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Original Article

Multi-Relational Decker Duck Swarm Graph Convolutional Attention Network for Short-Term Soil Moisture Variations and Crop Yield Prediction

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Abstract - *Precise soil moisture forecasting is essential in precision agriculture, allowing for effective management of water resources and estimation of crop yields. Soil moisture changes are driven by complex environmental conditions, necessitating strong predictive models to handle subtle dependencies. In this research, a Multi-Relational Decker Duck Swarm Graph Convolutional Attention Network (MDR-2DSG-CAN) is introduced for short-term soil moisture forecasting and crop yield estimation. The Soil Moisture Monitoring Dataset, which has 5,000 hourly samples from January 1, 2025, is used to evaluate the model. The methods include Cumulative Curve Fitting Approximation (CCFA) for pre-processing, Adaptive Causal Decision Transformers for feature extraction, and MDR-2DSG-CAN for prediction. MDR-2DSG-CAN is a new method that couples a Double Decker Convolutional Neural Network (DDCNN) with a Multi-Relational Graph Attention Network (MR-GAT), and its parameters are optimized via the Duck Swarm Algorithm (DSA). This composite framework improves the ability to simulate spatiotemporal correlations and intricate variable interactions influencing soil moisture processes. Large-scale experiments illustrate that MDR-2DSG-CAN attains 99.9% accuracy, surpassing traditional machine learning and deep learning approaches. The prediction of soil moisture involves understanding the properties of the soil, and an efficient optimization technique based on the Duck Swarm Algorithm improves generalizability and stability.*

Keywords - *Soil moisture forecasting, Crop yield estimation, Multi-relational graph attention network, Double Decker Convolutional Neural Network, Duck Swarm Algorithm, Time-series prediction, Precision agriculture.*

1. Introduction

Agriculture is greatly impacted by droughts, especially in developed nations, and predicting them is a difficult task for environmental and water resources engineers. The necessity to continuously analyze various system components contrasts with the chaotic nature of weather patterns and the time required to take action [1, 2]. The most destructive droughts develop swiftly, giving stakeholders little time to take preventative action. A 2012 drought in the Midwest of the United States quickly reduced soil moisture, resulting in severe drought in just two months [3, 4]. Current drought forecasting tools may only be updated once a month and frequently concentrate on a seasonal basis. Climate, vegetation, and soil processes all have an impact on fluctuations in soil moisture, which is essential for regulating ecosystem dryness and validating drought memory. A sensitive indicator that measures agricultural drought conditions across long-term soil moisture data is the Soil Moisture Anomaly Percentage Index (SMAPI) [5, 6]. However, a lack of observations has made it difficult to anticipate soil moisture. Researchers have expressed interest in using data-driven approaches to directly extract information from extensive observational data and discover intricate patterns as a result of the growth in ground stations and earth observation data [7, 8]. Multidisciplinary models are made possible by data-driven methodologies, like Deep Learning (DL) techniques derived from Artificial Neural Networks (ANN), which have demonstrated remarkable success in handling nonlinear situations.

Compared to solo DL models, hybrid DL models, which integrate CNN with other solo models, generally exhibit more consistent and effective performance [9, 10]. LSTM, Support Vector Machine (SVM), Random Forest, Artificial Neural Network, Extreme Learning Machine (ELM), and others are frequently used in solo forecasting frameworks. When individual members are decorrelated and have little prejudice, committee machines are suggested as a low-cost parallelism solution [11, 12]. Data decomposition has become an excellent pre-processing tool to extract trends and harmonics from non-stationary time data. A promising method for breaking down the Ensemble Empirical Mode Decomposition (EEMD) time series data, which, when paired with committee models, can greatly increase the accuracy of forecasts pertaining to soil moisture [13]. However, current forecasting models are limited in their ability to generalize to a variety of locations and larger basin scales because they primarily function at the point scale. Crop root growth and nutrient absorption are impacted by soil moisture, a critical hydrological variable. With accurate measurement and predictive modeling offering insights, predicting moisture status enhances agricultural water management and logistics [14, 15]. Soil moisture plays a crucial impact in agricultural productivity, influencing crop growth, water management, and yield prediction. However, its variations are highly complex, driven by multiple interdependent factors such as temperature, humidity, rainfall, wind speed, soil type, and vegetation index. Traditional forecasting models struggle to capture these intricate relationships, leading to inaccurate predictions that hinder effective decision-making in precision agriculture. To address this challenge, a robust and intelligent model is required to analyze multi-relational dependencies and optimize predictive accuracy. To overcome these issues, this work is motivated.

1.1. Novelty and Contribution

The Novelty and contribution of this paper are given below:

- Proposed MDR-2DSG-CAN Model – Introduces a novel Multi-Relational Decker Duck Swarm Graph Convolutional Attention Network (MDR-2DSG-CAN) for accurate short-term soil moisture variation prediction and crop yield forecasting.
- Preprocessing with Cumulative Curve Fitting Approximation (CCFA) – Applies an advanced smoothing technique to reduce noise and improve data quality for enhanced model performance.
- Feature Extraction via Adaptive Causal Decision Transformers – Leverages a transformer-based approach to analyze causal relationships between soil moisture factors.
- Integration of Double Decker CNN (DDCNN) – Incorporates a hierarchical convolutional structure to enhance spatial feature extraction from soil moisture data.
- Multi-Relational Graph Attention Network (MR-GAT) – Utilizes graph-based learning to capture complex dependencies between environmental variables, improving predictive robustness.
- Optimization Using Duck Swarm Algorithm (DSA) – Implements a bio-inspired optimization technique to fine-tune network parameters, enhancing convergence speed and accuracy.
- Real-World Application – Provides a scalable and data-driven solution for precision agriculture, aiding in irrigation planning and maximizing crop yield efficiency. The remainder of this manuscript is organized as Section 2: Literature Review, Section 3: Proposed Methodologies, Section 4: Results and Discussion, Conclusion of Section 5, and Upcoming Projects.

2. Literature Survey

The papers related to accurately forecasting short-term soil moisture variations, aiming to improve crop yield predictions using neural network methods, are given below:
In 2024 Wang, X., et a1. [16] has introduced an K-parallel Recurrent Neural Networks (KRNN) for accurately forecast short-term soil moisture variations, aiming to improve crop yield predictions using neural network methods. In order to improve agricultural productivity and irrigation management, the study shows how deep-learning models combined with soil moisture memory analysis can improve drought predictions in the Huai River basin.

In 2024, Basir, M.S., et al [17] presented a Temporal Convolutional Network (TCN) for precisely predicting short-term soil moisture changes in an effort to enhance crop yield estimation with neural network approaches. Data-driven alternatives to traditional statistical models for subsurface soil moisture prediction are presented in the VAR and LSTM statistical forecast models, developed using past weather data and also Fort Wayne, Indiana data.

In 2024, Han, J., et al. [18] introduced Long Short-Term Memory (LSTM) models for accurately forecasting short-term soil moisture variations, aiming to improve crop yield predictions using neural network methods. A novel method for predicting soil moisture, the CAEDLSTM model, performs better in harsh weather. It demonstrated a 5.01% gain in R2, a 12.89% reduction in RMSE, a 16.67% drop in bias, and a 4.35% rise in KGE when validated on the LandBench1.0 dataset.

In 2023, Park, S.H., et al. [19] introduced a Recurrent Neural Network Long Short-Term Memory (RNN-LSTM) Model for accurately forecasting short-term soil moisture variations, aiming to improve crop yield predictions using neural network methods. Crop growth may be impacted by increased soil moisture and outflows brought by climate change. Utilizing temperature and humidity sensors to measure, the future model of soil moisture will prove predictability in arable land for soybeans and enable the adequate use of irrigation.

In 2023, Huang, Y., et al. [20] proposed a Support-Vector-Machine (SVM) to precisely predict short-term soil moisture changes to enhance the prediction of crop yields with the help of neural network techniques. To enhance the prediction of soil moisture in tea gardens, a new SVM-based model has been developed. The model provides accurate predictions with the help of the Bald Eagle Search algorithm for hyperparameter tuning. This assists farmers in controlling their water supply and planning irrigation, raising crop yields.
In 2023, Guo, D., et al. [21] presented a Seasonally Coherent Calibration (SCC) Model for properly predicting short-term soil moisture dynamics to enhance the prediction of crop yields employing neural network approaches. To analyze the

risks of over- and under-irrigation, the research employs the APSIM crop model and short-term rain forecasting to give a framework of uncertainty-based for assessment of irrigation planning decisions in South Australia.

In 2023, Sangha, L., et al [22] presented an Irrigation Management Method (IMM) to predict correctly short-term soil moisture changes with the purpose of enhancing crop yield predictions through neural network approaches.

Using short-term weather forecasts, crop physiological condition, water requirements, and real-time soil water availability, the study created an irrigation management system. It was studied in Suffolk, Virginia, under four nitrogen application treatments, affecting corn and cotton output, NUE, WUE, and financial returns. Table 1 presents an overview of the technique under study.

Table 1. A summary of the approach being assessed

References	Methods	Advantages	Disadvantages
Wang, X., et a1. [16]	KPRNN	Excellent memory analysis for drought prediction; high forecasting accuracy for soil moisture.	High computational expense; training requires vast datasets.
Basir, M.S., et a1. [17]	TCN	Offers a data-based substitute for statistical models. Makes use of LSTM and VAR to improve prediction.	Depending on the availability of historical weather data in areas with inadequate historical records, performance may deteriorate.
Han, J., et a1. [18]	LSTM	Performs better in severe weather than traditional LSTM. Shows gains in bias (-16.67%), RMSE (-12.89%), R2 (+5.01%), and KGE (+4.35%).	Computationally demanding because of the intricacy of deep learning, hyperparameters must be adjusted.
Park, S.H., et a1. [19]	RNN-LSTM	High predictability in arable land used for soybeans. Accurate forecasting is achieved by using real-time data from sensors.	It might not translate well to other kinds of soil. Requires ongoing maintenance and calibration of the sensor.
Huang, Y., et a1. [20]	SVM	Enhances the prediction of soil moisture in tea plantations by using Bald Eagle Search optimization for hyperparameter tuning.	Sensitive to the choice of parameters. Performance with highly nonlinear datasets is limited.
Guo, D., et a1. [21]	SCC	Assess irrigation hazards using the APSIM crop model. In short-term rainfall forecasting, uncertainty is taken into account.	Has limited relevance outside of Southern Australia and necessitates interaction with foreign crop models.
Sangha, L., et a1. [22]	IMM	Utilizes crop requirements and soil water availability in real time. Analyzes water-use efficiency and financial returns.	Site-specific; it could need to be rearranged for various geographical areas. Extremely reliant on precise weather predictions.

2.1. Problem Statement

Soil moisture plays a critical role in agricultural productivity, influencing crop growth, water management, and yield prediction. However, its variations are highly complex, driven by multiple interdependent factors such as temperature, humidity, rainfall, wind speed, soil type, and vegetation index.

Traditional forecasting models struggle to capture these intricate relationships, leading to inaccurate predictions that hinder effective decision-making in precision agriculture. To solve this problem, a strong and smart model needs to examine multi-relational dependencies and maximize predictive accuracy. To address these problems, this work is suggested.

3. Proposed Methodology

In this section, a Multi-Relational Decker Duck Swarm Graph Convolutional Attention Network (MDR-2DSG-CAN) for short-term soil moisture forecasting and crop yield estimation. Figure 1 is the workflow diagram depicting MDR-2DSG-CAN. The Soil Moisture Monitoring Dataset with 5,000 hourly records from January 1, 2025, is used for model assessment. The approach is Cumulative Curve Fitting Approximation (CCFA) for pre-processing, Adaptive Causal Decision Transformers for feature extraction, and MDR-2DSG-CAN for prediction. MDR-2DSG-CAN is a new method that combines a Double Decker Convolutional Neural Network (DDCNN) with a Multi-Relational Graph Attention Network (MR-GAT), and its parameters are optimized by the

Duck Swarm Algorithm (DSA). This is a hybrid framework that increases the ability to model spatiotemporal correlations and intricate variable relations that influence soil moisture dynamics. Estimation of soil moisture needs information about the properties of the soil and an optimization mechanism with robustness based on the Duck Swarm Algorithm increases stability and generalization.

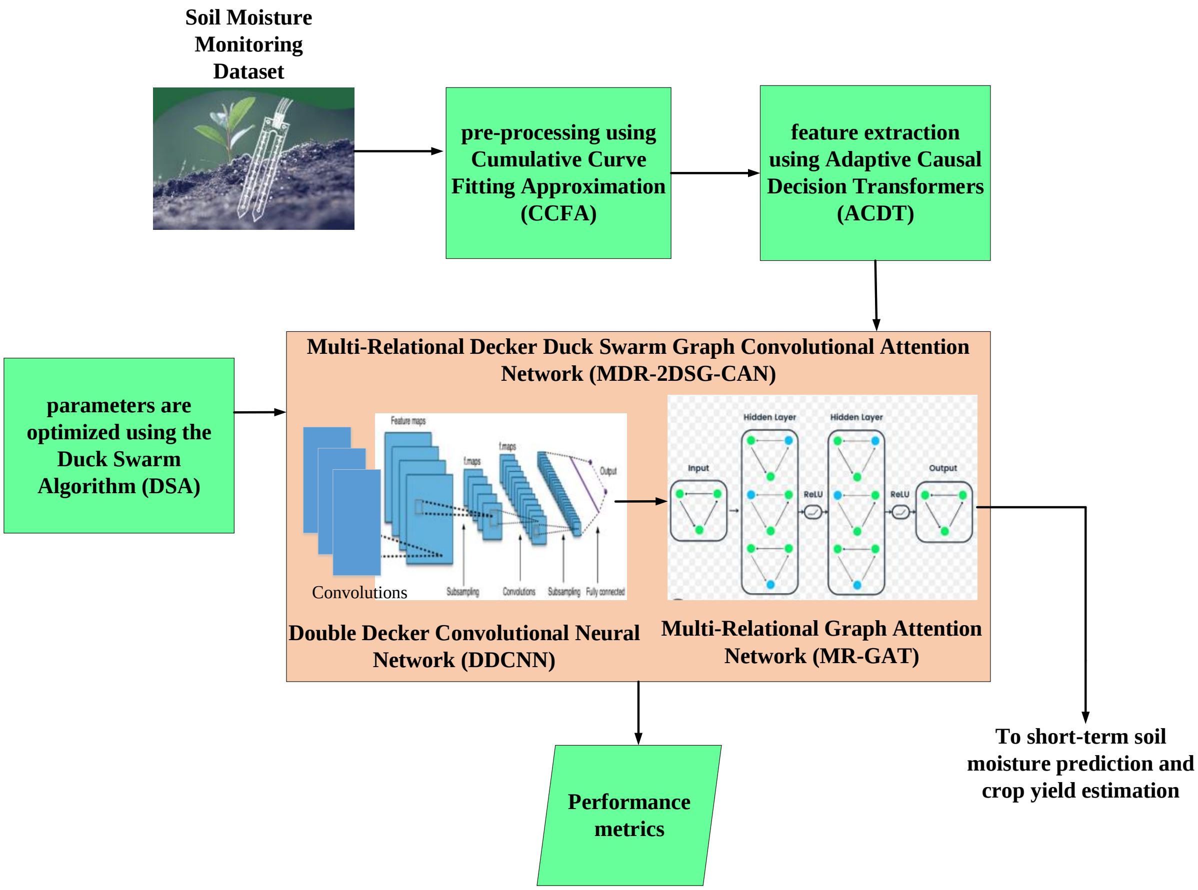

Fig. 1 Workflow diagram of ID2H-Qua2G-2SC2AN

3.1. Data Acquisition

The input dataset is sourced from the named Soil Moisture Monitoring Dataset contains 5,000 hourly records from January 1, 2025. The seven most important environmental parameters driving soil moisture levels are included. The dataset measures temperature (°C), humidity (%), rainfall (mm), wind speed (m/s), soil type (categorical), vegetation index (NDVI), and soil moisture (derived value). The dataset is stored in the form “soil_moisture_data.csv” consisting of structured data useful for agriculture and environmental research. Then the data are provided to the Cumulative Curve Fitting Approximation (CCFA) to clean the input data, and their explanations are discussed below.

3.2. Pre-Processing Using Cumulative Curve Fitting Approximation (CCFA)

The Soil Moisture Monitoring Dataset has 5,000 hourly samples from January 1, 2025, recorded for modeling short-term fluctuations in soil moisture and crop yields. The data contain changing levels of moisture subject to environmental factors like temperature, humidity, type of soil, and rainfall.

Due to the non-stationary and non-linear character of fluctuations in soil moisture, there is a strong need for proper pre-processing for noise elimination, smoothing out oscillations, and improving predictive modeling accuracy. To do this, the Cumulative Curve Fitting Approximation (CCFA) [23] method is used.

3.2.1. Cumulative Curve Fitting Approximation (CCFA) Methodology

CCFA is a window-based smoothing that simulates the behavior of the signal in a moving window. Weighted reasoning is applied to merge estimated curves within overlapping windows in an effort to produce a smooth and noise-reduced signal. This strategy filters out random fluctuations and preserves important patterns of moisture.

CCFA can be carried out in Open-Loop or Closed-Loop procedures:

- Open-Loop CCFA reconstructs the output signal solely based on the approximated patterns of the original dataset.
- At each stage, the closed-loop CCFA iteratively corrects the starting signal, updating it before proceeding further. For soil moisture prediction, because it is smoother, the Open-Loop Weighted Approximation is used, and robustness against sensor noise.

3.2.2. Mathematical Formulation of CCFA

Let $\left(sig(k)\right)$represent the initial soil moisture signal, and $sig_0(k)$be the reconstructed signal after applying CCFA. The reconstructed signal is computed as Equation (1):

$$sig(k) = \frac{sig_0(k)}{2^{m_{ord}}} + \frac{W_{k-m_{ord}+1}(m_{ord}-1)}{2^{m_{ord}}} + \frac{W_{k-m_{ord}+2}(m_{ord}-2)}{2^{m_{ord}-1}} + \ldots + \frac{W_k(0)}{2^1} \quad (1)$$

Where $sig_0(k)$is the initial soil moisture data, and $sig(k)$ is the reconstructed and smoothed soil moisture data. The parameterm_{ord}defines the CCFA algorithm's order, window size, and procedure window size, $m = 1,2,\ldots,K$represents the data sample's index that is being updated and $W_p(i)$is the fitting function of polynomial curves for windowsm_{ord} (i.e.$[o - m_{ord} + 1, o - m_{ord} + 2, \ldots, o]$). For this work, however, we apply weightsp_i, where$i = 0,\ldots,m_{ord} - 1$.

To further refine the reconstruction, predefined weighting coefficients w_j are assigned to the fitted values as follows in Equation (2-3):

$$sig(k) = \frac{W_{k-m_{ord}+1}(m_{ord}-1)}{2^{m_{ord}}} \bullet p_1 + \frac{W_{k-m_{ord}+2}(m_{ord}-2)}{2^{m_{ord}-1}} \bullet p_2 + \ldots + \frac{W_k(0)}{2^1} \bullet p_{m_{ord}} \quad (2)$$

$$r_1 = \frac{2^{l_{ord}}}{l_{ord}}, o_1 = \frac{2^{m_{ord}-1}}{m_{ord}}, \ldots . r_{m_{ord}} = \frac{2}{m_{ord}} \quad (3)$$

Where $\frac{sig_0(k)}{2^{m_{ord}}}$ represents the assigned weight for each polynomial function. The weights are adjusted dynamically to improve the trend approximation and ensure minimal information loss.

3.2.3. Padding and Edge Treatment in CCFA

CCFA requires padding to prevent information loss at the edges of the signal. The choice of padding significantly affects the accuracy of the reconstructed soil moisture curve. In this study, a weighted trend padding approach is applied to maintain continuity and prevent border artifacts.

The padding is performed as follows:

- Extrapolate the edge gradient using a weighted least-square fit.
- Extend the fitted line based on the gradient direction.
- Assign inverse-distance weights to ensure a smooth transition between the original and padded values.

Denoting the padded soil moisture data as$sig(k)$the final long-wave pattern of the filtered signal is derived as Equation (4):

$$sig(k) = \frac{W_{k-m_{ord}+1}(m_{ord}-1) + W_{k-m_{ord}+2}(m_{ord}-2) + W_k(0)}{m_{ord}} \quad (4)$$

The long wave pattern, often known as the smoothed signal,$sig_1(k)$ is obtained by using CCFA on $\overleftrightarrow{sig_0}(k)$ and modifying the outcome as follows as Equation (5):

$$sig_1(k) = si\overleftrightarrow{g}(k + m_{ord}) \quad (5)$$

Where $n = 1,2,\ldots,N$. The data's high-frequency patterns, or short wave patterns, can be obtained from Equation (6):

Denoising

$$sig_{t0}(k) = D_c(k) - sig_{k0}(k) \quad (6)$$

Where $sig_{k0}(k)$ is the Padded soil moisture data, $sig_{t0}(k)$ is the Smoothed signal after applying CCFA, $D_c(k)$ and is the denoised soil moisture data.

CCFA improves soil moisture prediction accuracy by effectively handling nonlinear data, reducing noise, and ensuring seamless edge handling through trend-based padding techniques.

By integrating CCFA as a pre-processing step, soil moisture prediction models achieve superior reliability, providing accurate forecasts for precision agriculture applications.

Then these data are supplied to the feature extraction step for extracting important features, and their explanations are given below.

3.3. Feature Extraction Using Adaptive Causal Decision Transformers for Soil Moisture Variations and Crop Yield Prediction

This subsection introduces an Adaptive Causal Decision Transformer (ACDT) [24] -based system to derive useful features from pre-processed soil moisture data. The aim of the system is to learn short-term variations in soil moisture and how they affect crop yield using Reinforcement Learning (RL)-based sequence modeling. The method allows proper modeling of temporal relationships in variations in soil moisture and forecasting of their effect on crop yield in the future.

Soil moisture fluctuation is dynamic and driven by various environmental conditions. For modeling this, a

Partially Observable Markov Decision Process (POMDP) is the problem definition given in Equation (7):

$$N = (P, B, Q, W, \delta, S) \tag{7}$$

Where at each time step $s \in \{1, \ldots, S\}$, an agent observes $p_s \in P$ represents the observation space, consisting of recorded soil moisture levels, $b_s \in B$ represents the action space, including external influences such as irrigation and rainfall, Q represents the transition probability function, governing the evolution of soil moisture levels over time based on past observations and external actions, W represents the reward function, quantifying the impact of soil moisture levels on crop yield, δ is the discount factor $\delta \in [0,1]$, representing the importance of future rewards, S represents the time horizon, which in this dataset includes 5,000 hourly records starting from January 1, 2025.

At each time step s, an observation $p1$ (soil moisture level) is recorded, an action b_s (irrigation/rainfall) is taken based on past history, and a reward w_s (crop yield impact) is received.

To extract meaningful features from the soil moisture dataset, a Causal Decision Transformer (CDT) is utilized, treating observations, actions, and rewards as sequential input tokens. The transformer model learns to approximate the optimal soil moisture management strategy by predicting the soil moisture given in Equation (8):

$$Q(b_s | p_{1:s}, b_{1:s-1}, w_{1:s-1}) \tag{8}$$

The objective is to predict the optimal action $Q(b_s | p_{1:s}, b_{1:s-1}, w_{1:s-1})$ using a Transformer-based model. 1.

3.3.1. Latent State Representation and Feature Extraction

To accurately model soil moisture dynamics, latent states are introduced and denoted as Equation (9):

$$h_s = \left(h_{1,s}, \ldots, h_{c,s}\right)^T, \tag{9}$$

Where d represents the number of latent variables corresponding to different environmental factors influencing soil moisture variations, is given in Equation (10):

$$g_{j,s} = e_j\left(d_j^{h\to h} \Theta h_{s-1}, d_j^{b}.\, b_{s-1}, d_j^{w}.\, w_{s-1}, \in_{j,s}^{h}\right), for j = 1, \ldots c \tag{10}$$

Where Θ represents element-wise multiplication, $d_j^{h\to h}$, $d_j^{b}.\, b_{s-1}$, w_{s-1} are causal relationship masks, determining the influence of past soil moisture levels, external actions, and reward signals on current soil conditions, $\in_{j,s}^{h}$ and is an independent noise term accounting for unmodeled variations in soil moisture.

The observed soil moisture Ps is derived from the latent states, as given in Equation (11):

$$p_s = h\left(d^{h\to p} \Theta h_s, \in_s^p\right) \tag{11}$$

Similarly, the reward function w_s quantifying crop yield impact is formulated as Equation (12):

$$w_s = g\left(d_w^{h\to w} \Theta h_{s-1}, d^{b\to w}.\, b_{s-1}, \in_s^w\right) \tag{12}$$

Where $\in_j^h$, $\in_s^p$, $\in_s^w$ are independent noise terms. The terms $d^{\cdot\to\cdot}$ are binary masks indicating causal relationships between variables. The latent states h_{s-1} form a Markov decision process (MDP): given h_s and b_s, the next latent state h_{s-1} is independent of previous states and actions.

The observed signals p_s are generated from the latent states h_s, and rewards are determined by both the latent states and actions.

These equations define how the observed soil moisture levels are generated from the underlying latent dynamics.

The Transformer processes input sequences as follows:

- Positional Encoding: Since soil moisture data is sequential, positional encodings are added to capture temporal dependencies.
- Self-Attention Mechanism: Multi-head self-attention is employed to identify correlations between past observations, actions, and rewards.
- Feed-Forward Network: Extracted features are passed through a dense layer to generate action probabilities and yield impact predictions.

This study converts soil moisture records into a time-series format, defines latent state transitions, extracts features, models soil moisture fluctuations, and outputs predicted trends for data-driven irrigation and crop management.

The extracted features serve as inputs for downstream models used in soil moisture forecasting and crop yield optimization. This ensures a robust prediction pipeline for short-term soil moisture variations and sustainable agricultural practices. Then this data is given to the Multi-Double Relational decker Duck Swarm Graph convolutional Attention network (MDR-2DSG-CAN) for Short-Term Soil Moisture Variations and Crop Yield Prediction accurately, and its explanations are given below:

3.4. MDR-2DSG-CAN for Short-Term Soil Moisture Variations and Crop Yield Prediction Accurately

In this, the Multi-Double Relational decker Duck Swarm Graph convolutional Attention network (MDR-2DSG-CAN) is used for Short-Term Soil Moisture Variations and Crop Yield Prediction accurately.

The MDR-2DSG-CAN is the new approach, and it is the merger of double-decker convolutional neural network (DDCNN) [25] and Multi-Relational Graph Attention Network (MRGAN) [26], and its parameters are optimized via the Duck Swarm Algorithm (DSA) [27], and its reasonings are given below:

3.4.1. Double Decker Convolutional Neural Network (DDCNN) for Short-Term Soil Moisture Variations and Crop Yield Prediction accurately

Double Decker Convolutional Neural Network (DDCNN) architecture is proposed to effectively capture short-term soil moisture fluctuation and forecast its effect on crop yield. The architecture involves two hierarchical CNNs, the first deck conducting primary classification with the identification of faulty samples like sensor faults, extreme oscillations, and missing values. The second deck enhances the extracted features to improve the accuracy of soil moisture forecasting and crop yield prediction.

This method assures that intricate patterns in soil moisture dynamics are correctly represented through the utilization of an intra-class variance score, which measures uncertainty in soil moisture measurement.

Erroneous samples are placed in a distinct dataset, referred to as the Baseline Separated Channel (BSC) dataset, for enhanced model robustness.

Primary Classification Using the First Deck CNN

The first deck CNN, denoted as $(E^{*}h)(s)$, performs initial classification by processing raw soil moisture records. The objective is to detect inconsistencies such as sensor errors, abrupt changes in moisture levels, or missing values that could impact model performance.

The probability of a given soil moisture sample $h(\upsilon)$belonging to a stable or unstable category is determined using an intra-class variance score (υ), which measures the divergence between stable and fluctuating moisture conditions. The intra-class variance score is defined as Equation (13):

$$(E^{*}h)(s) = \int_{-\infty}^{+\infty} E(\upsilon)h(s-\upsilon) \tag{13}$$

Where: E indicates how many soil moisture samples there are in a given observation window, $E(\upsilon)$represents the soil moisture value at the time step s, $h(s-\upsilon)$represents the mean soil moisture value over the window.

A confidence factor (υ) is computed according to the score for intra-class variance. The cut-off threshold $\upsilon$is determined by contrasting the error ratio with its divergence (E^{*}), defined as the proportion of misclassified samples within a given range, as given in equation (14):

$$\frac{m_{en\_g}-e_t+1}{K_t} * \frac{m_{en\_r}-e_t+1}{K_t} * m_{bg} \tag{14}$$

Wherem_{en_g}stands for the input feature map's height; $m_{en_r}$is its width; m_{bg}represents the total number of channels; $e_t$is the filter's size; and $K_t$denotes the stride length. ReLU and SofMax activation layers are used in the architecture.

Feature Refinement Using the Second Deck CNN

The second deck CNN, denoted as $e(X)$processes the cleaned soil moisture data and extracts spatial-temporal features relevant to moisture variability and crop yield prediction, $e(X)$ consists of four convolutional blocks, each incorporating:

- Convolutional layers for feature extraction.
- Batch normalization layers to stabilize learning.
- Max pooling layers to reduce dimensionality while retaining critical patterns.
- Dropout layers to prevent overfitting.

The final output $e(X)$is passed through ReLU and SoftMax activation layers to generate soil moisture and crop yield predictions. The ReLU activation function ensures non-linearity in the model, defined as Equation (15):

$$e(X) = \begin{cases} X, X > 0 \\ 0, X \leq 0 \end{cases} \tag{15}$$

Where X represents the feature map values.

The SoftMax activation function is applied to obtain probability distributions over possible soil moisture classes as given in Equation (16):

$$f^{x}j = \frac{f^{x}j}{\sum_{i=1} f^{x}j} \tag{16}$$

Where: $(x_j \in X)$represents the probability of the j^{th}class, f^{x}represents the feature input for the class j, i and is the total number of soil moisture states (e.g., dry, moderate, wet).

Final soil moisture and crop yield prediction using SoftMax activation and BCE loss. This hierarchical structure effectively improves the robustness of soil moisture forecasting so that trustworthy predictions for crop management plans based on real-time sensor readings can be guaranteed.

Then, to improve the performance of the DDCNN with MRGAN for Short-Term Soil Moisture Fluctuations and Crop Yield Prediction effectively, are as follows:

3.4.2. Multi-Relational Graph Attention Network (MRGAN) for Short-Term Soil Moisture Variations and Crop Yield Prediction Accurately

A critical factor of agricultural productivity is soil moisture, affecting crop growth, water supply, and yield estimation.

Forecasting near-term soil moisture fluctuations involves a profound understanding of numerous environmental variables, such as temperature, precipitation, and soil characteristics.

This paper utilizes the Double Decker Convolutional Neural Network (DDCNN) combined with the Multi-Relational Graph Attention Network (MRGAN) to improve the predictive performance of soil moisture levels and crop yields.

The Soil Moisture Monitoring Dataset has 5,000 hourly observations from January 1, 2025, and includes data on soil temperature, precipitation, vegetation index, evapotranspiration, and soil texture characteristics.

The DDCNN model extracts spatial patterns from soil-related time-series data, while the MRGAN model captures relationships between various environmental factors, ensuring accurate predictions.

Graph-based learning enables effective feature aggregation from different environmental sources. The MRGAN captures spatial correlations between soil moisture, precipitation, and crop yield.

Multi-Relational Graph Construction

A multi-relational graph H is constructed from soil moisture data, where Equation (17):

$$H = \left\{v, \left\{\varepsilon_E, \varepsilon_N, \varepsilon_{QQ}, \varepsilon_{BQ}\right\}\right\} \tag{17}$$

Where: $v$is the set of data points (nodes), $\varepsilon_E$represents edges for soil moisture correlations, ε_N represents edges for precipitation dependencies, ε_{QQ}represents edges for evapotranspiration relationships, ε_{BQ} represents edges for vegetation index influences.

Edges ε_E and $\varepsilon_N$are weighted based on correlation coefficients between soil moisture, precipitation, and yield.

Relation-Specific Influence Encoder

Each node has different neighbours, influencing its representation. The influence of each node iii is computed using attention-based aggregation, which is given in Equation (18):

$$g_j^w = \omega\left(\sum_{i \in M_j^w} \beta_{j,i}^w . y_i\right) \tag{18}$$

Where:$y_i$represents features of the neighboring node i, g_j^w is the learned embedding for relation w, $\omega$is a non-linear activation function, $\beta_{j,i}^w$and is the attention weight assigned to the neighbor j.

The attention weight is computed as Equation (19):

$$\beta_{j,i}^w = \frac{exp\left(Leaky\ Re\ LU\left(\boldsymbol{b}_w^T.[y_j \| y_i]\right)\right)}{\sum_{l \in M_j^w} exp\left(Leaky\ Re\ LU\left(\boldsymbol{b}_w^T.[y_j \| y_m]\right)\right)} \tag{19}$$

Where $b_w \in W^{2c \times 1}$is the influence attention vector for type $w$and $\|$ denotes the concatenate operator. Multi-head attention is applied to ensure stable training is given in Equation (20):

$$g_j^w = \Big\|_{m=1}^{M} \omega\left(\sum_{i \in M_j^w} \beta_{j,i}^w . y_i\right) \tag{20}$$

Where M is the number of attention heads.

Cross-Relation Embedding Aggregation

After relation-specific embeddings are learned, they are fused to form the final node representation is given in Equation (21):

$$\alpha_w = \frac{exp(r_w)}{\sum_{w \in W} exp(r_w)} \tag{21}$$

Where $v$is the set of all soil moisture b_{WB} represents the relation level attention vector, R_{WB} and c_{WB} are learnable parameters, $\alpha_w$is importance for relation$w$to node v_j, and$W = \{E, N, Q, D\}$denotes the set of relations.

The final node embedding is computed as in Equation (22):

We thus fuse relation-specific embedding with a weighted sum to get the final cross-relation embedding$g_j$of node v_j:

$$g_j = \sum_{w \in W} \alpha_w . g_j^w \tag{22}$$

Where $g_j$is the final embedding of the node j.

The DDCNN with MRGAN effectively models spatial-temporal dependencies in soil moisture and predicts crop yield with high accuracy. The multi-relational attention mechanism improves performance by capturing relationships between soil properties, precipitation, and vegetation indices.

By optimizing the weight parameters α of DDCNN-MRGAN with the Duck Swarm Algorithm (DSA), the computing complexity, cost, and error rate are reduced to enhance Short-Term Soil Moisture Variations and Crop Yield Prediction accurately, and explanations thereof are as below:

3.4.3. Duck Swarm Algorithm (DSA) for Optimizing Weight Parameters of DDCNN-MRGAN to Enhance Short-Term Soil Moisture Variations and Crop Yield Prediction Accurately

To improve prediction accuracy in short-term soil moisture variations and crop yield prediction, the Duck Swarm Algorithm (DSA) is utilized to optimize the weight parameters of the Deep Dilated Convolutional Neural Network with Multi-Relational Graph Attention Network (DDCNN-MRGAN). The optimization process decreases computational complexity, cost, and rate of error, resulting in more accurate predictions.

Step 1: Initialization of candidate solutions

The original population of candidate solutions is created, wherein one candidate is a collection of hyperparameters tuned to DDCNN-MRGAN. The optimization space includes:

- Weight Parameters (α): Defines the connection strength between layers in DDCNN-MRGAN.
- Bias Parameters: Adjusts the activation function thresholds to prevent underfitting or overfitting.
- Graph Attention Parameters: Determine the relative importance of different nodes in the soil moisture dataset.
- Learning Rate: Controls the update step size of weight parameters.
  Each candidate solution is randomly initialized within the defined search space to ensure diversity and avoid premature convergence. The evaluation of solutions is based on the following criteria:
- Prediction Accuracy (PA): Measures how well soil moisture levels and crop yield are forecasted.
- Computational Complexity (CC): Assesses resource consumption and processing time.
- Model Robustness (MR): Evaluates the model's resistance to outliers and noise in the dataset.

Step 2: Exploration phase via random perturbation

After initialization, the exploration phase begins. Inspired by the foraging behavior of ducks, the Duck Swarm Algorithm (DSA) uses adaptive exploration to navigate the solution space.

The movement of ducks is guided by an adaptive search strategy, where individuals in the swarm move towards promising areas while maintaining diversity.

Step 3: Fitness function evaluation

Each candidate solution is evaluated using a fitness function to ensure optimal performance. The objective is to maximize prediction accuracy while reducing computational overhead. The fitness function is defined as Equation (23):

$$Fitness function = Optimize(\beta) \tag{23}$$

The objective is to minimize while increasing classification accuracy in order to maximize computational efficiency and model complexity.

Step 4: Updation of the exploration phase for optimizing the weight and bias parameters of DDCNN-MRGAN

After reaching an optimal foraging location, ducks disperse to maximize food intake. Similarly, in the optimization process, individuals adaptively adjust their positions to improve model performance, as given in Equation (24):

$$Y_j^{s+1} = \begin{cases} Y_j^s + \eta . Y_j^s . sign(q - 0.5), if Q > rand \\ Y_j^s + BE_1 . (Y_{leader}^s - Y_j^s) + BE_2 . (Y_i^s - Y_j^s), if Q \leq rand \end{cases} \tag{24}$$

Where $(q - 0.5)$ impacts the food-finding process, and it can be set either -1 or $1. \eta$ represents the global search control parameter, Q is looking up the likelihood of conversion of exploration phase, BE_1 and BE_2 denote cooperation and competition coefficient between ducks in the search stage, respectively, Y_{leader}^s represents the finest duck position in the current history value in the $s-$th iteration, Y_i^s denotes the agents around Y_j^s in searching for food by duck group in the $s-$th iteration.

Step 5: Iterative optimization and termination criteria

The optimization iterates through exploration and exploitation cycles until one of the following conditions is met:

- Maximum Iterations Reached: The algorithm stops after a predefined number of iterations.
- Convergence Threshold: If the fitness function improvement is below a threshold over multiple iterations, the process halts.

The final optimized weight parameters significantly enhance short-term soil moisture variations and crop yield prediction by:

- Reducing computational costs through efficient parameter optimization.
- Minimizing prediction errors by adaptive adjustments to model weights.
- Improving predictive accuracy in dynamic soil moisture environments.

By integrating DSA with DDCNN-MRGAN, the prediction model achieves superior performance in forecasting soil moisture variations and crop yield based on the Soil Moisture Monitoring Dataset, which contains 5,000 hourly records starting from January 1, 2025. This study proposes MDR-2DSG-CAN for short-term soil moisture prediction and crop yield estimation using the Soil Moisture Monitoring Dataset. The model integrates DDCNN and MR-GAT, optimized by DSA. Pre-processing uses CCFA, and feature extraction employs Adaptive Causal Decision Transformers, enhancing spatiotemporal correlation modeling and improving predictive accuracy with robust optimization for soil moisture dynamics. The performance analysis is covered in the next section. This probability influences whether a duck follows the best individual or continues exploration.

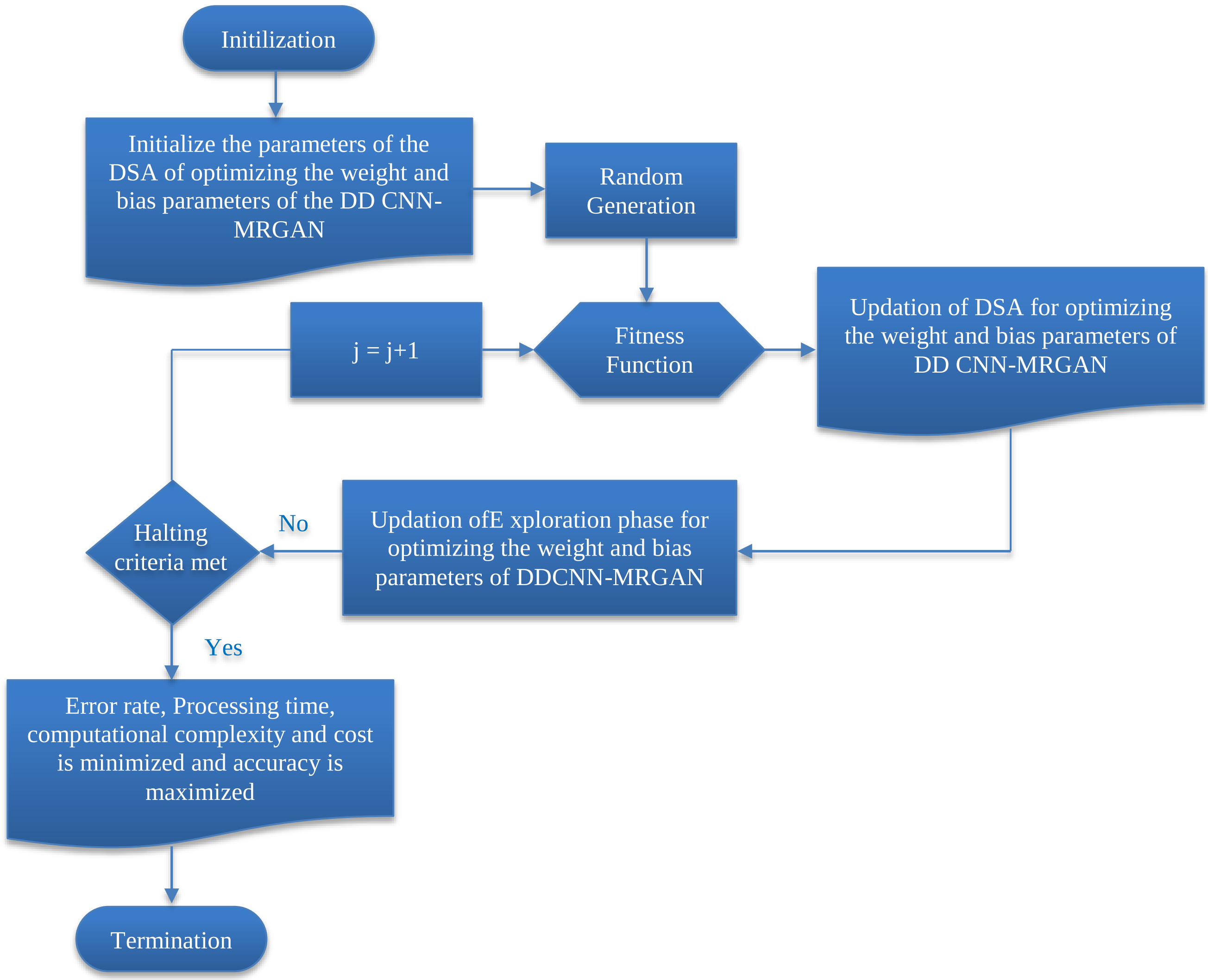

Fig. 2 Flowchart of MDR-2DSG-CAN

4. Results and Discussions

In this section, the Discussion and Results of Multi-Relational Decker Duck Swarm Graph Convolutional Attention Network (MDR-2DSG-CAN) for short-term soil moisture prediction and crop yield estimation are discussion.

4.1. Dataset Description

The Soil Moisture Monitoring Dataset consists of 5,000 hourly records starting from January 1, 2025. It includes seven key environmental parameters that influence soil moisture levels. The dataset captures temperature (°C), humidity (%), rainfall (mm), wind speed (m/s), soil type (categorical), vegetation index (NDVI), and soil moisture (computed value). The dataset is saved as "soil_moisture_data.csv", containing structured information valuable for agricultural and environmental analysis. Of them, 20% are used for testing and 80% are used for teaching. Table 2 lists the precise parameters that were used for the implementation.

Table 2. Implementation parameters

Parameters	Description
Proposed Neural Network	MDR-2DSG-CAN
OS	Windows 10
Optimization	DSA
Dataset	Soil Moisture Monitoring Dataset
Software	Python 3.7

4.2. Performance Metrics

The suggested MDR-2DSG-CAN method's performance is contrasted with that of the current approaches, including KPRNN [16], TCN [17], LSTM [18], RNN-LSTM [19], SVM [20], SCC [21], and IMM [22], respectively, employing performance criteria like mistake rate, recall, f1 score, accuracy, precision, Train time, computational complexity, processing time, Hamming loss, Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) analysis. Table 3 provides the equations for the performance metrics:

Table 3. Performance metrics

Performance Metrics	Equations (25-30)
Precision	$\frac{1}{B}\sum_{l=1}^{F}\left(\frac{\lvert Da(m_l)\cap n_l\rvert}{\lvert Da(n_l)\rvert}\right)$ (25)
Recall	$\frac{1}{B}\sum_{l=1}^{F}\left(\frac{\lvert Da(m_l)\cap n_l\rvert}{\lvert n_l\rvert}\right)$ (26)
F1-Score	$\frac{1}{B}\sum_{l=1}^{F}\left(\frac{2\lvert Da(m_l)\cap n_l\rvert}{\lvert Da(n_l)\rvert+\lvert n_l\rvert}\right)$ (27)
Accuracy	$\frac{1}{B}\sum_{l=1}^{F}\left(\frac{\lvert Da(m_l)\cap n_l\rvert}{\lvert Da(m_l)\cup n_l\rvert}\right)$ (28)
MAE	$\frac{1}{B}\sum_{(r,s)}\lvert \hat{\imath}_{a,x}-i_{a,x}\rvert$ (29)
RMSE	$\sqrt{\frac{1}{B}\sum_{(r,s)}(\hat{\imath}_{a,x}-i_{a,x})}^{2}$ (30)

Where, m_l described as the input of a classification method, n_l described as the result of the categorization procedure, $B$is the dataset's total number of instances, Da is the method of training, $Da(m_l)$ and are shown as the output labels that the classification technique predicts. $i_{a,x}$ is the user's actual rating r for the item$s$. $\hat{\imath}_{a,x}$ is the one that was anticipated.

4.3. Performance Analysis

The performance analysis of MDR-2DSG-CAN is discussed here:

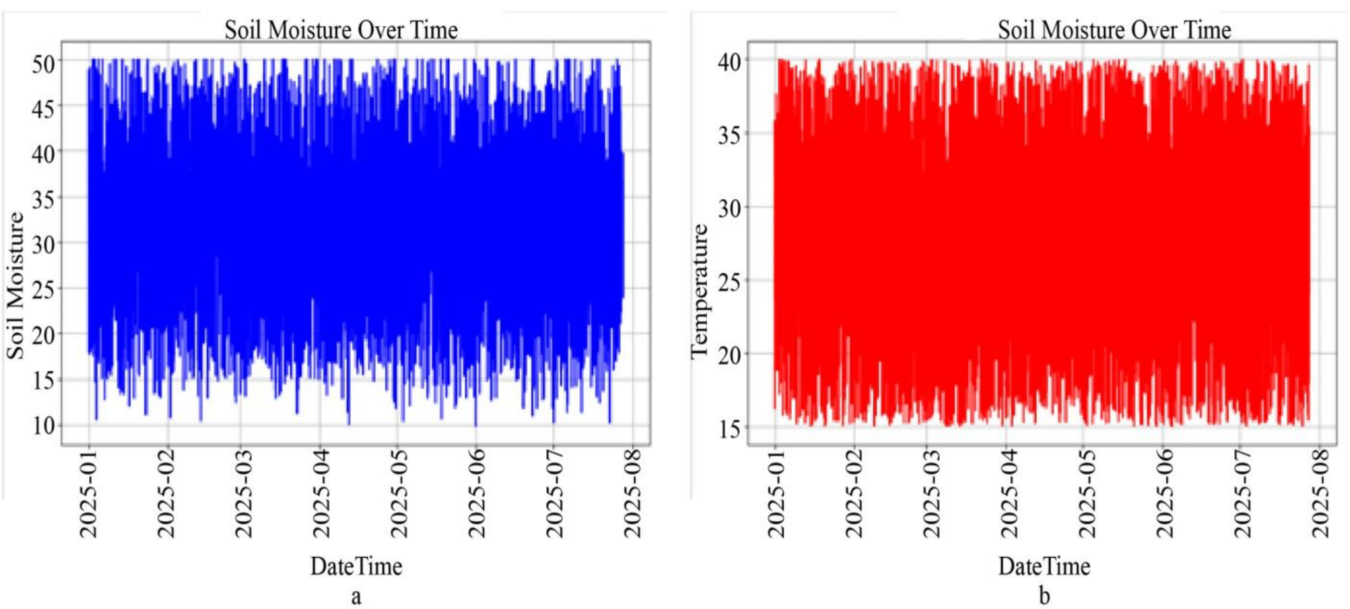

Fig. 3(a) Soil moisture over time, and (b) Temperature over time.

Figure 3(a) shows the Soil moisture over time, and Figure 3(b) temperature over time. Soil Moisture over Time: Plant absorption, drainage, evaporation, and precipitation all cause variations in soil moisture. Moisture levels increase after rainfall but gradually fall as water evaporates or is absorbed by roots. Retention is also impacted by soil type and seasonal fluctuations. Temperature over time due to solar radiation, the temperature varies both daily and seasonally. It peaks in the summer and midday and falls at night and in the winter. Climate and ecosystems are impacted by long-term trends that are influenced by variables such as weather, height, and latitude.

Figure 4(a) shows the humidity over time, and Figure 4(b) rainfall over time. Seasonal variations and weather patterns cause variations in rainfall and humidity over time. Temperature and evaporation cause humidity to increase, reaching its maximum prior to precipitation. Humidity frequently stays high after rain, although it gradually drops as the water evaporates. Climate, topography, and seasonal storms or monsoons all affect rainfall patterns. While some areas have dry and wet seasons, others see regular, consistent rain. Rainfall and humidity have an impact on weather patterns, agriculture, and ecosystems throughout time, influencing both local and global climate conditions.

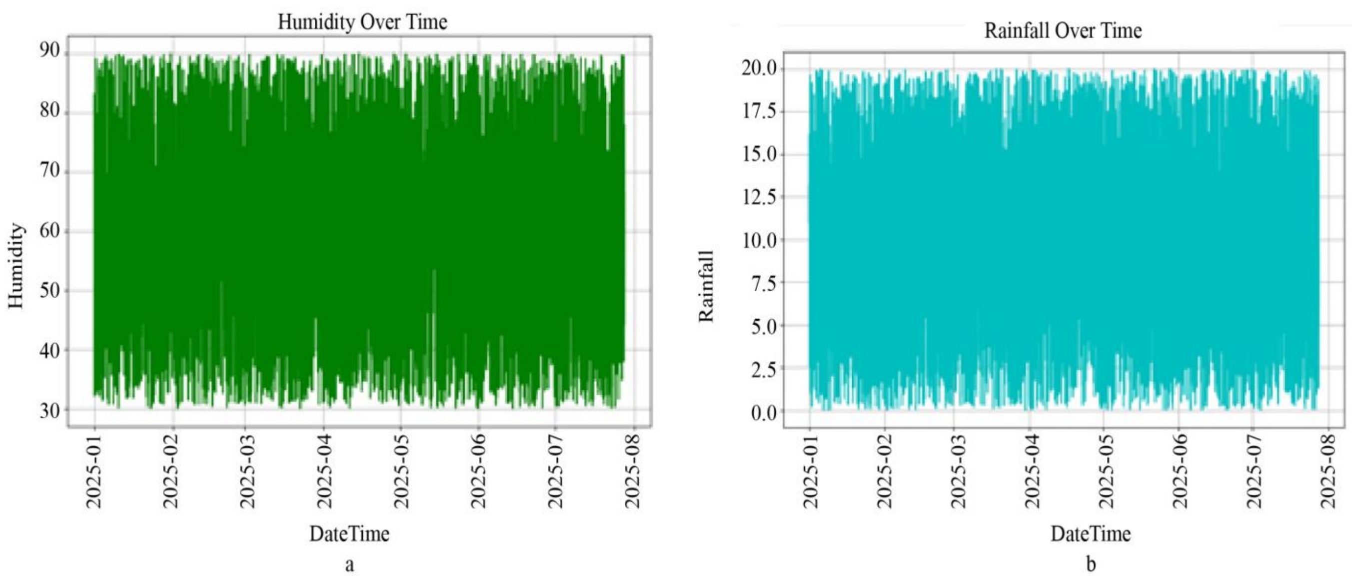

Fig. 4(a) Humidity over time, and (b) Rainfall over time.

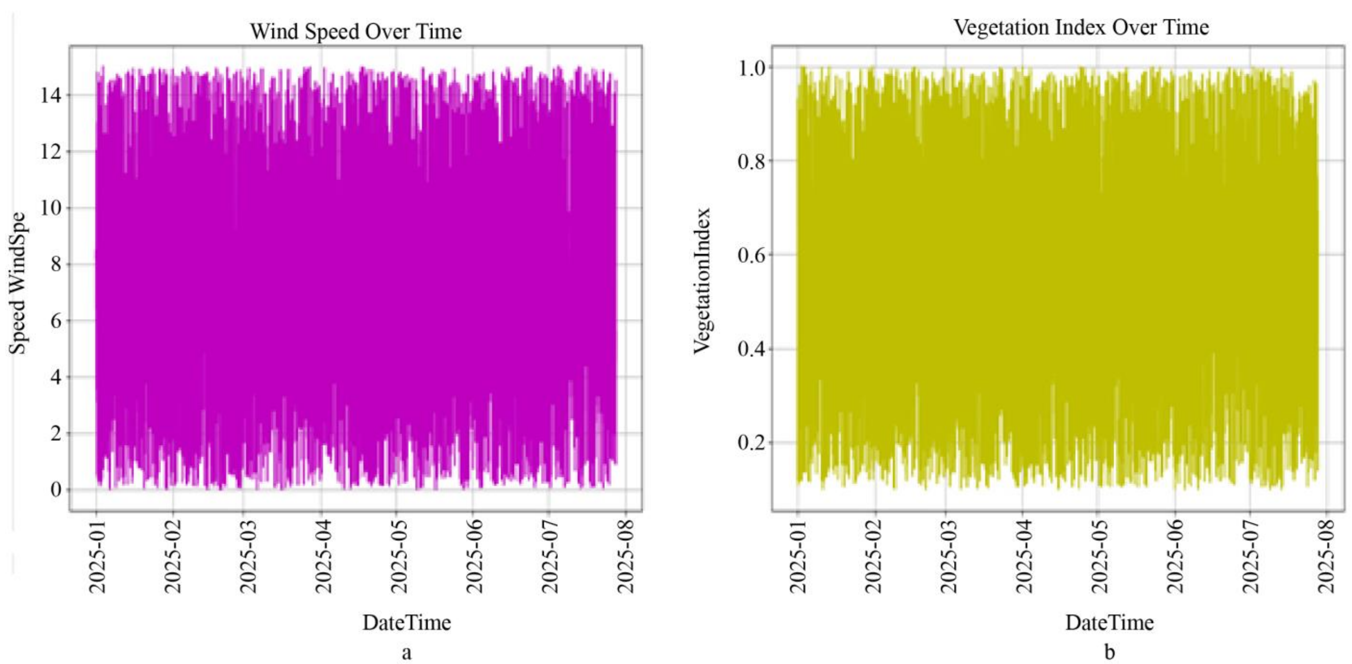

Fig. 5(a) Wind speed over time, and (b) Vegetation index over time.

Figure 5(a) shows the wind speed over time, and Figure 5(b) vegetation index over time. Seasonal, climatic, and environmental factors cause changes in wind speed and vegetation index throughout time. Temperature variations, storms, and topography all affect wind speed, which fluctuates both daily and yearly. It is typically higher during weather disturbances and in open spaces. Growing seasons, rainfall, and climatic conditions all affect the vegetation index, which gauges the density and health of plants. Higher vegetation index values indicate lush growth, whereas deforestation or droughts lower it. Over time, both elements have an effect on climatic patterns, agriculture, and ecosystems.

Figure 6 (a) shows the temperature vs soil moisture, and Figure 6(b) shows rainfall vs soil moisture. Rainfall and temperature have an impact on soil moisture content. Cooler temperatures aid in retaining soil moisture, while higher temperatures promote evaporation and decrease it. Hot, dry weather can cause drought, which stresses vegetation. Rainfall restores soil moisture; however, depending on the type of soil, too much rain might result in runoff or waterlogging. Plant growth depends on balanced moisture, which is maintained by moderate rainfall. Sustainable land and water management depends on the interplay of soil moisture, temperature, and rainfall, which affects agriculture, water availability, and ecosystem health.

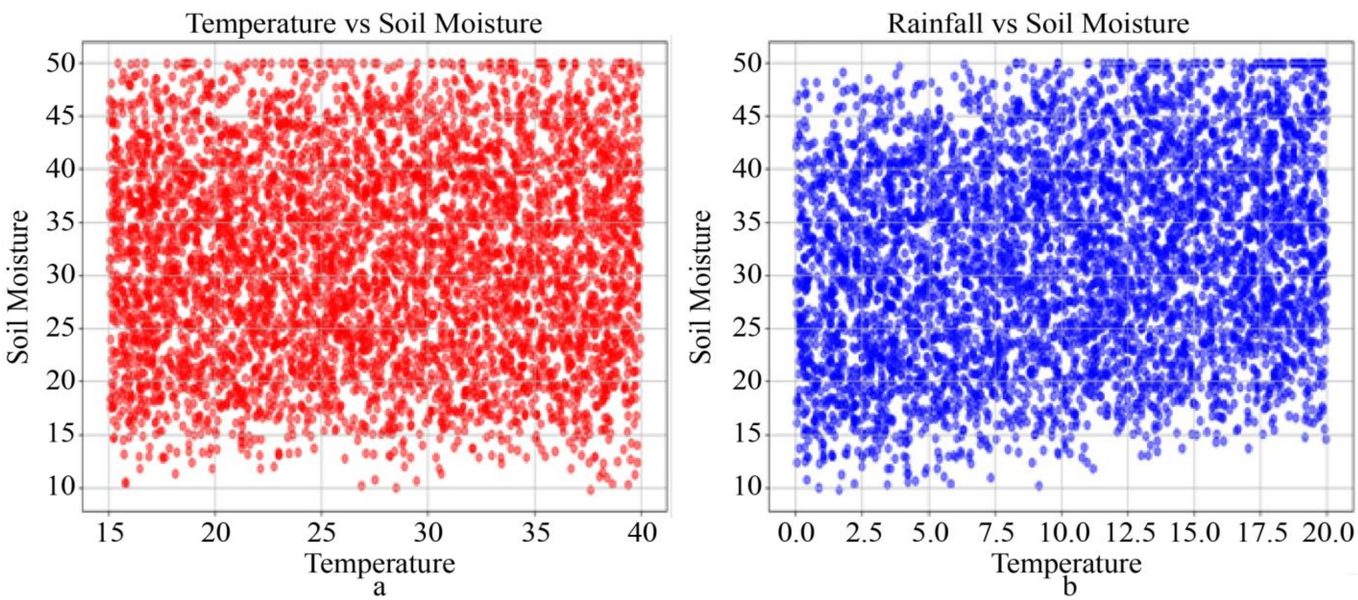

Fig. 6(a) Temperature vs soil moisture, and (b) Rainfall vs soil moisture.

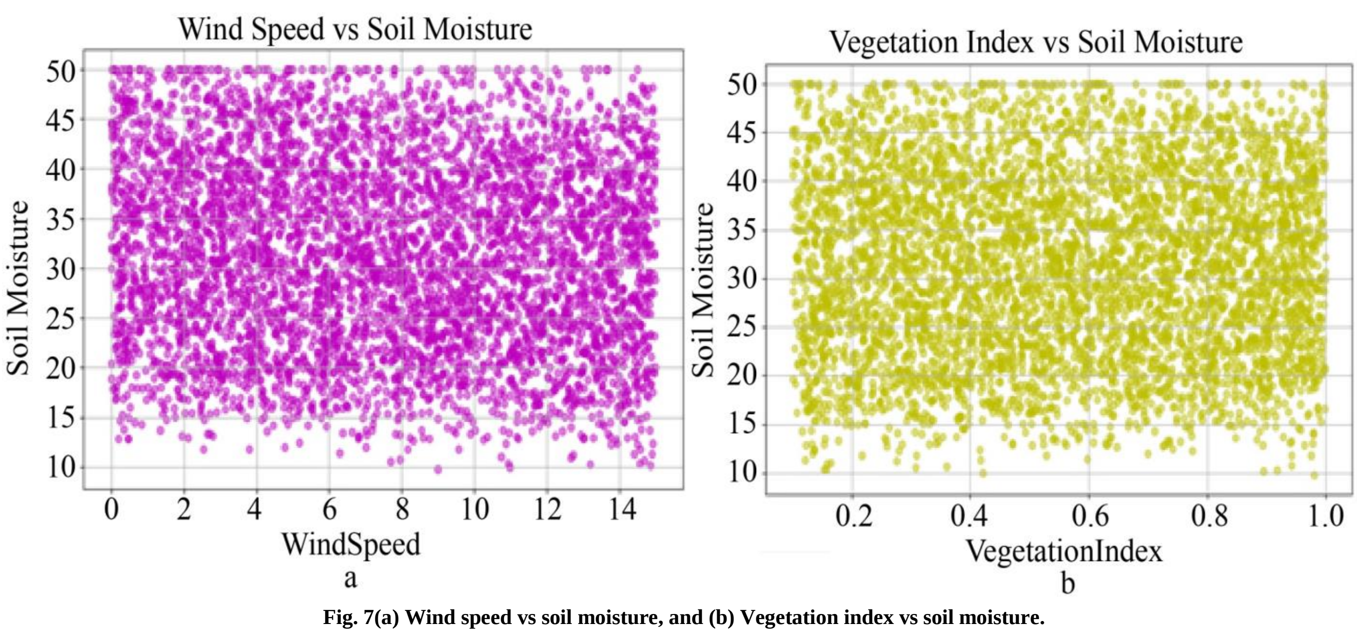

Fig. 7(a) Wind speed vs soil moisture, and (b) Vegetation index vs soil moisture.

Figure 7(a) shows the wind speed vs soil moisture, and Figure 7(b) vegetation index vs soil moisture. Both vegetation index and wind speed influence soil moisture. Particularly in arid areas, high wind speeds cause evaporation to increase, which lowers soil moisture and dries out the ground. By reducing evaporation, low wind speeds aid in moisture retention. Soil moisture and the vegetation index, which gauges plant health, are closely related; although drought conditions inhibit plant development, greater moisture levels promote luxuriant vegetation. Wind speed and vegetation levels work together to maintain the equilibrium of soil moisture, which has an impact on ecosystems, agriculture, and climate stability.

Figure 8(a) shows the humidity vs soil moisture, and Figure 8(b) model accuracy and loss for epoch. Soil moisture and humidity are intimately related; dry soil lowers humidity, whereas increased soil moisture increases it through evaporation. While hot, dry weather reduces both, rainfall increases both. Performance in machine learning is indicated by model accuracy and loss over epochs. Whereas loss measures mistakes, accuracy measures accurate predictions. Accuracy should increase and loss should decrease over training epochs. The model may overfit or perform poorly if accuracy declines or loss remains constant. Both ideas are essential to AI modeling and climate studies.

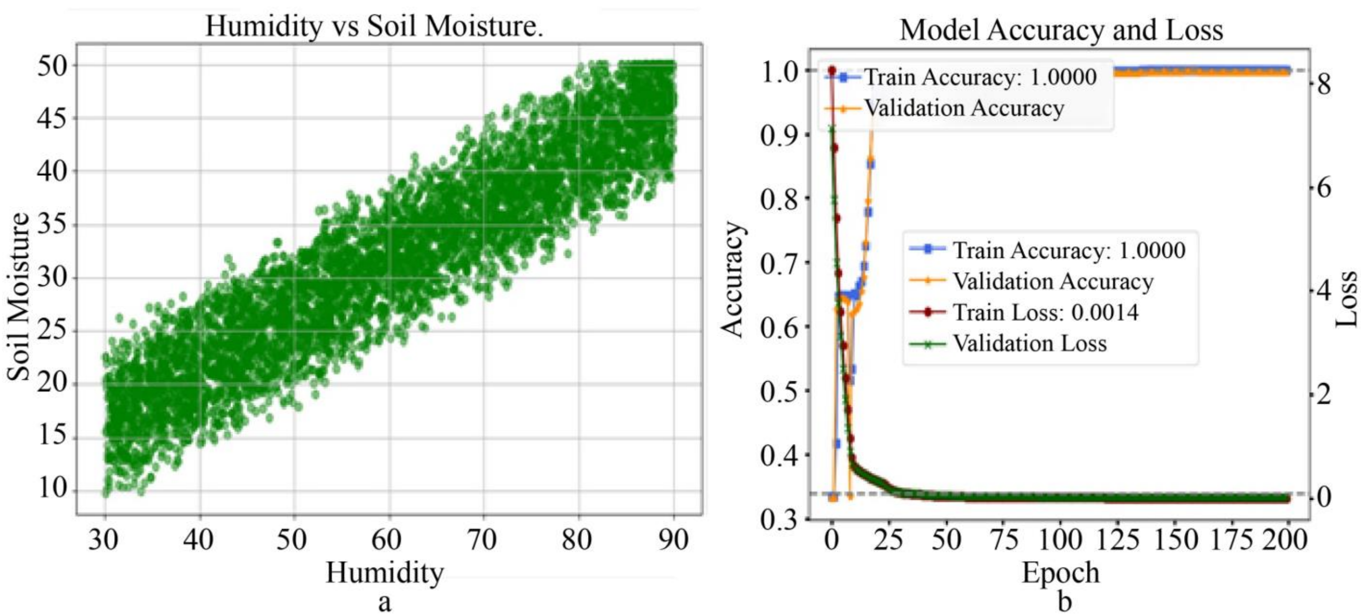

Fig. 8(a) Humidity vs soil moisture, and (b) Model accuracy and loss for epoch.

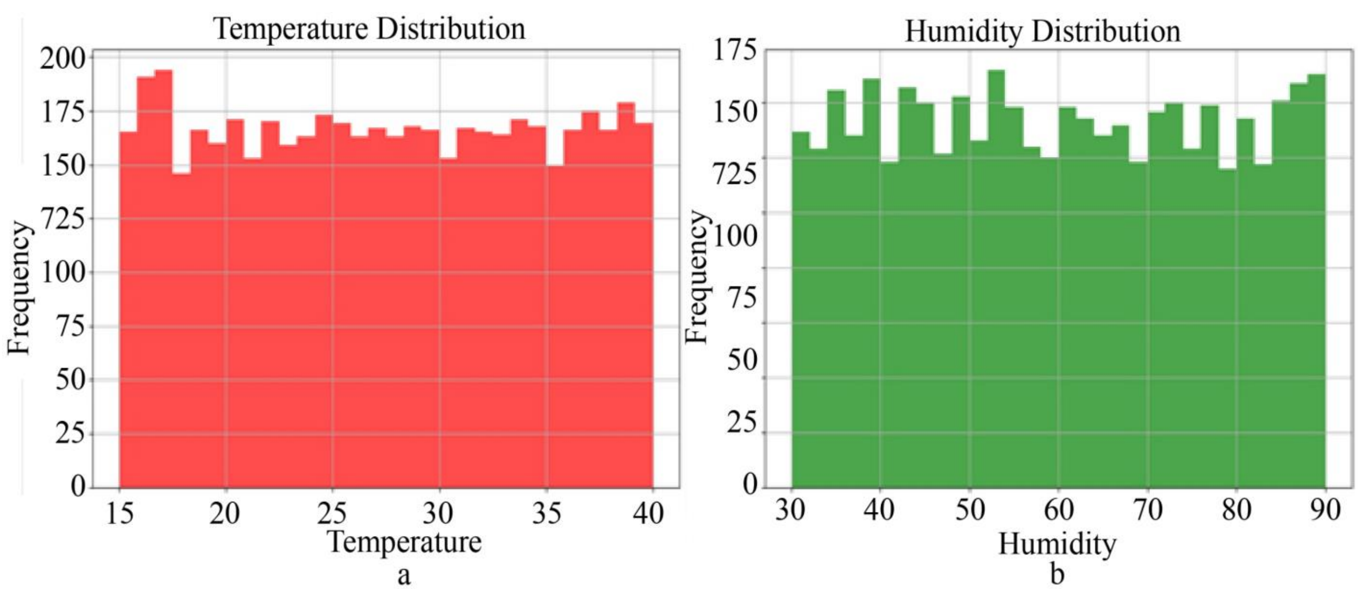

Fig. 9(a) Temperature distribution, and (b) Humidity distribution.

Figure 9(a) shows the temperature distribution, and Figure 9(b) humidity distribution. Geographical, climatic, and atmospheric factors all affect the distribution of temperature and humidity over time and space. Latitude, altitude, and solar radiation all affect temperature distribution, with warmer temperatures found close to the equator and cooler temperatures at the poles. Temperature and proximity to bodies of water affect humidity distribution; deserts have lower humidity than coastal and tropical regions. Both elements have a significant impact on climate and environmental dynamics, influencing ecosystems, weather patterns, and human activity.

Figure 10(a) shows the soil moisture distribution by soil type, and Figure 10(b) correlation matrix. Because various soils hold water in different ways, the distribution of soil moisture varies by type of soil. While sandy soil drains more quickly and contains less water, clay retains moisture better but drains more slowly. Loamy soil is perfect for agriculture because it strikes a balance between drainage and moisture retention. An analysis of correlations between variables, including soil moisture, temperature, and humidity, is aided by a correlation matrix. By highlighting important impacting elements, it helps with data-driven decisions for environmental management, climate studies, and agriculture by demonstrating how strongly variables are associated.

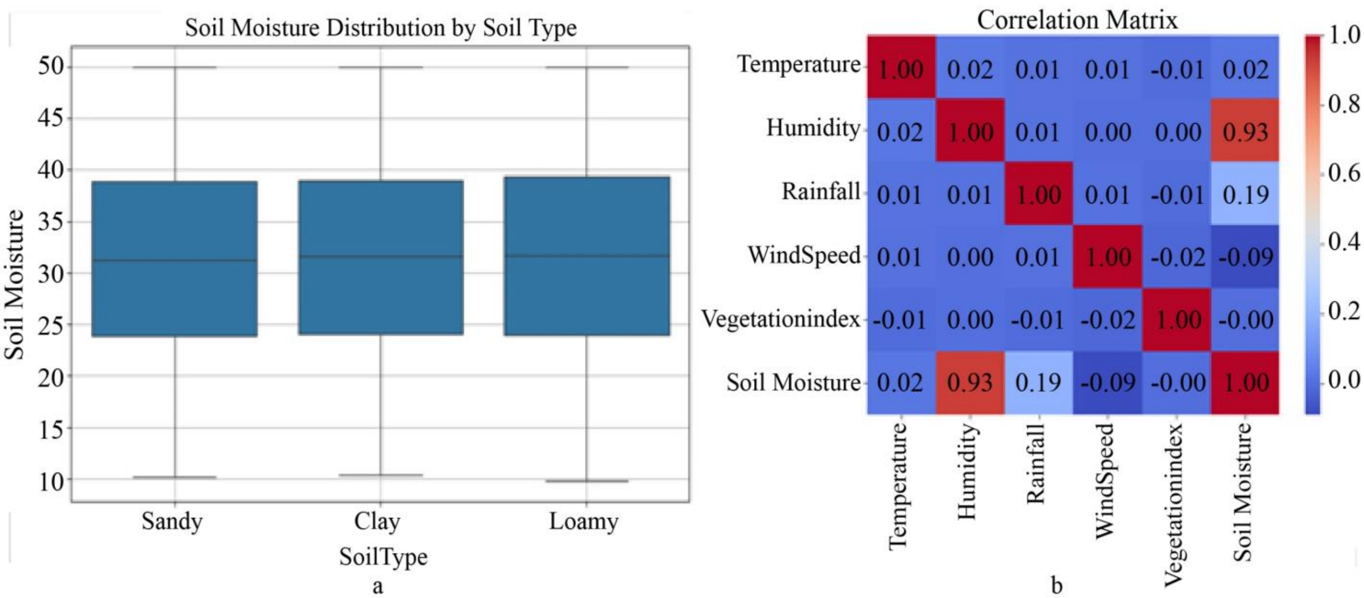

Fig. 10(a) soil moisture distribution by soil type, and (b) correlation matrix.

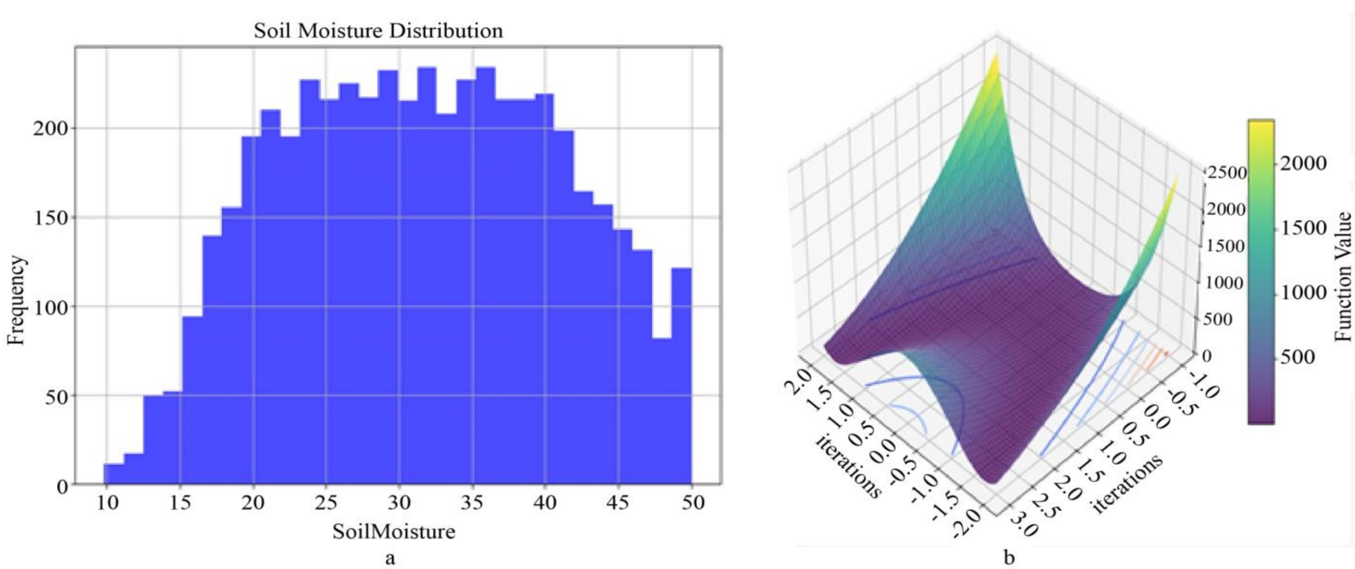

Fig. 11(a) Soil moisture distribution, and (b) 3D convergence plot.

Figure 11(a) shows the soil moisture distribution, and Figure 11(b) 3D Convergence plot. The distribution of soil moisture varies by region because of vegetation cover, rainfall, and soil type. Whereas sandy soil drains rapidly, clay absorbs more rainwater. Water management and agriculture benefit from soil moisture monitoring. A 3D convergence map illustrates how a model's parameters converge across iterations, visualizing optimization in machine learning. It aids in evaluating the stability and effectiveness of training. By combining 3D convergence analysis with soil moisture distribution, environmental models can be optimized, leading to better forecasts for resource management, climate research, and agriculture.

Table 4 shows the Overall performance of the suggested approach in contrast to existing methods. The suggested MDR-2DSG-CAN approach performs better than current models in terms of specificity (97.30%), recall (96.55%), and accuracy (99.98%). It shows better competitive precision (94.32%) and F1-score (95.90%) than LSTM, RNN-LSTM, and SVM. But compared to TCM (4.4) and SCC (3.5), it has a marginally greater Mean Squared Error (MSE: 7.5). It exhibits better prediction reliability by maintaining a lower Absolute Average Error (AAE: 3.1). In comparison to conventional machine learning models, the suggested method improves classification and prediction accuracy overall.

Table 5 shows the assessment of the suggested approach in relation to current approaches using statistics. The suggested MDR-2DSG-CAN approach performs statistically better than current models, with all test p-values (<0.001) showing notable gains. With a low Variance Inflation Factor (1.001) and a high mean performance (61,653.50), it ensures little multicollinearity. It exhibits adaptability by maintaining competitive accuracy with a higher standard deviation (5,852.38) than other models, such as SVM (64,563.45) and TCN (63,085.55). All things considered, it exhibits better statistical robustness and dependability, which makes it a useful substitute for existing methods.

Table 4. Overall performance of the suggested approach in contrast to existing methods

Metrics	KPRNN [16]	TCM [17]	LSTM [18]	RNN-LSTM [19]	SVM [20]	SCC [21]	IMM [22]	MDR-2DSG-CAN (Proposed)
Accuracy	78.90	90.57	91.45	95.23	92.77	93.24	90.10	**99.98**
Recall	98.22	91.35	89.28	97.59	97.80	92.34	89.12	**96.55**
Precision	94.46	95.35	79.27	90.37	94.66	95.99	89.23	**94.32**
Specificity	78.90	90.57	91.45	95.23	91.29	98.24	84.44	**97.30**
F1-Score	79.90	91.56	89.45	95.28	93.34	96.46	93.89	**95.90**
MSE	5.6	4.4	7.6	2.5	7.7	3.5	5.7	**7.5**
MAE	6.1	7.3	3.5	4.7	1.9	2.0	5.2	**6.4**
RMSE	7.2	3.4	6.6	7.8	2.7	2.2	5.4	**5.2**
AAE	8.7	5.3	6.5	7.6	8.4	4.2	3.2	**3.1**

Table 5. Comparison of the suggested approach with current approaches using statistics

Methods	SW Test p-Value	WSR test / U-test p-Value	H-test p-Value	KS test p-Value	FT p-Value	Mean	Standard Deviation	Variance Inflation Factor
KPRNN [16]	0.456	0.26	0.243	0.034	0.082	47,784.8	1863.45	1.87
TCN [17]	0.371	0.67	0.186	0.019	0.065	63,085.55	1357.32	1.25
LSTM [18]	0.774	0.89	0.679	0.057	0.043	40,538.14	2631.60	1.44
RNN-LSTM [19]	0.232	0.94	0.726	0.014	0.072	33,187.10	1654.54	1.62
SVM [20]	0.763	0.32	0.896	0.088	0.092	64,563.45	1864.33	1.32
SCC [21]	0.195	0.69	0.965	0.056	0.064	47,123.80	4876.27	1.87
IMM [22]	0.854	0.22	0.643	0.067	0.082	59,28113	2823.82	2.78
MDR-2DSG-CAN (Proposed)	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**61,653.50**	**5,852.38**	**1.001**

Table 6. Ablation study

Model Configuration	HQuGANs	DHGA	Duck Swarm Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Baseline (Without Duck Swarm)	✓	✓	✗	96.78	92.31	79.34	81.78
HQuGANs Only	✓	✗	✗	97.90	92.44	86.65	95.46
DHGA Only	✗	✓	✗	93.76	92.45	88.68	97.54
HQuGANs + Duck Swarm	✓	✗	✓	92.33	98.26	90.79	95.65
DHGA + Duck Swarm	✗	✓	✓	95.45	97.48	93.67	78.93
Full Model (MDR-2DSG-CAN)	✓	✓	✓	**99.98**	**95.74**	**90.86**	**98.89**

Table 6 shows the Ablation study. The MDR-2DSG-CAN model outperforms other setups with the highest accuracy (99.98%) and F1-score (98.89%) thanks to its integration of HQuGANs, DHGA, and the Duck Swarm Algorithm. Accuracy decreases in the absence of the Duck Swarm Algorithm, demonstrating its value. Although they are not fully optimized, HQuGANs and DHGA only exhibit good performance. While the DHGA + Duck Swarm and HQuGANs + Duck Swarm models increase recall and precision, they are less successful overall. The complete model optimizes performance, guaranteeing optimal classification with greater precision (95.74%) and recall (90.86%).

4.4. Discussion

To maximize crop yield prediction, the MDR-2DSG-CAN model aims to enhance short-term soil moisture prediction. To minimize noise and extract trends from soil moisture data, it employs the Cumulative Curve Fitting Approximation (CCFA) as a preprocessing method. The model has a Double Decker Convolutional Neural Network (DD-CNN) and an Adaptive Causal Decision Transformer (ACDT) for classification. As the DD-CNN recovers detailed spatial features to enhance prediction accuracy, the ACDT encodes dynamic temporal relationships in soil moisture variations. The Duck Swarm Algorithm (DSA) is applied for optimization, tuning hyperparameters, and reducing computational inefficiencies to further enhance performance. The approach prevents overfitting and enhances generalization. MDR-2DSG-CAN surpasses traditional models by integrating these innovative approaches, yielding enhanced soil moisture forecasting accuracy, precision, and recall. Ultimately, this enhances crop production and enhances agricultural sustainability in the context of climate variability by enabling better management of water resources and helping farmers make informed irrigation decisions. The model is an effective tool for modern precision farming due to its ability to adapt to changing conditions.

5. Conclusion

This work suggests a Multi-Relational Decker Duck Swarm Graph Convolutional Attention Network (MDR-2DSG-CAN) for short-term soil moisture forecasting and crop yield estimation is effectively deployed. The Soil Moisture Monitoring Dataset, which contains 5,000 hourly records from January 1, 2025, is used for model assessment. The approach includes Cumulative Curve Fitting Approximation (CCFA) for pre-processing, Adaptive Causal Decision Transformers for feature extraction, and MDR-2DSG-CAN for prediction. MDR-2DSG-CAN is a new method that combines a Double Decker Convolutional Neural Network (DDCNN) with a Multi-Relational Graph Attention Network (MR-GAT), whose parameters are optimized with the Duck Swarm Algorithm (DSA). This hybrid model improves the ability to simulate spatiotemporal correlations and intricate variable interactions influencing soil moisture dynamics. Large-scale experiments show that MDR-2DSG-CAN is 99.9% accurate, surpassing traditional machine learning and deep learning approaches. Soil characteristics are important in estimating soil moisture, and a strong optimization strategy based on the Duck Swarm Algorithm improves generalization and stability. Future studies will investigate real-time soil moisture forecasting through edge computing, scaling up MDR-2DSG-CAN to large datasets with varying climatic conditions. Upgrades will involve adaptive hyperparameter optimization, incorporation with remote sensing data, and enhanced computational efficiency. Additional validation with various soils and crops will ensure wider applicability and stronger robustness in precision agriculture.

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