Features generation and selection

Different features selected/generated for the process of forecasting are not limited to air temperature, solar radiation, surface soil temperature, relative humidity, time-related variables (when the value was measured), and lagged soil moisture [48], wind speed, radiation, rainfall and evapotranspiration [15]. As feature selection plays a significant role in the model performance, utilizing the most important features for the training is essential. We summarise all the features mentioned in the found articles to answer **RQ№4**.

For organization purposes, all features are grouped into specific categories based on where they originated (e.g., from the soil, air, rain, or irrigation). These features' groups with their definitions are outlined as follows:

5.4.1 **Soil-related features**.

In this group, we consider soil physical characteristics which include all the aspects that one can see and touch, or measure.

(a) *Soil Moisture* is an indicator of soil wetness. Usually measured by sensors. Several factors affect the change in soil water content: e.g., rainfall, irrigation, deep soil and groundwater recharge for soil moisture in the root zone, evaporation between plants, crop transpiration, deep leakage, etc. [23].

Table 5
Models types granularity in sensor-based SM forecasting.

Problem-Related	Model Type	Models
Regression	Bayesian Theory	Naive Bayes, Probabilistic Particle Filter, Relevance Vector Machine
	Parametric Regression	Linear Regression: Additive Exponential Accumulative Representation (AEAR), Autoregressive integrated moving average (ARIMA), Linear Regression (LR), Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Vector Autoregression (VAR), Weighted Linear Regression (LR) Non-linear Regression: Exponential Smoothing (ES), Polynomial Regression (R), Variational Mode Decomposition
	Regularization	Elastic-Net, Lasso R, Ridge Regression (RR)
	Optimization	Arithmetic optimization algorithm (AOA), Hyperparameters tuning over Seasonal Trend Decomposition Based on Loess (HyperSTL), Sparrow Search, Genetic Algorithm (GA)
	Dimensionality reduction	Principal Component Analysis (PCA)
	Ensemble Learning	Boosting: Adaptive Boosting (AdaBoost), Boosting, Extreme Gradient Boosting (EGB), Gradient Boost Machine (GBM), Histogram-Based Gradient Boosting (HBGB), eXtreme Gradient Boosting (XGBoost) Boostrap aggregation: Bagging Others: Max-Voting, Multiple Linear Regressions (MLRs), Stacking
	Non-parametric Regression	Gaussian Process, Prophet, Support Vector Machines (SVM), Decision Tree (DT), Random Forest (RF), Naive Accumulative Representation (NAR), K-Nearest Neighbours (KNN) Neural Networks: Artificial Neural Networks (ANNs), Convolutional Neural Network (CNN), Deep Learning, Dynamic ANNs, Extreme Learning Machine (ELM), Elman ANNs, Encoder-decoder, Graph Neural Network (GNN), Multilayer Perceptron Feed-Forward Network (MLP-FFN), Neural basis expansion analysis for interpretable time series forecasting (N-BEATS), Cuckoo Search supported ANN (NN-CS), Modified Flower Pollination Algorithm supported ANN (NN-MFPA), Particle Swarm optimization supported ANN (NN-PSO), Spectral Temporal Graph Neural Network (StemGNN) Recurrent Neural Network: LSTM (Long Short-Term Memory Network), Bidirectional Long Short-Term Memory (BLSTM), CNN-LSTM, Convolutional Long Short-Term Memory (ConvLSTM), Attention-LSTM, Recurrent Neural Networks (RNN) Self-Attention mechanism: Informer
Classification	Bayesian Theory	Naive Bayes
	Non-linear Regression	Logistic R
	Non-parametric Regression	SVM, DT, RF, KNN Neural Networks: ResNet50
Simulation and modelling	Simulation	Simulation
	Modelling	Modelling

(a) Sandy Loam (Jiang et al., 2023)
(b) Silty Loam (Jiang et al., 2023)
(c) Silt (Jiang et al., 2023)
(d) Clay (Abeje et al., 2024)

Fig. 4. Soil types employed for forecasting [37,78].

(b) *Soil Temperature (ST)* is an indicator of soil temperature. Like SM, it is measured by sensors.

(c) *Soil Type* indicates which kind of soil was used in the study [2]. It can be classified (but not limited to) based on soil texture: 1 - coarse, 2 - medium, 3 - medium fine, 4 - fine [24]. Another classification is made based on the soil inner material: in [78], soils were differentiated as 'sandy loam' (Fig. 4a), 'silty loam' (Fig. 4b), 'silt' (Fig. 4c) [37], and 'clay' (Fig. 4d).

(d) *Leakage Depth* is one of the factors affecting SM, depending on the soil types and indicates how deep water can leak into the soil [23].

(e) *Soil evaporation* is a dynamic process which can be divided into several stages [29]. The following formula expressed it [27]:

$$E_T = x_0 + x_1 E_1 + x_2 E_2 \tag{2}$$

where E_1 includes relative humidity, air temperature, radiation and the velocity of ground wind, and E_2 latent heat of vaporization per unit mass and global radiation, x_0, and x_1 are constant parameters.

(f) *Soil electrical conductivity* measures the ability of soil water to carry electrical current [33].

(g) *Sandy Proportion* is a ratio of sand in the land [57].

(h) *Soil ph* is a measure of the acidity or basicity (alkalinity) of a soil [7,16].
(i) *Infiltration Rate* is a velocity or speed at which water enters into the soil [16].
(j) *Land Cover* is one of the static physiographic attributes [47].

5.4.2 **Air-related features**.
These characteristics represent physical characteristics of air (including wind) at some specified time point.
(a) *Air temperature* indicates how warm/cold air is [52].
(b) *Atmospheric pressure* is air weight [57], can be expressed by formula [25]:

$$P_h = P_0 e^{-\frac{ghM}{RT}} \tag{3}$$

where P_h - pressure at height h, P_0 - sea level pressure, g - gravitational acceleration constant, R - Boltzmann's constant, T - absolute temperature, M - mass of one air molecule.
(c) *Wind direction* the direction from or to which wind is blowing [33].
(d) *Wind Speed* reports how fast the current wind flow is at a certain time. The formula for wind speed is given as follows [16]:

$$S = \sqrt{\bar{u^2} + \bar{v^2}} \tag{4}$$

where u is the magnitude of the wind vector in the east-west direction, and v is the magnitude of the wind vector in the north-south direction.
(e) *Humidity* is the concentration of water vapour present in the air [37].
(f) *Drought* - binary value that states whether the sensor is out-of-threshold [20].
(g) *Vapour pressure deficit* can be expressed by formula [24]:

$$D = E(T) - E(T_d) \tag{5}$$

where E stands for the saturation vapour pressure following Magnus's formula, T is the average temperature, and T_d is the average dew-point temperature.
(h) *Latent heat flux* is heat exchange per unit area at constant temperature [32]. It involves a transition from gas to liquid, or vice-versa, by absorbing (releasing) energy.
(i) *Wet bulb temperature* is the lowest temperature that can be reached under current ambient conditions by the evaporation of water only [45].
(j) *Air Flow Rate* measures the amount of air per unit of time that flows through a particular device (e.g., airflow meter or anemometer) [46].
(k) *Air CO_2* indicates how much CO_2 in the air [46].
(l) *Dew Point* - a temperature the air must cool to become completely saturated with water [23].

5.4.3 **Rain-related features**.
The aspects representing information about precipitation quantity are included in this group.
(a) *Rainfall* indicates how much rain it was at a certain period [23].
(b) *Precipitation* indicates information about water amount in the atmosphere [3].
(c) *Runoff* - precipitation that reaches a surface stream without ever passing below the soil surface [89].

5.4.4 **Irrigation-related features**.
These features constitute information about irrigation activity performed within the specified field.
(a) *Water Pressure* - a force that makes a flow of water strong or weak [20].
(b) *Water Amount* - information about how much water was given to a certain location [23].

5.4.5 **Sun-related features**.
Characteristics providing knowledge about current sun effects.
(a) *Solar Radiation* - an amount of sun energy sent through space by electromagnetic waves [74].
(b) *Light intensity* measures the intensity of sunlight [46].
(c) *Sunrise Time* indicates time when the sun rises [46].
(d) *UV index* - the ultraviolet index, or an international standard measurement of the strength of the sunburn-producing ultraviolet radiation [46]
(e) *Sun hours* refers to sunshine duration, or period during which it was sunny [57].
(f) *Longwave Radiation* indicates the amount of heat radiated from the Earth to the space [83].
(g) *Shortwave Radiation* is the sunlight amount coming from the space. It can be described as the amount of heat from the sun at a certain period [83].
(h) *Illuminance* - the amount of light falling on, or illuminating, a given surface [71].

5.4.6 **Relief-related features**.
These features supply facts about terrain where the measurements are performed.
(a) *Elevation* - information about the height above or below a fixed reference point [55].
(b) *Slope* - a measure of change in elevation. It is defined as the ratio of the vertical change to the horizontal change between two distinct points on the line [55].

5.4.7 **Vegetation-related features**.
(a) *Crop Evapotranspiration* represents soil evaporation and the water a crop uses for growth and cooling purposes [74].
(b) *Age of plant* indicates how old is certain plant [20].
(c) *Vegetation Type* is related to the information about the plant type (e.g., vinegar, apple, orchard, etc.) [62].
(d) *Vegetation Indices* is a surface reflectance combination of two or more wavelengths used in remote sensing to highlight a vegetation property [10].
(e) *Skin Reservoir Content* is the amount of water in the vegetation canopy and a thin layer of soil [21].
(f) *Leaf wetness* shows the water amount in the leaf at a certain point [45].

5.4.8 **Weather forecast-related features**.
Aspects posses knowledge about current weather situation.
(a) *weather prediction system* designed for both atmospheric research and operational forecasting applications [79].

5.4.9 **Snow-related features**.
Characteristics showing facts about current snow level.
(a) *snow depth* [4].

5.5. Evaluation

Different researchers employed several various evaluation metrics [22,53]. Addressing **RQ№5**, we classify these metrics according to forecasting methods granularity outlined in Section 5.3.

5.5.1 Regression-based metrics

i. **MSE** is mean squared error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - y_i'| \tag{6}$$

where y_i' - predicted value or model forecast, y_i - real value or actual SM, n - total number of observations.

ii. **RMSE** is root mean squared error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(y_i - y_i'\right)^2} \tag{7}$$

iii. **Bias** is used for checking if the SM prediction is over- or underestimated [48].

$$Bias = \frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)}{n} \quad (8)$$

iv. **Unbiased RMSE** describes fluctuation amplitude between predicted SM and observed SM.

$$ubRMSD = \sqrt{\frac{\sum_{i=1}^{n}\left(\left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_j\right) - \left(y_i' - \frac{1}{n}\sum_{j=1}^{n} y_j'\right)\right)^2}{n}} = \sqrt{\left(\sqrt{\frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)}{n}}\right)^2 - Bias^2} \quad (9)$$

v. **R2** is the coefficient of determination, which measures the proportion of the variation in the dependent variable that is predictable from the independent variable(s).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)^2}{\sum_{i=1}^{n}\left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_j\right)^2} \quad (10)$$

vi. **MAPE** is mean absolute percentage error. In some studies, scientists referred to mean absolute relative error (MARE).

$$MARE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i'}{y_i}\right| \quad (11)$$

vii. **MASE** is mean absolute scaled error [24].

$$MASE = \frac{\frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i'\right|}{\frac{1}{n-1}\sum_{i=2}^{n}\left|y_i - y_{i-1}\right|} \quad (12)$$

viii. **SMAPE** is symmetric mean absolute percentage error [24].

$$SMAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\left|y_i - y_i'\right|}{\frac{\left(|y_i| + |y_i'|\right)}{2}} \quad (13)$$

ix. **Max error** is maximum absolute error, which is particularly important for SM forecast since the SM peaks estimation is critical for irrigation [9].

$$MaxError = \max_{i=1,\ldots,n}\left|y_i' - y_i\right| \quad (14)$$

x. **R** is the Pearson correlation coefficient measured between real and predicted values.

$$r = \frac{\sum_{i=1}^{n}\left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_j\right)\left(y_i' - \frac{1}{n}\sum_{j=1}^{n} y_j'\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_j\right)^2 \sum_{i=1}^{n}\left(y_i' - \frac{1}{n}\sum_{j=1}^{n} y_j'\right)^2}} \quad (15)$$

xi. **Mean biased error** indicates a tendency of the model to underestimate or overestimate the real value. The perfect model has a value close to zero.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i' - y_i\right) \quad (16)$$

xii. **NSE** is Nash-Sutcliffe efficiency coefficient (E_{N-S}) which is standard quantitative statistical performance evaluation measures [56].

$$E_{N-S} = 1 - \frac{\sum_{i=1}^{n}\left(y_i' - y_i\right)}{\sum_{i=1}^{n}\left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_i\right)} \quad (17)$$

xiii. **Residuals** measures the difference between predicted and actual values.

$$residual_i = y_i - y_i' \quad (18)$$

xiv. **Accuracy** in some studies was defined as forecast accuracy. It can be calculated by taking the absolute difference between the forecast and actual values divided this difference by the actual value [16].

$$accuracy = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i'}{y_i}\right| \quad (19)$$

5.5.2 **Classification-based metrics** Sometimes, when the SM levels have discrete distribution, the SM forecast is considered a classification problem. The models were evaluated using various classification measures. Let FP be false positives, FN be false negatives, TP be true positives, TN be true negatives. The measured metrics for classification problems can be defined as follows.

i. **Accuracy** is the model's overall accuracy.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (20)$$

ii. **Precision** is the ability of the model to avoid false positives.

$$precision = \frac{TP}{TP + FP} \quad (21)$$

iii. **Recall** is the ability of the model to detect positive cases.

$$recall = \frac{TP}{TP + FN} \quad (22)$$

iv. **F1** is the harmonic mean of precision and recall.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (23)$$

v. **AUC** is the area under the Receiver Operating Characteristic curve.

The above-posted metrics cover mostly all typical evaluation assessment methods performed in the field of SM forecasting.

5.6. SM forecasting models usage

The soil moisture (SM) prediction serves several purposes across a variety of fields, including water resource management, crop farming, and disaster prevention. These purposes are outlined below to address **RQ№6**:

5.6.1 irrigation planning. It optimizes irrigation schedules to ensure that crops receive adequate moisture [35,12,11,3]. In addition, this scheduling can consider crop harm estimation [88]. Another term is used for this purpose is smart irrigation [79,16].

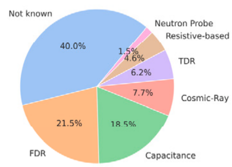
5.6.2 water saving. It is essential factor in investing in research, resulting in large amount articles written for irrigation management and scheduling [74,72,12].

5.6.3 precision farming. The further purpose of SM future estimation is for crop farming [20] and optimal plant growth [7,54].

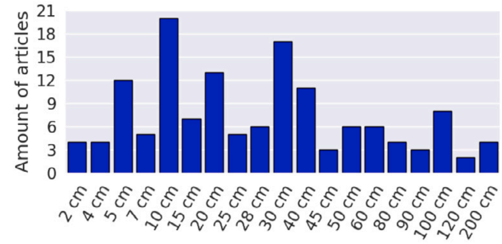
5.6.4 drought monitoring. An efficiency of predictability of drought events can be considered [47].

6. Discussions

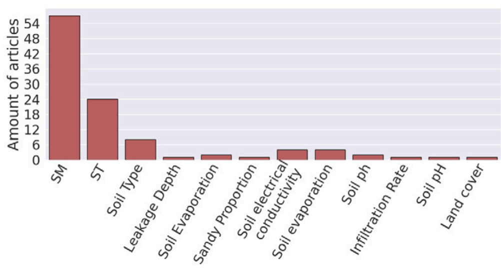
This literature review provides an overall analysis of current developments in the field of SM forecast from sensor-based observations including SM, irrigation and weather information. Some interesting insights were gained from the distribution graphs of articles for some aspects mentioned in Section 5. These insights are shown in Fig. 5. As such, the first conclusion comes from the sensor types used in the past ten years (see Fig. 5a). In Section 5.2, we outlined nine groups for each sensor type mentioned by the researchers in the SM forecast domain. As expected, not all these sensor groups were employed for the SM forecast. We can see from the pie chart that the largest segment is labelled



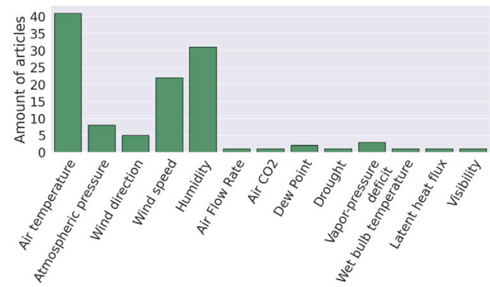
(a) Distribution of sensor types.



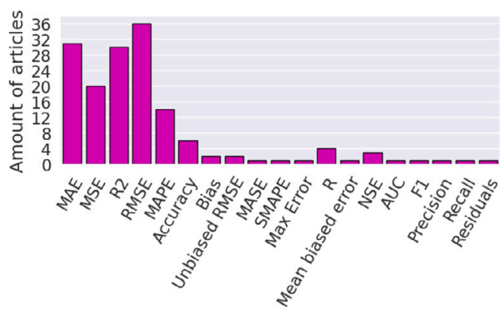
(b) Distribution of sensors depth position used for collection.



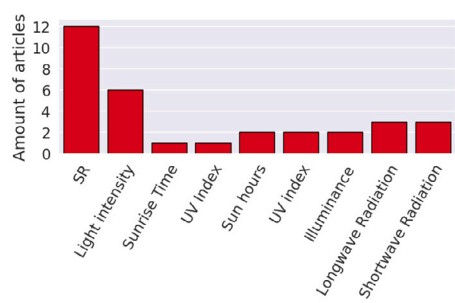
(c) Distribution of soil-related features used in studies.



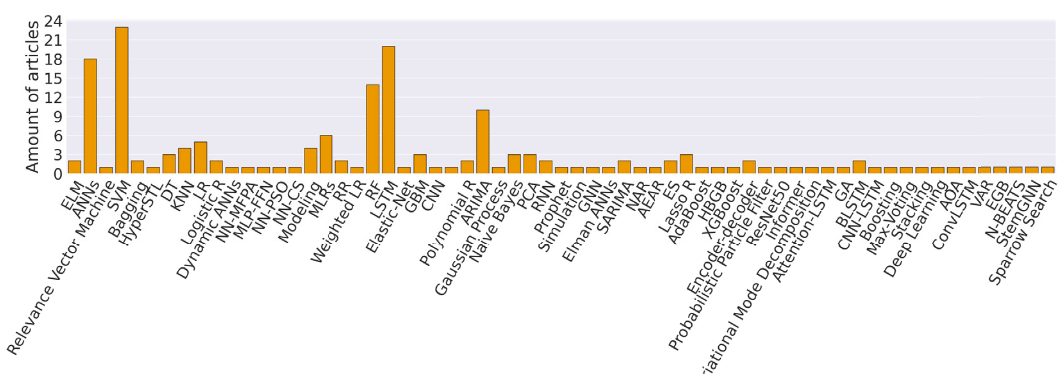
(d) Distribution of air-related features used in studies.



(e) Distribution of metrics utilized in the studies.



(f) Distribution of sun-related features



(g) Distribution of forecasting methods.

Fig. 5. Papers statistics insight: distribution of different related features used in studies for soil moisture forecasting within 2014-2024.

“Not known”, accounting for 40%, indicating a significant portion of the sensors whose type is unidentified. The second-largest category is FDR, which represents 21.5% of the total. Following this is the Capacitance category, making up 18.5%. Smaller contributions come from Cosmic-Ray sensors, comprising 7.7%, and TDR (Time Domain Reflectometry), which accounts for 6.2%. Even less significant are Resistive-based sensors, contributing 4.6%, and the Neutron Probe category, which is the smallest at 1.5%. At the same time, some sensor types were not referred to at all, e.g., tensiometers and granular matrix sensors. This situation can be considered a research gap for scientists who want to advance the SM prognosis. Some articles were published about cosmic-ray neutron sensing. At the same time, we noted at the beginning of this study that it covers only earth-located sensors for SM collection and forecast.

The second insight comes from the sensor position depth distribution, shown in Fig. 5b. The depth level where the sensor is placed is indeed vital for SM moisture estimation: a small amount of precipitation does not reach a certain level of the earth, and sensors can not capture rain information. Some studies reported depth position within a wide range without explicit information on the interval's specific values (e.g., 0-20 cm, 7-28 cm). Hence, these intervals were then equally distributed between an existing range of depths (e.g., if the article reported a range of 0-20 cm interval, then we consider this article to have sensor depth positions for 2 cm, 4 cm, 5 cm, 7 cm, 10 cm, 15 cm, 20 cm, respectively). Overall, the data shows that the most common lengths are 15 cm and 30 cm, with both having the highest count of articles, reaching peaks of 19 and 16, respectively. In contrast, articles of shorter lengths, such as 2 cm, 4 cm, and 5 cm, are relatively less frequent, with counts below four each, probably due to the inefficiency of SM collection at this position. Similarly, lengths above 60 cm show minimal representation, except for the spike at 100 cm, which has approximately 10 articles. The chart highlights a tendency for articles to cluster around medium lengths, particularly between 10 cm and 40 cm, with notable fluctuations within this range.

Further, the third insight is about soil-related data distribution shown in Fig. 5c. As expected, SM is the most utilized feature for SM forecast: more than 90% of studies reported it. Interestingly, ST is the second most frequent feature reported by the researchers: 24 out of 60 articles used it. The third most utilized feature is soil type (around seven papers delivered their models using it). These parameters are probably the most evident when building a forecasting system. Other prominent values are soil evaporation (9% of articles operated it) and soil electrical conductivity (5% of studies correspondingly).

The subsequent exciting distribution of air-related features is shown in Fig. 5d. One can see that air temperature is the most frequent parameter being used in prognosis systems. This aspect is followed by humidity and wind speed, the second and third most frequently employed parameters. We suggest including such parameters to deliver well-established estimation systems is essential.

In addition, metrics allocation among studies are provided in Fig. 5e. Not surprisingly, RMSE is the most frequent evaluation metric. The subsequently followed most-used metrics are MAE (with more than 50% reported articles), R2 (with 29 reported papers), MSE (with 20 reports), MAPE (with 14 articles) and Accuracy (with six documents). Considering these metrics for forecasting systems planned to be designed is essential.

Another graph shows sun-related feature distribution among the studies in Fig. 5f. From this image, it's clear that SR is an obvious parameter affecting SM, and a large amount of sun heat is correlated with SM. In addition, light intensity also plays an essential role: at least six studies have reported this. The other features can be considered as weaker prognosis providers as they were reported in only a few papers: sun hours, UV index, illuminance, longwave and shortwave radiation, and sunrise time.

The last but not least meaningful plot shows the distribution of forecasting methods among the articles in Fig. 5g.

From this Figure, one can conclude that SVM, LSTM and ANNs are forecasting methods which were used the most (with 37%, 33% and 31% overall studies registering them, respectively). Not surprisingly, RF and ARIMA are the second most-used methods: 13 and 14 articles delivered them accordingly. Several studies employed such methods as LR, KNN, DT, GBM, Modelling, Naive Bayes, Lasso R and PCA. Only a few papers reported Logistic R, RR, Polynomial R, RNN, SARIMA, ES, Encoder-decoder, and BLSTM. All the other methods were only used in a single article.

7. Conclusion

This literature review is a deep dive into the cutting-edge forecasting systems designed for future SM prediction, using sensor-based measurements of SM, weather, and irrigation information. We outline the existing research advancements in the SM forecasting field to provide a unified framework for designing SM forecasting systems and highlight areas that warrant further investigation. The review answers six research questions, each crucial to understanding the sensor types, various forecasting methods, feature generation scenarios, and evaluation methods used in current systems. Following the standard procedure for literature review in the computer science domain, we detail the search unique strings used to identify the articles included in this review, demonstrating the rigour of our survey approach. Our search spanned five different e-sources: ACM Digital Library, IEEE Digital Library, ISI Web of Science, Scopus, and Springer Link, resulting in the inclusion of 60 studies in this review. These articles were carefully analyzed to address the posed research questions, and we delivered an analysis of several distribution figures for each related question. In conclusion, we provide potentially interesting research gaps in SM prognosis from sensor-based observation.

From the reported results, one can see that some recently developed software solutions report precise accuracy for SM prognosis, which is unsurprising considering how Artificial Intelligence has advanced the general forecasting domain. At the same time, we notice some unresolved issues: first, it needs to be clarified which type of sensors deliver better performance, accuracy, and battery life cycle efficiency. Some attempts have been made to find a way to address this problem, e.g., in [18], but only a couple of sensors have been included for comparison. Another open research question relates to the computation memory necessary for each forecasting method: memory limit is the most important consideration when deploying an automatic system in small devices (e.g., chips). The researcher still needs to analyze this aspect. The third unresolved issue pertains to features and their significance. The research question here is which features can better enhance the performance of forecasting methods. While several features relied solely on SM measurements, other studies still rely on more than this. The sub-sequential question then becomes: to what extent can all potential features be utilized? In addition, SM estimation models must be incorporated into recommendation systems for plant growth or irrigation scheduling. Several studies have described such systems [82,68], without considering SM predictive models. These are some of the challenges that await future research, offering exciting opportunities for further exploration and innovation in the field.

CRediT authorship contribution statement

Iustina Ivanova: Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Iustina Ivanova reports a relationship with Bruno Kessler Foundation that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

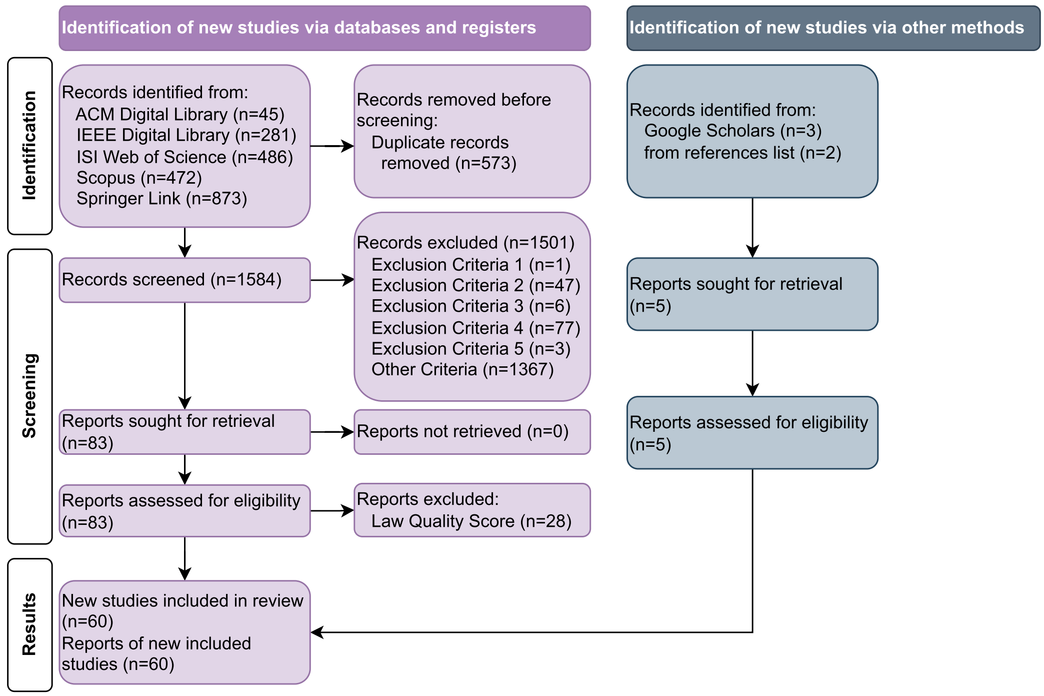

Fig. 6. Flowchart of the study screening procedure according to PRISMA.

Table 6
Literature review summary.

Publ. Year	Source	Sensor type	Sensor position depth	Soil-related features	Air-related features	Rain-related features	Irrigation-related features	Sun-related features	Relief-related features	Vegetation-related features	Evaluation Metrics	Mathematical Models	Weather forecast	Training data period	Country	Snow-related features
2014	[52]	Unk	20, 40, 60	SM	Air temperature, Atmospheric pressure, Wind direction, Wind speed, Humidity	Rainfall	-	SR	-	-	MAE	ELM	-	2 years	Australia	-
2015	[46]	Unk	-	SM, ST, Soil Type	Air temperature, Humidity, Air Flow Rate, Air CO2	-	-	Light intensity, Sunrise Time, UV Index	-	-	MSE, R2, RMSE	ANNs	-	Unk	India	-
2016	[30]	resistive-based	10, 5	ST, SM	Wind speed, Air temperature, Humidity	Precipitation	-	SR	-	-	MAE, MSE, R2	Relevance Vector Machine, SVM	-	8 years	United States	-
2016	[66]	Neutron Probe, TDR	10-30	SM	-	-	-	-	-	-	MAE, MAPE, RMSE	Bagging, ANNs, SVM	-	9 years	United States, Australia	-
2017	[8]	capacitance	5, 10, 15, 20, 28, 30	SM	-	-	-	-	-	-	MAE, RMSE	HyperSTL	-	1 year	United States	-
2017	[55]	FDR	10	SM, Soil Type	Air temperature	Precipitation	-	-	Elevation, Slope	-	Accuracy, MSE	DT, KNN, LR, Logistic R, SVM	-	1 year	Romania	-
2017	[67]	FDR	30	SM	Wind speed, Air temperature	Rainfall	-	-	-	-	RMSE	ANNs	-	6 months	China	-

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Table 6 (*continued*)

Publ. Year	Source	Sensor type	Sensor position depth	Soil-related features	Air-related features	Rain-related features	Irrigation-related features	Sun-related features	Relief-related features	Vegetation-related features	Evaluation Metrics	Mathematical Models	Weather forecast	Training data period	Country	Snow-related features
2018	[3]	cosmic-ray	-	SM, soil type	Wind speed, Air temperature, Humidity	Precipitation	-	SR	-	-	MAE, R2, RMSE	Dynamic ANNs	-	4 years	United Kingdom	-
2018	[17]	Unk	-	ST	Air temperature, Humidity	-	-	-	-	-	RMSE	NN-MFPA, MLP-FFN, NN-PSO, NN-CS	-	1 year	Canada	-
2018	[23]	Unk	-	Leakage Depth, SM	Dew Point	Rainfall	✓	-	-	Crop Evapotranspiration	MAE, R2, RMSE	Modelling	-	58 years	China	-
2018	[27]	resistive-based	Unk	SM, Soil Evaporation	Air temperature, Humidity	-	-	SR	-	-	Accuracy, MSE, R2	MLRs, RR, SVM, Weighted LR	-	1 week	India	-
2018	[57]	Unk	0-20, 20-40	Sandy Proportion, SM	Atmospheric pressure, Wind speed, Air temperature, Humidity	Precipitation	-	Sun hours, UV index	-	-	Accuracy, R2, RMSE	ANNs, RF, SVM	-	2 years	China	-
2018	[64]	capacitance	5	SM	-	-	-	-	-	-	MSE, R2	LSTM, MLRs, SVM	-	6 months, 2 years	United States	-
2019	[72]	capacitance	Unk	SM, ST	Humidity	-	-	UV index, SR	-	-	MSE, R2	Elastic-Net, GBM, MLRs, RF	✓	37 days	India	-
2019	[13]	FDR	10, 20	ST	Air temperature, Atmospheric pressure, Humidity, Wind speed	Precipitation	-	-	-	-	MAE, MSE, RMSE, R2	CNN,	-	4 years	China	-
2020	[5]	Unk	10, 30, 50	SM, ST	Air temperature	-	-	-	-	-	Accuracy	KNN, ANNs, Polynomial R, SVM	-	7 years	Romania	-
2020	[20]	Unk	20, 30, 40	SM, Soil Type	Air temperature, Drought	Rainfall	✓	-	-	Age of plant	MAE, R2, RMSE	ANNs, RF, SVM	✓	3 years	France	-
2020	[51]	Unk	-	SM	-	-	-	-	-	-	MAE, MAPE, RMSE	ARIMA, Gaussian Process	-	4 years	China	-
2020	[62]	FDR	-	SM	Air temperature, Humidity	-	-	-	-	Vegetation Type	LR, Naive Bayes, PCA, SVM		-	3 months	India	-
2020	[63]	capacitance, TDR	5	SM	-	Rainfall	-	-	-	-	MSE, R2	MLRs, ANNs, SVM	-	6 months, 3 months	United States, Australia	-
2020	[73]	capacitance	10, 25, 50, 80	SM	-	-	-	-	-	-	MAE, MAPE, MSE, RMSE	LSTM	-	1 year	India	-
2021	[15]	FDR	10, 20, 40, 5, 80	SM	Wind speed, Air temperature, Humidity	Rainfall	-	SR	-	Vegetation Indices, Vegetation Type, Crop Evapotranspiration	Bias, R2, RMSE, Unbiased RMSE	RF	-	2 years	Netherlands	-

Table 6 (*continued*)

Publ. Year	Source	Sensor type	Sensor position depth	Soil-related features	Air-related features	Rain-related features	Irrigation-related features	Sun-related features	Relief-related features	Vegetation-related features	Evaluation Metrics	Mathematical Models	Weather forecast	Training data period	Country	Snow-related features
2021	[21]	Unk	0-7	ST, SM, Soil Evaporation	Air temperature, Humidity, Dew Point	Rainfall	-	Light intensity	-	Skin Reservoir Content, Vegetation Index	MSE, R2	SVM	-	1 year	India	-
2021	[24]	Unk	0-7, 7-28, 28-100, 100-289	SM, Soil Type	Vapor-pressure deficit, Air temperature	Precipitation	-	-	-	-	MAE, MASE, SMAPE	ARIMA, RNN, LSTM, RF	-	9 years	Serbia	-
2021	[33]	Unk	Unk	SM, ST, Soil electrical conductivity	Wind direction, Wind speed, Air temperature, Humidity	Rainfall	-	Light intensity	-	-	MSE, R2	SVM	-	1 year	China	-
2021	[37]	Unk	-	SM, ST	Wind direction, Wind speed, Air temperature, Humidity	Rainfall	-	Light intensity	-	Vegetation Type	MAE, MAPE, RMSE	LSTM, ANNs, PCA	-	3 years	China	-
2021	[41]	FDR	10, 45, 80	SM	-	-	-	-	-	-	MAE, MSE, RMSE	ARIMA, LSTM, Prophet	-	Unk	India	-
2021	[50]	FDR	-	SM, ST	Air temperature, Humidity	-	-	-	-	-	MAPE, R2, RMSE	LSTM	-	3 months	China	-
2021	[71]	Unk	Unk	ST, Soil electrical conductivity, SM	Air temperature, Humidity	-	-	Illuminance	-	-	MAE, MSE	ANNs	-	2 months	China	-
2021	[74]	capacitance	10, 20, 30, 40, 50	SM	Vapor-pressure deficit, Wind speed, Air temperature	-	-	SR	-	Crop Evapotranspiration	-	Simulation	-	2 months	Spain	-
2021	[79]	Unk	20, 40, 60	SM, Soil Type	Air temperature, Humidity, Wind speed	Precipitation	-	SR	-	-	MAE, MAPE, R2, RMSE	DT, GNN, LR, LSTM, ANNs, RF	✓	4 years	Brazil	-
2022	[4]	Unk	10, 100, 200, 40	Soil evaporation, SM	-	-	-	-	-	-	MAPE, RMSE, MAE	RNN, LSTM, SVM, RF, Elman ANNs		9 years	Mongolia	✓
2022	[7]	capacitance	-	SM, Soil ph	Air temperature, Humidity	-	-	Light intensity	-	-	MAE, RMSE	LSTM, SARIMA	-	18 days	Sri Lanka	-
2022	[9]	capacitance, FDR	5, 10, 15, 20, 28, 30	SM	-	-	-	-	-	-	MAPE, max error	NAR, AEAR, ARIMA, SVM, Polynomial R, LSTM, SEM	-	1 year	United States	-
2022	[16]	TDR	120, 30, 7, 90	Infiltration Rate, SM, Soil Type, Soil pH	Air temperature, Vapor-pressure deficit, Humidity	-	-	SR	-	-	Accuracy	LR, LSTM, Lasso R, Modelling, SVM	-	1 year	Australia	-

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Table 6 (*continued*)

Publ. Year	Source	Sensor type	Sensor position depth	Soil-related features	Air-related features	Rain-related features	Irrigation-related features	Sun-related features	Relief-related features	Vegetation-related features	Evaluation Metrics	Mathematical Models	Weather forecast	Training data period	Country	Snow-related features
2022	[45]	Unk	15, 30, 45	SM	Air temperature, Wet bulb temperature, Humidity	Precipitation	-	-	-	Leaf wetness	MAE, R2, RMSE	AdaBoost, GBM, HBGB, LR, Lasso R, RF, RR, XGBoost	-	2 years	Turkey	-
2022	[48]	Unk	5	SM, ST	Air temperature	Precipitation	-	-	-	Vegetation Type	Bias, MAE, R2, Unbiased RMSE	Encoder-decoder, LSTM	-	18 years	China, +	-
2022	[49]	FDR	4	SM, ST, Soil Type	-	-	-	-	-		MAE, RMSE	ARIMA, LSTM, SVM	-	6 months	China	-
2022	[77]	capacitance and FDR	30, 60	SM	-	-	-	-	-	-	R, Mean biased error, NSE, RMSE	ANNs, Probabilistic Particle Filter	-	4 years	United States	-
2023	[12]	Unk	-	SM, ST	Wind direction, Wind speed, Air temperature, Humidity	-	✓	Illuminance	-	-	AUC, Accuracy, F1, Precision, Recall	ResNet50, DT, KNN, Logistic R, Naive Bayes, RF, SVM	-	-	United States	-
2023	[28]	resistive-based	Unk	SM, ST	Air temperature, Humidity	-	-	SR	-	-	MSE, R2	GBM, MLRs, RF	-	40 days	India	-
2023	[31]	Unk	10, 100, 40	SM	Air temperature, Wind speed	Precipitation	-	-	-	-	MAE, MAPE, RMSE	ARIMA, LSTM	-	1 year	China	-
2023	[32]	Unk	-	Soil evaporation	Latent heat flux	Precipitation	-	-	-	-	Residuals, R2	ARIMA, Modelling	-	9 years	Mongolia	-
2023	[34]	Unk	5	SM	Wind speed, Air temperature, Humidity	Rainfall	-	-	-	-	R, MAPE, R2, RMSE	RF, SVM	-	40 years	Bangladesh	-
2023	[36]	Unk	0-10	SM	-	-	-	-	-	-	MAE, R2, RMSE	Informer, PCA, Variational Mode Decomposition	-	16 years	China	-
2023	[38]	FDR	30	SM, ST	Air temperature, Humidity	-	-	-	-	-	MAE, RMSE	Attention-LSTM, GA, LSTM, ANNs, SVM	-	9 years	Canada	-
2023	[44]	cosmic-ray	-	SM	Air temperature, Atmospheric pressure, Wind direction, Wind speed, Humidity	Precipitation	-	Longwave Radiation, Shortwave Radiation, SR			MAE, MSE, R2, RMSE	BLSTM, LSTM, CNN-LSTM	-	6 years	United Kingdom	-
2023	[54]	FDR	-	SM, ST, Soil ph	Atmospheric pressure, Humidity, Wind speed, Air temperature	Precipitation, Rainfall	-	Sun hours	-	-	MAE, MSE, NSE, R2, RMSE	Bagging, Boosting, Max-Voting, RF, SVM, Stacking	-	3 years	India	-
2023	[56]	Unk	2, 25, 50	SM, ST	Wind speed, Air temperature	Rainfall	-	-	-	-	MAPE, NSE, R2, RMSE	Deep Learning, MLRs, ANNs, SVM	-	1 year	India	-
2023	[60]	TDR	10, 20, 30	SM, ST	Air temperature, Humidity	Precipitation	-	-	-	-	MSE, R2	LSTM	-	1 year	South Korea	-

Table 6 (*continued*)

Publ. Year	Source	Sensor type	Sensor position depth	Soil-related features	Air-related features	Rain-related features	Irrigation-related features	Sun-related features	Relief-related features	Vegetation-related features	Evaluation Metrics	Mathematical Models	Weather forecast	Training data period	Country	Snow-related features
2023	[70]	capacitance	Unk	SM, ST	Air temperature, Wind speed, Humidity	Precipitation, Rainfall	-	Light intensity	-	Vegetation Indices	R, MSE	KNN, Lasso R, ANNs, RF, SVM	-	6 months	Africa	-
2023	[78]	capacitance and FDR	30	SM	-	-	-	-	-	-	RMSE	ANNs	-	9 years	United States	-
2023	[81]	Unk	-	SM	-	-	-	-	-	-	MAE, MAPE	ARIMA, ANNs	-	8 days	China	-
2023	[85]	FDR	-	SM, ST, Soil electrical conductivity	Air temperature	-	-	-	-	-	MAE, MSE, R2	AOA, ELM, ANNs, SVM	-	8 months	China	-
2023	[89]	Unk	10, 100, 200, 40	Soil evaporation, SM	Wind speed	Runoff	-	-	-	Vegetation Indices	MAE, MAPE, RMSE	BLSTM, Encoder-decoder, LSTM	-	11 years	Mongolia	-
2023	[88]	cosmic-ray	10, 30, 60, 100	SM, Soil electrical conductivity	Air temperature, Humidity, Atmospheric pressure, Wind speed	Precipitation	-	Longwave Radiation, Shortwave Radiation	-	Crop Evapotranspiration	RMSE, R2	Modelling	✓	1 year	US	-
2024	[47]	cosmic-ray	0-7, 0-10	Land cover, ST, SM	Wind speed, Air temperature	Precipitation	-	Longwave Radiation, Shortwave Radiation	Elevation	-	R, RMSE	ConvLSTM	-	8 years	China	-
2024	[19]	capacitance	100, 15, 30, 5, 50, 60, 90	ST, SM	Air temperature	Precipitation	-	-	-	-	MAE, MAPE, RMSE	Naive Bayes, VAR, ES, ARIMA, EGB, RF, N-BEATS, StemGNN	-	2 years	United States +	-
2024	[43]	cosmic-ray	-	SM, ST	Atmospheric pressure, Humidity	Precipitation	-	SR	-	-	MAE, MSE, R2, RMSE	LSTM	-	6 years	United Kingdom	-
2024	[87]	Unk	10, 100, 200, 40	Soil evaporation, SM	Atmospheric pressure, Visibility, Wind speed, Air temperature	Precipitation, Rainfall	-	-	Elevation	-	MAE, R2, RMSE	ARIMA, LSTM, ANNs, SARIMA, Sparrow Search	-	10 years	Mongolia	-

Appendix B. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.atech.2024.100692.

Data availability

I have provided data as supplementary material. Statistical analysis will be made available on request.

References

[1] M.I. Abdulraheem, W. Zhang, S. Li, A.J. Moshayedi, A.A. Farooque, J. Hu, Advancement of remote sensing for soil measurements and applications: a comprehensive review, Sustainability 15 (2023), https://doi.org/10.3390/su152115444, https://www.mdpi.com/2071-1050/15/21/15444.

[2] B.T. Abeje, A.O. Salau, B.M. Gela, A.D. Mengistu, Soil type identification model using a hybrid computer vision and machine learning approach, Multimed. Tools Appl. 83 (2024) 575–589, https://doi.org/10.1007/s11042-023-15692-4.

[3] O. Adeyemi, I. Grove, S. Peets, Y. Domun, T. Norton, Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling, Sensors 18 (2018), https://doi.org/10.3390/s18103408, https://www.mdpi.com/1424-8220/18/10/3408.

[4] L. Ai, X. Sun, Q. Zhang, Z. Miao, G. Li, S. Song, Soil moisture prediction model based on lstm and Elman neural network, in: Proceedings of the 4th International Conference on Advanced Information Science and System, Association for Computing Machinery, New York, NY, USA, 2023.

[5] A. Avram, O. Matei, C.M. Pintea, P.C. Pop, C.A. Anton, Context-aware data mining vs classical data mining: case study on predicting soil moisture, in: F. Martínez Álvarez, A. Troncoso Lora, J.A. Sáez Muñoz, H. Quintián, E. Corchado (Eds.), 14th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2019), Springer International Publishing, Cham, 2020, pp. 199–208.

[6] D.M. Bai, Z.S. Guo, M.C. Guo, Forecasting soil moisture in the soil under the caragana shrubland using wavelet analysis and narx neural network, https://doi.org/10.21203/rs.3.rs-977050/v1, 2021.

[7] S. Balasooriya, C. Nguyen, I. Kavalchuk, L. Yasakethu, Forecasting model comparison for soil moisture to obtain optimal plant growth, in: 2022 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), 2022, pp. 1–7.

[8] A. Basak, O.J. Mengshoel, C. Kulkarni, K. Schmidt, P. Shastry, R. Rapeta, Optimizing the decomposition of time series using evolutionary algorithms: soil moisture

analytics, in: Proceedings of the Genetic and Evolutionary Computation Conference, Association for Computing Machinery, New York, NY, USA, 2017, pp. 1073–1080.

[9] A. Basak, K.M. Schmidt, O.J. Mengshoel, From data to interpretable models: machine learning for soil moisture forecasting, Int. J. Data Sci. Anal. 15 (2023) 9–32, https://doi.org/10.1007/s41060-022-00347-8.

[10] B. Basso, D. Cammarano, P. De Vita, et al., Remotely sensed vegetation indices: theory and applications for crop management, Riv. Ital. Agrometeorol. 1 (2004) 36–53.

[11] D. Braga, T.L.C. da Silva, A. Rocha, G. Coutinho, R.P. Magalhaes, P.T. Guerra, J.A. de Macêdo, Time series forecasting for purposes of irrigation management process, in: Anais do XXXIII Simpósio Brasileiro de Banco de Dados, SBC, 2018, pp. 217–222.

[12] S.R. Burri, D.K. Agarwal, N. Vyas, R. Duggar, Optimizing irrigation efficiency with iot and machine learning: a transfer learning approach for accurate soil moisture prediction, in: 2023 World Conference on Communication & Computing (WCONF), 2023, pp. 1–6.

[13] Y. Cai, W. Zheng, X. Zhang, L. Zhangzhong, X. Xue, Research on soil moisture prediction model based on deep learning, PLoS ONE 14 (2019) 1–19, https://doi.org/10.1371/journal.pone.0214508.

[14] F. Capitanio, S. Di Falco, R. Zucaro, D. Zilberman, Italian agriculture in the context of climate change: the role of irrigation for sustainable development of rural areas, Riv. Stud. Sosten. (2015) 131–152, http://digital.casalini.it/10.3280/RISS2015-002011.

[15] C. Carranza, C. Nolet, M. Pezij, M. van der Ploeg, Root zone soil moisture estimation with random forest, J. Hydrol. 593 (2021) 125840, https://doi.org/10.1016/j.jhydrol.2020.125840.

[16] V.Y. Chandrappa, B. Ray, N. Ashwatha, P. Shrestha, Spatiotemporal modeling to predict soil moisture for sustainable smart irrigation, Int. Things 21 (2023) 100671, https://doi.org/10.1016/j.iot.2022.100671, https://www.sciencedirect.com/science/article/pii/S2542660522001524.

[17] S. Chatterjee, N. Dey, S. Sen, Soil moisture quantity prediction using optimized neural supported model for sustainable agricultural applications, Sustain. Comput. Inf. Syst. 28 (2020) 100279, https://doi.org/10.1016/j.suscom.2018.09.002, https://www.sciencedirect.com/science/article/pii/S2210537918302464.

[18] S. Chowdhury, S. Sen, S. Janardhanan, Comparative analysis and calibration of low cost resistive and capacitive soil moisture sensor, arXiv preprint, arXiv:2210.03019, https://doi.org/10.48550/arXiv.2210.03019, 2022.

[19] G. Custódio, R.C. Prati, Comparing modern and traditional modeling methods for predicting soil moisture in iot-based irrigation systems, Smart Agric. Technol. 7 (2024) 100397, https://doi.org/10.1016/j.atech.2024.100397, https://www.sciencedirect.com/science/article/pii/S2772375524000029.

[20] A. Dubois, F. Teytaud, S. Verel, Short term soil moisture forecasts for potato crop farming: a machine learning approach, Comput. Electron. Agric. 180 (2021) 105902, https://doi.org/10.1016/j.compag.2020.105902, https://www.sciencedirect.com/science/article/pii/S0168169920331070.

[21] R. Dutta, R. Maity, P. Patel, Short and medium range forecast of soil moisture for the different climatic regions of India using temporal networks, Water Resour. Manag. 36 (2022) 235–251, https://doi.org/10.1007/s11269-021-03025-9.

[22] D. Entekhabi, R.H. Reichle, R.D. Koster, W.T. Crow, Performance metrics for soil moisture retrievals and application requirements, J. Hydrometeorol. 11 (2010) 832–840, https://doi.org/10.1175/2010JHM1223.1, https://journals.ametsoc.org/view/journals/hydr/11/3/2010jhm1223_1.xml.

[23] X.R. Fan, Y.R. Wang, C.B. Wu, H.W. Liu, Research of soil moisture content forecast model based on reference evapotranspiration in neighboring periods, in: 2018 7th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), 2018, pp. 1–6.

[24] N. Filipović, S. Brdar, G. Mimić, O. Marko, V. Crnojević, Regional soil moisture prediction system based on long short-term memory network, Biosyst. Eng. 213 (2022) 30–38, https://doi.org/10.1016/j.biosystemseng.2021.11.019, https://www.sciencedirect.com/science/article/pii/S1537511021002865.

[25] А Х Хргиан, физика атмосферы//гидрометеорологическое издательство, 1969, pp. 113–114, Ленинград.

[26] A. Garg, P. Munoth, R. Goyal, Application of soil moisture sensor in agriculture, in: Proceedings of Internation Conference on Hydraulic, 2016, pp. 8–10.

[27] A. Goap, D. Sharma, A.K. Shukla, C.R. Krishna, Comparative study of regression models towards performance estimation in soil moisture prediction, in: M. Singh, P.K. Gupta, V. Tyagi, J. Flusser, T. Ören (Eds.), Advances in Computing and Data Sciences, Springer Singapore, Singapore, 2018, pp. 309–316.

[28] D.N. Gupta, V. Veeraiah, H. Singh, R. Anand, N. Sindhwani, A. Gupta, Iot-dependent intelligent irrigation system with ml-dependent soil moisture prediction, in: 2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS), 2023, pp. 1296–1300.

[29] J. Han, J. Lin, Y. Dai, Numerical modeling of soil evaporation process and its stages dividing during a drying cycle, Geofluids 2017 (2017) 5892867, https://doi.org/10.1155/2017/5892867.

[30] Z. Hong, Z. Kalbarczyk, R.K. Iyer, A data-driven approach to soil moisture collection and prediction, in: 2016 IEEE International Conference on Smart Computing (SMARTCOMP), 2016, pp. 1–6.

[31] L. Hu, H. Xu, J. Zhang, Q. Luo, Soil moisture prediction based on the arima time-series model, in: 2023 35th Chinese Control and Decision Conference (CCDC), 2023, pp. 5193–5198.

[32] X. Huang, Research on soil moisture prediction based on mechanism analysis and ARIMA model, in: X. Chen, H.M. Srivastava (Eds.), 3rd International Conference on Applied Mathematics, Modelling, and Intelligent Computing (CAMMIC 2023), in: International Society for Optics and Photonics. SPIE., 2023, p. 1275607.

[33] Y. Huang, H. Jiang, W.f. Wang, W. Wang, D. Sun, Soil moisture content prediction model for tea plantations based on svm optimised by the bald eagle search algorithm, Cogn. Comput. Syst. 3 (2021) 351–360, https://doi.org/10.1049/ccs2.12034, https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/ccs2.12034, arXiv:https://ietresearch.onlinelibrary.wiley.com/doi/pdf/10.1049/ccs2.12034.

[34] M. Hussain, N. Sharmin, S.B. Shafiul, Estimation of soil moisture with meteorological variables in supervised machine learning models, in: 2023 International Conference on Electrical, Computer and Communication Engineering (ECCE), 2023, pp. 1–6.

[35] M.N. Islam, D. Logofătu, Machine learning models to predict soil moisture for irrigation schedule, in: 2022 24th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC), 2022, pp. 226–232.

[36] Z. Jia, Y. Liu, Y. Wang, W. Chen, Study on soil moisture prediction based on the vmd-pca-informer model, in: 2023 IEEE 9th International Conference on Cloud Computing and Intelligent Systems (CCIS), 2023, pp. 547–551.

[37] S. Jiang, G. Chen, D. Chen, T. Chen, Application and evaluation of an improved lstm model in the soil moisture prediction of southeast Chinese tobacco-producing areas, J. Indian Soc. Remote Sens. 51 (2023) 1843–1853, https://doi.org/10.1007/s12524-021-01438-y.

[38] A. Kara, E. Pekel, E. Ozcetin, G.B. Yıldız, Genetic algorithm optimized a deep learning method with attention mechanism for soil moisture prediction, Neural Comput. Appl. 36 (2024) 1761–1772, https://doi.org/10.1007/s00521-023-09168-7.

[39] R.K. Kasera, T. Acharjee, A comprehensive iot edge based smart irrigation system for tomato cultivation, Int. Things 28 (2024) 101356, https://doi.org/10.1016/j.iot.2024.101356, https://www.sciencedirect.com/science/article/pii/S254266052400297X.

[40] B. Kashyap, R. Kumar, Sensing methodologies in agriculture for soil moisture and nutrient monitoring, IEEE Access 9 (2021) 14095–14121, https://doi.org/10.1109/ACCESS.2021.3052478.

[41] A. Khanna, S. Kaur, Evaluation of soil moisture for estimation of irrigation pattern by using machine learning methods, in: M. Singh, V. Tyagi, P.K. Gupta, J. Flusser, T. Ören, V.R. Sonawane (Eds.), Advances in Computing and Data Sciences, Springer International Publishing, Cham, 2021, pp. 343–352.

[42] B. Kitchenham, S. Charters, Guidelines for performing Systematic Literature Reviews in Software Engineering, Technical Report EBSE 2007-001, Keele University and Durham University Joint Report, 2007, http://www.dur.ac.uk/ebse/resources/Systematic-reviews-5-8.pdf.

[43] B.A.T. Koné, B. Bouaziz, R. Grati, K. Boukadi, Boruta-attlstm: a novel deep learning architecture for soil moisture prediction, in: A. Bennour, A. Bouridane, L. Chaari (Eds.), Intelligent Systems and Pattern Recognition, Springer Nature, Switzerland, Cham, 2024, pp. 234–246.

[44] B.A.T. Koné, R. Grati, B. Bouaziz, K. Boukadi, A new long short-term memory based approach for soil moisture prediction, J. Ambient Intell. Smart Environ. (2023) 1–14, https://doi.org/10.3233/AIS-230035.

[45] C. Kucuk, D. Birant, P. Yildirim Taser, An intelligent multi-output regression model for soil moisture prediction, in: C. Kahraman, S. Cebi, S. Cevik Onar, B. Oztaysi, A.C. Tolga, I.U. Sari (Eds.), Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation, Springer International Publishing, Cham, 2022, pp. 474–481.

[46] S.K. Lenka, A.G. Mohapatra, Gradient descent with momentum based neural network pattern classification for the prediction of soil moisture content in precision agriculture, in: 2015 IEEE International Symposium on Nanoelectronic and Information Systems, 2015, pp. 63–66.

[47] L. Li, Y. Dai, Z. Wei, W. Shangguan, N. Wei, Y. Zhang, Q. Li, X.X. Li, Enhancing deep learning soil moisture forecasting models by integrating physics-based models, Adv. Atmos. Sci. (2024), https://doi.org/10.1007/s00376-023-3181-8.

[48] Q. Li, Z. Li, W. Shangguan, X. Wang, L. Li, F. Yu, Improving soil moisture prediction using a novel encoder-decoder model with residual learning, Comput. Electron. Agric. 195 (2022) 106816, https://doi.org/10.1016/j.compag.2022.106816, https://www.sciencedirect.com/science/article/pii/S0168169922001338.

[49] X. Li, J. Tang, C. Yin, Sequence-to-sequence learning for prediction of soil temperature and moisture, IEEE Geosci. Remote Sens. Lett. 19 (2022) 1–5, https://doi.org/10.1109/LGRS.2022.3141072.

[50] H. Liu, Y. Yang, X. Wan, J. Cui, F. Zhang, T. Cai, Prediction of soil moisture and temperature based on deep learning, in: 2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), 2021, pp. 46–51.

[51] M. Liu, C. Huang, L. Wang, Y. Zhang, X. Luo, Short-term soil moisture forecasting via Gaussian process regression with sample selection, Water 12 (2020), https://doi.org/10.3390/w12113085, https://www.mdpi.com/2073-4441/12/11/3085.

[52] Y. Liu, L. Mei, S.K. Ooi, Prediction of soil moisture based on extreme learning machine for an apple orchard, in: 2014 IEEE 3rd International Conference on Cloud Computing and Intelligence Systems, 2014, pp. 400–404.

[53] Y. Liu, Y. Yang, X. Yue, Evaluation of satellite-based soil moisture products over four different continental in-situ measurements, Remote Sens. 10, https://doi.org/10.3390/rs10071161, 2018, https://www.mdpi.com/2072-4292/10/7/1161.

[54] P. Majumdar, D. Bhattacharya, S. Mitra, Prediction of evapotranspiration and soil moisture in different rice growth stages through improved salp swarm based feature optimization and ensembled machine learning algorithm, Theor. Appl. Climatol. 153 (2023) 649–673, https://doi.org/10.1007/s00704-023-04414-3.

[55] O. Matei, T. Rusu, A. Petrovan, G. Mihuţ, A data mining system for real time soil moisture prediction, in: 10th International Conference Interdisciplinarity in Engineering, INTER-ENG 2016, 6–7 October 2016, Tirgu Mures, Romania, in: Procedia Engineering, vol. 181, 2017, pp. 837–844, https://www.sciencedirect.com/science/article/pii/S1877705817310603.

[56] G.E. Nagashree, M.K. Nema, Comparative assessment of different machine learning models to estimate daily soil moisture, in: P.V. Timbadiya, P.L. Patel, V.P. Singh, A.B. Mirajkar (Eds.), Geospatial and Soft Computing Techniques, Springer Nature Singapore, Singapore, 2023, pp. 545–558.

[57] H. Nie, L. Yang, X. Li, L. Ren, J. Xu, Y. Feng, Spatial prediction of soil moisture content in winter wheat based on machine learning model, in: 2018 26th International Conference on Geoinformatics, 2018, pp. 1–6.

[58] R. Orth, Global soil moisture data derived through machine learning trained with in-situ measurements, Sci. Data 8 (2021) 170, https://doi.org/10.1038/s41597-021-00964-1.

[59] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J.M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting, D. Moher, The prisma 2020 statement: an updated guideline for reporting systematic reviews, Syst. Rev. 10 (2021) 89, https://doi.org/10.1186/s13643-021-01626-4.

[60] S.H. Park, B.Y. Lee, M.J. Kim, W. Sang, M.C. Seo, J.K. Baek, J.E. Yang, C. Mo, Development of a soil moisture prediction model based on recurrent neural network long short-term memory (rnn-lstm) in soybean cultivation, Sensors 23 (2023), https://doi.org/10.3390/s23041976, https://www.mdpi.com/1424-8220/23/4/1976.

[61] S.J. Patil, B. Ankayarkanni, Analysis and survey of soil moisture prediction techniques for agricultural applications, in: L. Garg, D.S. Sisodia, N. Kesswani, J.G. Vella, I. Brigui, P. Xuereb, S. Misra, D. Singh (Eds.), Information Systems and Management Science, Springer International Publishing, Cham, 2023, pp. 225–241.

[62] S. Paul, S. Singh, Soil moisture prediction using machine learning techniques, in: Proceedings of the 2020 3rd International Conference on Computational Intelligence and Intelligent Systems, Association for Computing Machinery, New York, NY, USA, 2021, pp. 1–7.

[63] S. Prakash, S.S. Sahu, Soil moisture prediction using shallow neural network, Int. J. Adv. Res. Eng. Technol. 11 (2020), https://ssrn.com/abstract=3656915.

[64] S. Prakash, A. Sharma, S.S. Sahu, Soil moisture prediction using machine learning, in: 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), 2018, pp. 1–6.

[65] L. Qiao, Z. Zuo, D. Xiao, L. Bu, Detection, attribution, and future response of global soil moisture in summer, Front. Earth Sci. 9 (2021) 745185, https://doi.org/10.3389/feart.2021.745185.

[66] N. Rajathi, L.S. Jayashree, Soil moisture forecasting using ensembles of classifiers, in: S.C. Satapathy, S. Das (Eds.), Proceedings of First International Conference on Information and Communication Technology for Intelligent Systems, vol. 1, Springer International Publishing, Cham, 2016, pp. 235–244.

[67] J. Ronghua, Z. Shulei, Z. Lihua, L. Qiuxia, I.A. Saeed, Prediction of soil moisture with complex-valued neural network, in: 2017 29th Chinese Control and Decision Conference (CCDC), 2017, pp. 1231–1236.

[68] M.K. Saggi, S. Jain, A survey towards decision support system on smart irrigation scheduling using machine learning approaches, Arch. Comput. Methods Eng. 29 (2022) 4455–4478, https://doi.org/10.1007/s11831-022-09746-3.

[69] R. Sehler, J. Li, J. Reager, H. Ye, Investigating relationship between soil moisture and precipitation globally using remote sensing observations, J. Contemp. Water Res. Educ. 168 (2019) 106–118, https://doi.org/10.1111/j.1936-704X.2019.03324.x.

[70] Y.T. Shan, Z.K. Zheng, Machine learning regression to predict soil moisture in domestic garden environments, in: 2023 14th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT), 2023, pp. 111–116.

[71] H. Shulin, L. Yong, S. Haiyang, Z. Kaiwen, Z. Yandi, Prediction of soil moisture content based on improved bp neural network, in: 2021 2nd International Conference on Artificial Intelligence and Information Systems, Association for Computing Machinery, New York, NY, USA, 2021.

[72] G. Singh, D. Sharma, A. Goap, S. Sehgal, A.K. Shukla, S. Kumar, Machine learning based soil moisture prediction for Internet of things based smart irrigation system, in: 2019 5th International Conference on Signal Processing, Computing and Control (ISPCC), 2019, pp. 175–180.

[73] S. Singh, S. Kaur, P. Kumar, Forecasting soil moisture based on evaluation of time series analysis, in: S.N. Singh, R.K. Pandey, B.K. Panigrahi, D.P. Kothari (Eds.), Advances in Power and Control Engineering, Springer Singapore, Singapore, 2020, pp. 145–156.

[74] J.P. Soininen, K. Kolehmainen, H. Tanner, J. Golnabi, R.A. Sales Dantas, G. Souza, Irrigation water saving estimation using soil moisture forecast simulation, in: 2021 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), 2021, pp. 300–304.

[75] J.C. Songara, J.N. Patel, Calibration and comparison of various sensors for soil moisture measurement, Measurement 197 (2022) 111301, https://doi.org/10.1016/j.measurement.2022.111301, https://www.sciencedirect.com/science/article/pii/S0263224122005425.

[76] M. Sportelli, L. Bonzi, G. Brunori, F. Hamouda, A. Puig-Sirera, S. Marasco, G. Rallo, Current state of irrigation decision support systems (idss) in Italy: critical insights, in: 2023 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), 2023, pp. 131–136.

[77] K. Tandon, S. Sen, K. Kasiviswanathan, B. Soundharajan, N.R. Tummuru, A. Das, Integration of machine learning and particle filter approaches for forecasting soil moisture, Stoch. Environ. Res. Risk Assess. 36 (2022) 4235–4253, https://doi.org/10.1007/s00477-022-02258-3.

[78] C. Thakur, M. Aadhityaa, S. Vijayalakshmanan, K.S. Kasiviswanathan, B. Soundharajan, S. Sen, N.R. Tummuru, Forecasting of soil moisture: an ann model integrated with empirical mode decomposition, in: Z.A. Ergüler, R. Hadji, H.I. Chaminé, J. Rodrigo-Comino, A. Kallel, B. Merkel, M. Eshagh, H. Chenchouni, S. Grab, M. Karakus, S. Khomsi, J. Knight, M. Bezzeghoud, M. Barbieri, S. Panda, A.C. Benim, H. El-Askary (Eds.), Selected Studies in Geotechnics, Geo-Informatics and Remote Sensing, Springer Nature, Switzerland, Cham, 2023, pp. 137–139.

[79] R. Togneri, D. Felipe dos Santos, G. Camponogara, H. Nagano, G. Custódio, R. Prati, S. Fernandes, C. Kamienski, Soil moisture forecast for smart irrigation: the primetime for machine learning, Expert Syst. Appl. 207 (2022) 117653, https://doi.org/10.1016/j.eswa.2022.117653, https://www.sciencedirect.com/science/article/pii/S0957417422009563.

[80] A. Trivedi, N. Nandeha, Y. Rajwade, K.V. Rao, Sens. Soil Moist. Meas. (2023).

[81] G. Wang, Y. Han, J. Chang, Research on soil moisture content combination prediction model based on arima and bp neural networks, Adv. Control Appl., Eng. Ind. Syst. (2023) e139, https://doi.org/10.1002/adc2.139.

[82] W. Wang, Y. Cui, Y. Luo, Z. Li, J. Tan, Web-based decision support system for canal irrigation management, Comput. Electron. Agric. 161 (2019) 312–321, https://doi.org/10.1016/j.compag.2017.11.018, https://www.sciencedirect.com/science/article/pii/S0168169917310931, bigData and DSS in Agriculture.

[83] G. Yan, Z.H. Jiao, T. Wang, X. Mu, Modeling surface longwave radiation over high-relief terrain, Remote Sens. Environ. 237 (2020) 111556, https://doi.org/10.1016/j.rse.2019.111556, https://www.sciencedirect.com/science/article/pii/S0034425719305760.

[84] P. Yao, H. Lu, J. Shi, T. Zhao, K. Yang, M.H. Cosh, D.J.S. Gianotti, D. Entekhabi, A long term global daily soil moisture dataset derived from amsr-e and amsr2 (2002–2019), Sci. Data 8 (2021) 143, https://doi.org/10.1038/s41597-021-00925-8.

[85] D. Yin, Y. Wang, Y. Huang, Predicting soil moisture content of tea plantation using support vector machine optimized by arithmetic optimization algorithm, J. Algorithms Comput. Technol. 17 (2023) 17483026221151198, https://doi.org/10.1177/17483026221151198.

[86] L. Yu, W. Gao, R. R Shamshiri, S. Tao, Y. Ren, Y. Zhang, G. Su, Review of research progress on soil moisture sensor technology, https://doi.org/10.34657/10037, 2021.

[87] Z. Zhang, W. Jiang, N. Xu, New approach for soil moisture prediction based on multiple influencing factors, in: R. Kountchev, S. Patnaik, W. Wang, R. Kountcheva (Eds.), Multidimensional Signals, Augmented Reality and Information Technologies, Springer Nature Singapore, Singapore, 2024, pp. 31–48.

[88] H. Zhao, L. Di, L. Guo, C. Zhang, L. Lin, An automated data-driven irrigation scheduling approach using model simulated soil moisture and evapotranspiration, Sustainability 15 (2023), https://doi.org/10.3390/su151712908, https://www.mdpi.com/2071-1050/15/17/12908.

[89] T. Zhou, Y. He, L. Luo, S. Ji, Research on soil moisture prediction based on lstm-transformer model, in: L. Pan, D. Zhao, L. Li, J. Lin (Eds.), Bio-Inspired Computing: Theories and Applications, Springer Nature Singapore, Singapore, 2023, pp. 329–342.