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AI-Based Drought Prediction for Farmers: Analysis of Crop Yield and its Relationship with Weather Variables

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Abstract- Drought is a severe natural event that affects agriculture greatly, particularly in regions where rain-fed agriculture is the main source of food. It has a major detrimental impact on society, the environment, and the lives of farmers. Drought prediction is an important component of early warning systems for drought management. Advances in machine learning (ML) and the Internet of Things have demonstrated potential to improve drought prediction and provide sustainable farming solutions. This paper proposes a machine-learning-based AI solution to predict drought occurrences through the conduit of the processed climatic, hydrological, and soil data which are collected in various ways. The experimental model is incorporating the historical data of rainfall patterns, temperature fluctuations, soil moisture levels, and others into the predictions with the highest possible probability of drought conditions. To predict the occurrence of droughts and thus act, the proposed framework integrates data pre-processing techniques, such as feature selection and machine learning algorithms such as Neural Networks, Gradient Boosting, and Random Forest, with the help of which the proposed method is approximately as good as or even better than using traditional methods in the drought prediction in regions with different climates.

Keywords: An AI-Based Drought Prediction System for Farmers Integrates Multi-Source Data, Processes It Through Machine Learning Models, And Delivers Actionable Alerts. This Approach Enables Early Identification of Drought, Allowing for Proactive Water Management

I. INTRODUCTION

Agriculture is highly dependent on climate and rainfall patterns. Drought is one of the major natural disasters that affects crop production, water availability, and farmers' livelihoods. Unpredictable weather conditions and climate change have increased the risk of droughts, leading to reduced agricultural productivity and economic losses. Therefore, early prediction of drought is essential for helping farmers make better farming decisions.

An AI-based drought prediction system uses Artificial Intelligence, Machine Learning, and weather data analysis to forecast drought conditions in advance. The system collects data such as rainfall, temperature, soil moisture, humidity, and satellite information to identify patterns and predict the possibility of drought. By analyzing historical and real-time data, AI models can provide accurate predictions and timely alerts to farmers.

This technology helps farmers plan irrigation, select suitable crops, manage water resources efficiently, and reduce crop damage. AI-based systems can also support governments and agricultural organizations in disaster management and food security planning. The use of AI in drought prediction improves agricultural sustainability, minimizes financial losses, and increases farmers' preparedness against climate-related challenges.

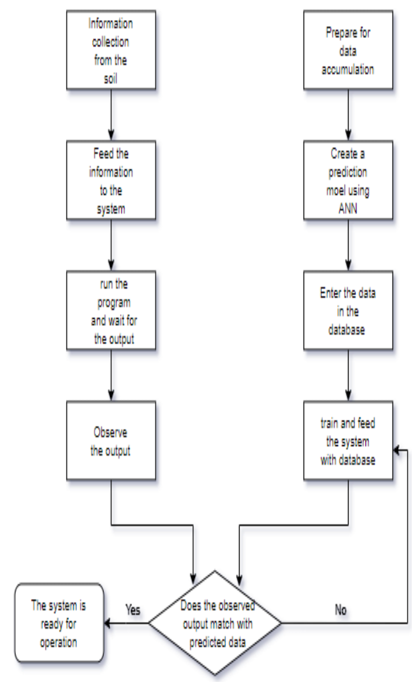
Overall, AI-based drought prediction is a smart and innovative solution that enhances modern agriculture and supports farmers in achieving better productivity and resource management.

II. BACKGROUND AND CONTEXT

Drought is a serious environmental problem that affects agriculture, water resources, and the economy. Farmers heavily depend on regular rainfall and favorable climatic conditions for successful crop production. However, due to climate change, irregular rainfall patterns, rising temperatures, and decreasing groundwater levels, drought occurrences have become more frequent and severe. These conditions create major challenges for farmers, especially in rural and drought-prone regions.

Traditional methods of predicting drought mainly rely on manual observation and historical weather analysis, which are often time-consuming and less accurate. Farmers may not receive timely information about upcoming drought conditions, leading to poor crop planning, reduced yields, and financial losses. As agriculture plays a vital role in food production and economic development, there is a strong need for advanced technologies that can provide early and accurate drought predictions.

- Drought is a major natural disaster affecting agriculture and water resources.
- Climate change has increased the frequency of droughts.
- Irregular rainfall and high temperatures reduce crop production.
- Farmers face financial losses due to poor harvests during drought conditions.
- Traditional drought prediction methods are slow and less accurate.
- Early drought prediction helps farmers take preventive measures.
- Artificial Intelligence (AI) can analyze large amounts of weather and soil data.
- Machine Learning algorithms identify patterns and predict future drought conditions.
- Data sources include rainfall, temperature, humidity, soil moisture, and satellite images.
- AI-based systems provide real-time alerts and recommendations to farmers.
- Farmers can plan irrigation and choose suitable crops using predictions.
- Efficient water management reduces wastage and improves productivity.
- AI-based drought prediction supports sustainable and smart agriculture.
- Governments and agricultural organizations can use predictions for disaster management.
- The system helps improve food security and protect farmers' livelihoods.



III. LITERATURE REVIEW

We implemented a comprehensive data collection approach employing advanced cloud-based platforms. NDVI, LST, TCI, VCI, VHI, MNWDI, and precipitation were systematically extracted from 2001 to 2023 using the Google Earth Engine (GEE). This multi-faceted approach ensures the model captures the complex interplay between the atmosphere, vegetation, and water. This section will cover the characteristics of the data sets employed in this research.

NDVI is a metric used to evaluate vegetation growth and health, frequently employed in assessing drought conditions. (Heetal., 2023). The data were derived from MOD13Q1, which measures vegetation reflectivity in the near-infrared (NIR) and red wavelengths and is computed using

The MNDWI was calculated using the short-wave infrared (SWIR) and green bands of MOD09GA.006 Terra Surface Reflectance features of exposed water resources using Furthermore, MNDWI minimizes the impact of built-up area features often linked to open water in other indices (K. Huangetal., 2024).

A.) Datasets description

Estimating LST is crucial for understanding the thermal characteristics of the Earth's surface. Calculating monthly averages for the research region using MOD11A1 Terra Land Surface Temperature and Daily Global data is one effective technique to anticipate land surface temperature. This technique utilizes a cloud-based system that facilitates the processing and analysis of remote sensing data.

The VHI quantifies plant health and is employed to monitor and forecast the impacts of agricultural drought stress. This reflects the adaptive responses of vegetation to stress, serves as an analytical tool for drought-related issues, and guides the formulation of adaptive and mitigation strategies. The distribution of VCI and TCI significantly influences the VHI (Lietal., 2024, Zengetal., 2022). VHI, TCI, and VCI were derived from MODI using (3), (4), (5).(3)(4)(5)where NDVI / LST is the duration and specific pixel value; NDVI min / LST min is the lowest NDVI and LST values throughout all pixels; NDVI max / LST max is the highest NDVI and LST over all pixels.

Monthly precipitation data at a high precision of 0.05 ° (about 5 km) was obtained using CHIRPS (Climate Hazards Group Infra Red Precipitation with Station data), which runs on the GEE platform (Jianget al., 2020, Smithetal., 2023, Yuetal., 2022).

The MODIS and CHIRPS datasets were selected for this study due to their extensive and consistent temporal availability, which is crucial for detailed time-series analysis of drought. MODIS provides calibrated, multispectral data necessary for deriving a variety of complementary vegetation and thermal indices (NDVI, LST, MNDWI, VCI, TCI) from a single sensor system, ensuring pixel-level compatibility (Badarnehetal., 2024). CHIRPS precipitation data, designed explicitly for drought monitoring, enhances these with high-resolution, station-blended outputs that improve accuracy over satellite-based estimates alone (Rahmanetal., 2025). Additionally, these datasets are easily integrated into the Google Earth Engine platform, enabling efficient and reproducible large-scale computations throughout the entire study period (2001–2023). To address missing data and outliers in the remote sensing inputs, we applied a combination of temporal interpolation, spatial smoothing, and statistical filtering techniques(Mpakairietal., 2025). Outliers were identified using z-score and IQR thresholds, while missing pixel values were reconstructed using temporal interpolation and spatial averaging. The corrected datasets were validated against independent satellite sources to ensure physical consistency.

Initially, each calculated dataset time series underwent decomposition into low-frequency and high-frequency sub-series by applying the discrete wavelet transform (DWT). These datasets were then used as input data for the XGBoost, Random Forest, and AdaBoost models to forecast drought severity and vegetation health, as represented by VHI. The study process flowchart is explained in . To assess the model's performance on novel data, the dataset is split into two parts: the training set, which covers 70 % of the total data, and the testing set, which covers 30 % of the data. The split ratio is a standard method in machine learning for time-series forecasting, effectively balancing the need for sufficient training data with the requirement for a statistically sound test set to evaluate model generalizability (Guptatal., 2022)

B) Discrete wavelet decomposition

Wavelet analysis has two types: continuous wavelet transformation (CWT) and discrete wavelet transformation (DWT) (Khanetal., 2020). Due to its computational complexity and processing time requirements, the continuous wavelet transformation is not often used for forecasting (Aonetal., 2024). DWT-enhanced features produce enhanced input representations for machine learning techniques, such as XGBoost, in drought modeling, resulting in more accurate and dependable predictions (Chidepudietal., 2023). Inverse DWT (IDWT) also enables the reconstruction of the original signal, facilitating the interpretation of results (Khanetal., 2020). Thus, DWT is vital for improving prediction accuracy and drought monitoring. The DWT is expressed with, the mother wavelet, where i and j are integers, regulates the scale and time. The DWT used the Coiflet–1 (coif1) mother wavelet with a four-level decomposition. This process generated a set of approximation coefficients representing the long-term trend, along with four sets of detail coefficients capturing higher-frequency components. For feature analysis and visualization, the trend and the first three detail levels were plotted and later incorporated as additional inputs into the machine learning models to improve drought forecasting accuracy.

Agriculture is highly dependent on climatic conditions such as rainfall, temperature, and soil moisture. Due to climate change and irregular weather patterns, drought has become one of the major challenges affecting farmers and agricultural productivity. Traditional drought monitoring methods are often slow, inaccurate, and unable to provide early warnings to farmers. As a result, farmers face crop failure, water scarcity, economic losses, and reduced food production.

Existing systems may not effectively analyze large amounts of environmental and agricultural data in real time. There is a need for an intelligent system that can predict drought conditions accurately and provide timely alerts to farmers. Artificial Intelligence and Machine Learning technologies can help analyze weather data, soil conditions, and satellite information to forecast drought risk efficiently.

Therefore, this project aims to develop an AI-based drought prediction system for farmers that can provide early drought warnings, improve agricultural planning, support water resource management, and help farmers make better decisions to reduce crop damage and increase productivity. involvement in the model's decision-making for drought evaluation. Additional characteristics, including LST, TCI, and VCI, contributed to the model, albeit their influence was negligible.

IV. METHODOLOGY

1. Data Collection
The first step is collecting historical and real-time data from multiple sources:

- Weather Data: temperature, rainfall, humidity, wind speed
- Soil Data: soil moisture, soil type, groundwater level
- Satellite Data: vegetation index (NDVI), land surface temperature
- Agricultural Data: crop type, irrigation details, yield records

Data can be collected from:
- Meteorological departments
- IoT sensors
- Satellite imagery
- Agricultural databases

2. Data pre-processing
Raw data may contain missing or inconsistent values. Pre-processing improves data quality.

Steps:

- Remove duplicate records
- Handle missing values
- Normalize numerical values
- Convert categorical data into numerical format
- Integrate datasets from different sources

1.) Machine Learning Theory
Machine Learning theory is used in AI-based drought prediction systems to enable computers to learn from historical climate and agricultural data. The system analyzes patterns in rainfall, temperature, soil moisture, and humidity to predict future drought conditions. Machine learning algorithms such as Decision Tree, Random Forest, and Support Vector Machine improve prediction accuracy by continuously learning from new data. This theory helps farmers receive early warnings and make better agricultural decisions.

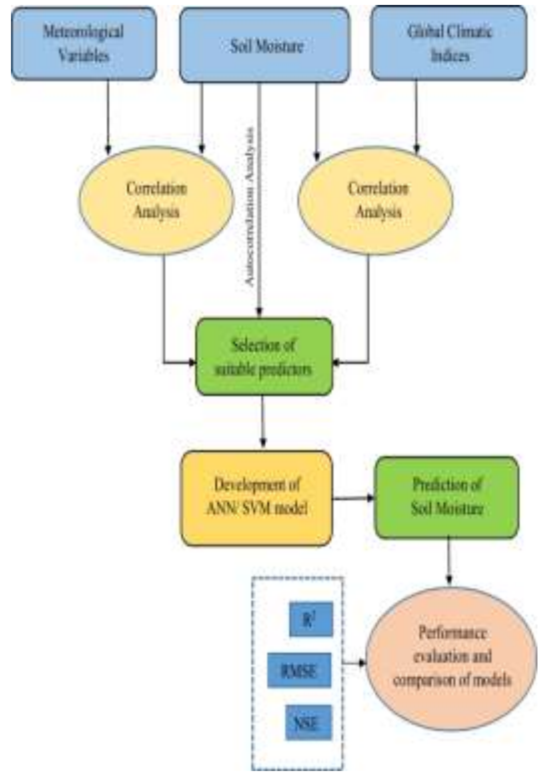
2.) Artificial Intelligence Theory
Artificial Intelligence theory focuses on developing intelligent systems that can simulate human thinking and decision-making. In drought prediction, AI processes large amounts of environmental and agricultural data quickly and efficiently. The AI system identifies drought risk levels, provides recommendations for crop management, and supports farmers in reducing agricultural losses. AI improves automation and real-time monitoring in smart farming systems.

3.) Neural Network Theory
Neural Network theory is inspired by the structure and functioning of the human brain. It is used to recognize complex patterns and relationships in climate data. Artificial Neural Networks (ANN) and deep learning models can analyze satellite images, weather records, and soil conditions to predict drought severity more accurately. This theory is useful for handling large and complex datasets in agricultural forecasting.

4.) Remote Sensing Theory
Remote Sensing theory involves collecting information about the Earth’s surface through satellites and sensors without physical contact. In AI-based drought prediction, remote sensing technology is used to monitor vegetation health, soil moisture, and land temperature. Satellite images provide real-time environmental data that helps detect drought-prone regions and supports accurate agricultural monitoring.

5.) Climate Change Theory
Climate Change theory explains long-term changes in weather patterns caused by global warming and environmental factors. Increasing temperatures and irregular rainfall contribute to drought occurrences in many regions. This theory helps researchers understand the relationship between climate variations and drought conditions, improving the accuracy of AI-based drought prediction systems.

6.) Statistical Prediction Theory
Statistical Prediction theory uses mathematical and probability models to analyze environmental data and estimate drought risk. Statistical methods help evaluate trends, calculate drought probability, and measure prediction accuracy. This theory supports decision-making by providing reliable analytical results for drought forecasting.



V. PROBLEM STATEMENT

A. Traditional Drought Prediction Methods
- Based on historical rainfall and weather records.
- Manual analysis was commonly used.
- Predictions were often slow and less accurate.

B. Artificial Intelligence in Drought Prediction
- AI helps analyze large climate datasets quickly.
- Machine Learning algorithms improve prediction accuracy.
- Systems provide early warning alerts for farmers.

C. Use of Machine Learning Techniques
- Algorithms such as Decision Tree, Random Forest, SVM, and Neural Networks are used.
- Models identify climate patterns and forecast drought conditions.
- Predictions become more reliable with training data.

D. Role of Satellite and Sensor Data
- Satellite imagery helps monitor environmental changes.

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- IoT sensors collect real-time soil moisture and temperature data.
- Remote sensing improves drought monitoring efficiency.

E. Benefits to Farmers and Agriculture
- Helps farmers plan irrigation and crop selection.
- Reduces water wastage and crop losses.
- Supports sustainable and smart farming practices.

Unified Framework: Data, Features, and Models

A. Data
The system collects data from multiple sources for drought prediction.

Types of Data
- Rainfall data
- Temperature data
- Humidity levels
- Soil moisture data
- Wind speed data
- Satellite imagery
- Groundwater levels
- Historical climate records

Data Sources
- Weather stations
- IoT sensors
- Satellite systems
- Agricultural databases
- Meteorological departments

B. Features
Features are the important factors used by the AI model for prediction.

Environmental Features
- Average rainfall
- Maximum and minimum temperature
- Soil moisture percentage
- Humidity levels
- Evaporation rate

Agricultural Features
- Crop type
- Irrigation usage
- Land condition
- Water availability

Time-Based Features
- Seasonal patterns
- Monthly climate trends
- Historical drought frequency

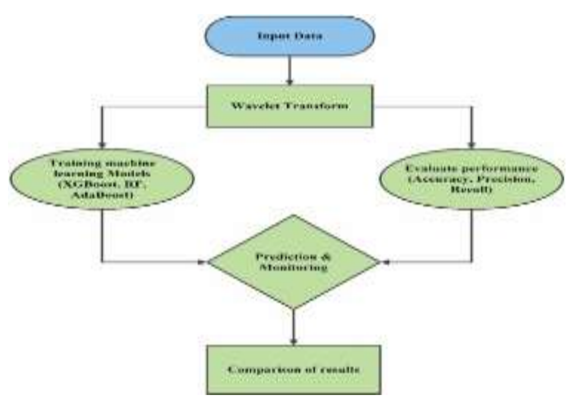
C. Models
AI and Machine Learning models are used to analyze data and predict drought conditions.

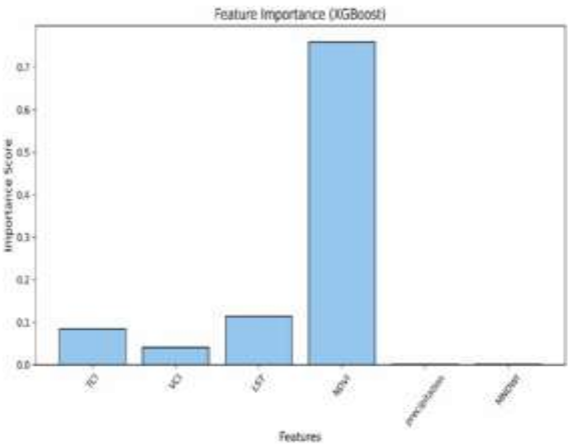
Machine Learning Models
- Decision Tree
- Random Forest
- Support Vector Machine (SVM)
- K-Nearest Neighbor (KNN)

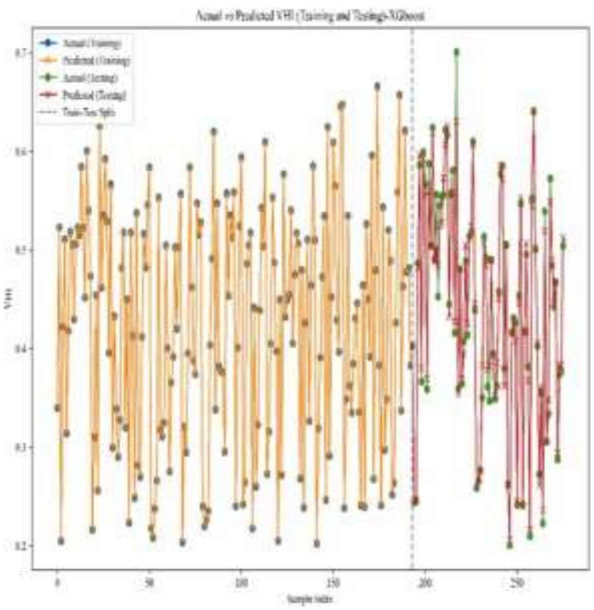
Deep Learning Models
- Artificial Neural Network (ANN)
- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)

Prediction Process
- Train models using historical data.
- Test model accuracy with new data.
- Generate drought predictions and alerts.

D. Output of the Framework
- Early drought warning
- Drought severity prediction
- Irrigation recommendations
- Crop planning suggestions
- Water management support







VI. CONCLUSION

The AI-based drought prediction system for farmers provides an intelligent and efficient approach for identifying drought conditions at an early stage. By using Artificial Intelligence, Machine Learning, climate data, soil moisture information, and satellite imagery, the system can accurately analyze environmental conditions and predict possible drought occurrences. Early prediction helps farmers take preventive actions such as proper irrigation planning, crop selection, and water conservation.

The system improves agricultural productivity, reduces crop losses, and supports sustainable farming practices. It also helps government agencies and agricultural organizations in managing water resources and planning drought relief activities. Compared to traditional methods, the AI-based approach offers faster analysis, better accuracy, and real-time monitoring capabilities. Overall, the project demonstrates how modern technologies can support smart agriculture and improve the livelihood of farmers.

VII. FUTURE WORK

1. Integration with IoT Sensors
Future systems can include advanced IoT sensors to collect real-time data on soil moisture, temperature, humidity, and water levels directly from agricultural fields. This will improve prediction accuracy and provide continuous monitoring.

2. Use of Advanced Deep Learning Models
More advanced deep learning algorithms such as Convolutional Neural Networks (CNN) and improved LSTM models can be implemented to increase forecasting performance and analyze complex climate patterns more effectively.

3. Mobile Application Development
A mobile application can be developed to provide farmers with real-time drought alerts, weather forecasts, and agricultural recommendations in regional languages for easy accessibility.

4. Satellite and GIS Integration
Future work can include stronger integration with satellite imaging and Geographic Information Systems (GIS) for accurate mapping of drought-prone areas and better environmental monitoring.

5. Smart Irrigation System
The system can be connected with automated smart irrigation systems that control water usage based on drought predictions and soil conditions, helping conserve water resources.

6. Multi-Region and Multi-Crop Support
Future models can be expanded to support different geographical regions, climate conditions, and multiple crop types to make the system more scalable and adaptable.

7. Cloud-Based Deployment

Deploying the system on cloud platforms can enable large-scale data storage, faster processing, and easy access for farmers, researchers, and government agencies.

8. Government and Agricultural Policy Support
The system can be integrated with government agricultural programs to support drought management policies, crop insurance planning, and disaster response strategies.

9. Real-Time Weather API Integration
Future systems can connect with live weather APIs to improve real-time prediction and provide up-to-date environmental information to farmers.

10. Explainable AI (XAI)
Explainable AI techniques can be added to make predictions more transparent and understandable for farmers and agricultural experts, increasing trust in the system.

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