Sustainable Crop Forecasting for Food Security: A Review of AI and Remote Sensing Methods

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Abstract. As the climate changes increase, forecasting crop yields correctly is very important for the achievement of agricultural sustainability, using resources effectively, and ensuring food security. The complex nonlinear connections between crop, soil, and climate factors cannot be fully shown by traditional methods like regression and ARIMA models. To improve the study, recent advancements in remote sensing and machine learning have made it possible to gather and combine data from different sources. In this work, we look at how ML and DL models combined with the outline include hybrid DL networks such as CNN-LSTM, and algorithms like RF, SVM, and Gradient Boosting that can capture both temporal and spatial needs in crop growth dynamics. The study's results displayed that, about calculating accuracy and scalability, hybrid DL models achieve much better results than traditional and standalone ML models. The presented system provides a path to data-driven, renewable agricultural decision-making and underlines the possibility of joining data from multiple sources and using detailed information for effective crop yield forecasting. RS indices, soil properties and weather variables to give a reliable evaluation of crop yield.

1 Introduction

Crop yield forecasting is still useful for expanding resource use, handling climate risk, and reaching sustainable production. Agriculture is the basis of both food security and economic durability. Therefore, policymakers, farmers, and agricultural businesses will be able to make up-to-date plans about planting schedules, irrigation, and market logistics with the help of precise yield projection. Due to their ease of use and illustration, linear regression and ARIMA models have been the main elements of traditional yield forecasting models. The complex nonlinear relation between biological, environmental, and management factors that affect crop growth is often missed by these models [1]. The use of the latest and data-driven methods has been encouraged by the increased variability in climate conditions as well as the heterogeneity of soil and crop systems.

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Crop yield calculation has changed increasingly as a result of recent growth in Remote Sensing (RS) and Machine Learning (ML). Using vegetation indices like Normalised Difference Vegetative Index (NDVI) and Enhanced Vegetation Index (EVI), high-resolution satellite data from MODIS, Landsat, and Sentinel satellites give useful spatiotemporal data on crop life, phenology, and stress conditions. By uniting these RS data with soil, weather, and management datasets, yield prediction accuracy using machine learning models like Random Forest (RF), Support Vector Machine (SVM), and gradient boosting has been purposely improved related to conventional techniques [2], [3]. In recent years, deep learning techniques like CNNs and LSTM systems have made it possible for models to frequently find complex patterns in time-series and multispectral data [4], [5]. By learning useful features that mix spatial and temporal relations, hybrid architectures that combine CNN and LSTM have been proven to perform better than single models, permitting increased precision and better generalisation across various crops and geographical areas [6].

The mixing of physical domain knowledge with predictive analytics has been studied through hybrid frameworks that unite data-centric ML algorithms with process-based crop simulation models, like Agricultural Production Systems Simulator (APSIM) or Decision Support System for Agrotechnology Transfer (DSSAT), in addition to pure data-driven ML and DL approaches [7]. With better interpretability and transferability, integrative systems give a detailed understanding of yield factors. However, there are still incomplete issues with data shortage, variation in spatial resolution between datasets, and understanding black-box models. More studies show that for yield forecasting at global scales, we should combine automated model optimisation, explainable AI techniques, and data fusion from different sources [8]. To improve the accuracy and reliability of crop yield forecasts, these ideas have motivated research into uniting remote sensing, environmental, and agronomic data using modern machine learning and deep learning models.

2 Background and Related Works

Accurate Crop Yield Prediction (CYP) is important for ensuring global security, boosting sustainable resource management, and understanding the ideas of modern agriculture, often referred to as Agriculture 5.0 [2]. The growth of CYP modelling has moved from simple statistical methods to complex, data-driven Artificial Intelligence (AI) solutions [12],[15]. This segment evaluates the literature on the required data, advanced modelling techniques, and the need for automation that defines current research.

2.1 The Imperative of Multi-Source Data Fusion for CYP

Traditional CYP approaches depend on finite data, which results in models to find it hard to capture non-linear and correlated variables of crop growth [3]. Modern methods need to combine different types of data to make strong predictions.

2.1.1 Remote Sensing and Spatio-Temporal Data

Satellite Time-Series: Many time-based remote sensing images are essential for tracking the stages of crop growth and finding different crop types throughout the entire season. This is true for time series of Vegetation Indices (VIs) taken from satellites like MODIS, Sentinel, or Landsat [16]. The best way to represent the change in growth is to use the complete time-series data rather than the study from a single date [15].

UAV-Based Phenotyping: Unmanned Aerial Vehicles (UAVs) provide important data for complete, field-specific insights known as High-Throughput Phenotyping. Studies provide

machine learning (ML) methods combined with UAV images (RGB, multispectral) to assess yield at the farm level with high accuracy [8, 10].

2.1.2 Integration of Environmental and Process Data

Soil Health and Agrochemical Properties: Crop yield progress is mainly determined by soil data, together with key agrochemical factors like organic carbon and nutrient levels (N, P, and K) [9]. Studies have successfully used ML models with remote sensing aspects to foresee the spatial allocation of these important soil parameters [6].

Model Integration (Data Assimilation): Combining machine learning models with physical or process-based crop models (like APSIM) is better. This hybrid approach combines mechanistic information with the ability of the ML to study complex features such as crop rotation effects. The physical models explain key parameters like starting soil water, temperature stress, or biomass [7].

2.2 The Imperative of Multi-Source Data Fusion for CYP

Traditional machine learning algorithms, such as RF and basic SVM, find it difficulty to analyse nonlinear problems that come from merging data from various sources. Advanced Deep Learning (DL) models [12] and architectures that combine or hybridise these models are now dominating the field.

2.2.1 Deep Neural Networks for Data Complexity

DLMLP and Feature Learning: When trained on rich, fused datasets such as soil health and RS variables, Deep Multi-Layer Perceptrons (DLMLP) have demonstrated superior performance compared to shallow models [5], [9]. However, image-like, spatiotemporal data is often difficult for purely dense networks to handle effectively.

Spatio-Temporal Architectures: Specialised models are needed to process time-series RS data efficiently. It is common to find architectures that combine Recurrent Neural Networks (RNNs), such as LSTMs, for temporal sequencing with Convolutional Neural Networks (CNNs) for spatial feature extraction [15], [16]. Highly complex hybrid networks, like ConvLSTM–ViT [13], which combine the global contextual understanding capabilities of a Vision Transformer (ViT) with the spatial sequence processing of ConvLSTM, are now considered state-of-the-art. By simultaneously capturing local features and long-range dependencies, this fusion overcomes the drawbacks of single networks.

2.2.2 Hybrid and Ensemble Modelling for Enhanced Robustness

Hybrid Models: Algorithms for specific subtasks are explicitly integrated into these models. A Hybrid CNN- SVM approach, for instance, uses CNN's powerful, automated feature engineering from spectral data to feed the SVM with the best features for incredibly efficient. Regression or classification [20]. Such hybrid ML and DL approaches result in more accurate and efficient prediction frameworks, according to other research [11], [18].

Deep Ensemble Techniques: It has been demonstrated that ensemble learning, which aggregates several base predictors, improves generalisation and lowers variance [17]. In order to improve feature selection and attain greater predictive accuracy than any single component model, deep ensemble models frequently use hybrid intelligence techniques in conjunction with a variety of deep learning architectures [19].

2.3 The Automation Imperative: AutoML in Yield Prediction

A major hyperparameter and architecture optimisation challenge is introduced by the mass availability of data variables, preprocessing methods, feature engineering techniques, and intricate hybrid model configurations. It is unsuitable and prevents the generalizability of the final model from being manually work through these combinations.
Automated Machine Learning (AutoML) has become vital as a result of this difficulty. In order to provide a quick and dependable deployment solution, autoML seeks to automate the entire machine learning process, from identifying the best features to searching for hyperparameters and model architectures [4]. Furthermore, an automated framework is used to maintain high-quality prediction and to adjust the changing field conditions without manual interference, as agricultural systems depend more and more on real-time data from sensors and Internet of Things (IoT) infrastructure [14].

2.4 Traditional Crop Forecasting Methods

Statistical models based on historical yield and climate data played a key part in early crop yield prediction methods. One of the most common was linear regression. This method finds the relationship between yield and important factors such as soil fertility, rainfall, and temperature. However, these simple presentations do not seize the nonlinear and dynamic relations that impact crop production. The AutoRegressive Integrated Moving Average (ARIMA) model is another known statistical method that studies trends and seasonal variations in yield data, making it useful for time-series forecasting. ARIMA finds it difficult to deal with unpredictable factors like pest outbreaks, extreme weather, or changes in farming practices. The limitations of these traditional methods show the need for new methods that can better report the difficulty and irregularity in agricultural systems.

3 Taxonomy of ML and Remote Sensing Approaches

This section presents a systematic classification of the existing machine learning (ML) and remote sensing (RS) techniques applied in crop yield prediction and agricultural monitoring. The taxonomy classifies the approaches based on the type of data used (spectral, temporal, and environmental), the learning pattern adopted (supervised, unsupervised, hybrid and satellite platforms), and the model architecture used.

3.1 Traditional Crop Forecasting Methods

Linear Regression (LR): Models produce results as a linear function of predictors (such as rainfall and NDVI). It has trouble with non-linearities but performs well in simple relationships. Support Vector Machines (SVM): Excellent for regression tasks like yield estimation and classification tasks like crop type identification. Effectively handle high-dimensional spectral data. Random Forests (RF): widely used for crop mapping and yield prediction. Effectively manages noisy remote sensing data and assigns feature importance. Gradient Boosting (XGBoost, LightGBM): In structured tabular data, like weather + vegetation indices, more potent ensemble methods frequently perform better than RF.

3.2 Deep Learning-Based Models

Artificial Neural Networks (ANN): multi-layer perceptrons for regression-based yield prediction. Convolutional Neural Networks (CNN): exploit spatial features from satellite images (e.g., crop health patterns). Recurrent Neural Networks (RNN)/LSTM: They are effective at forecasting seasonal yields because they can identify temporal patterns in vegetation

indices or weather series. CNN-LSTM Hybrids: integrate temporal and spatial learning, which is helpful for concurrent crop mapping and forecasting.

3.3 Hybrid and Ensemble Methods

Stacked/Bagging Ensemble: To balance bias and variance, combine neural nets, gradient boosting, and RF.
Hybrid crop model with ML: Apply machine learning (ML) to improve forecasts using weather and remote sensing data after using crop simulation models (such as DSSAT and APSIM) for physiological aspects.
Physics-guided deep learning: improves interpretability by embedding constraints from plant physiology into neural networks.

3.4 Satellite Platforms

Unmanned Aerial Vehicles (UAVs): These provide high-quality phenotyping and assess variability within fields. They give ultra-high spatial resolution imagery at the centimetre level through UAV-based remote sensing. While their limited spatial coverage restricts forecasts over large areas, UAVs are especially effective for accuracy management, breeding trials, and small-scale studies.
Multispectral Sensors: Reflectance across a small number of broad spectral bands, like visible, near-infrared, and shortwave infrared, is taken by multispectral imagery. These bands are often used to analyse vegetation indices. These indices compare well with crop vigor, biomass, and stress conditions. They are also effective in terms of calculation.
Hyperspectral Sensors: These capture hundreds of narrow continuous spectral bands, providing complete data about canopy biochemical properties like water content, nitrogen, and chlorophyll. Hyperspectral data provide a richer feature space for machine learning models, allowing for more precise yield prediction and stress detection, even though it can be computationally demanding. Fig.1 shows the End-to-End Workflow for Agricultural Yield Prediction.

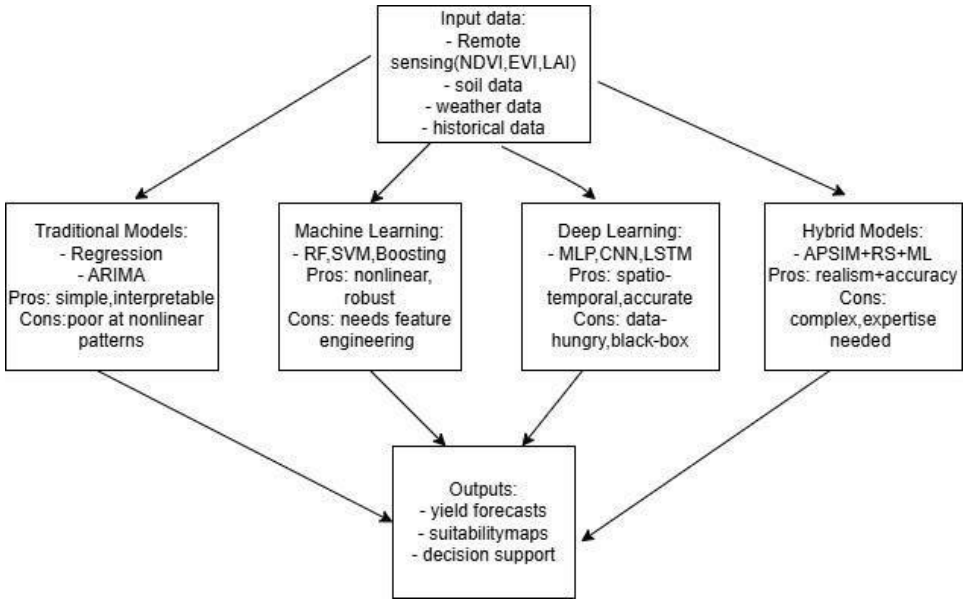

Fig. 1. Workflow architecture for Agricultural Yield Prediction.

4 Datasets and Evaluation Metrics

Crop forecasting studies rely on multi-source datasets that integrate remote sensing with ancillary data, which includes:

Remote Sensing Data: MODIS, Landsat, and Sentinel satellite imagery provide land surface temperature, canopy reflectance, and vegetation indices, including NDVI, EVI, and LAI. Plot-scale phenotyping uses UAV imagery and multispectral and hyperspectral data. This includes characteristics such as temporal trajectories, canopy structural metrics, and vegetation indices. Weather Data from the past (temperature, humidity, radiation, rainfall). products from climate reanalysis (ERA5, NASA POWER). [7], [12], [14], [17], [18], [19].
Soil and Agronomic Data: Agrochemical characteristics include nitrogen, phosphorus, and organic matter. This data also provides soil texture and fertility. Details about crop rotation, irrigation, and sowing dates are examples of management information. [4], [6], [7], [9], [11],
Yield Data (Ground Truth): FAOSTAT, USDA-NASS, ICAR, and state-level datasets provide national and regional crop statistics. Harvest measurements at the field level help with proof and tuning. [5], [8-10], [12], [13], [18], [19].

4.1 Evaluation Metrics

Error-Based Metrics

Root Mean Squared Error (RMSE) calculates the average difference between predicted and observed yield values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Where:
n = number of samples
yi actual observed yield
$\hat{y}i$ = predicted yield by the model

Mean Absolute Error (MAE) gives the measure of error size using the same unit as the yield.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

Mean Absolute Percentage Error (MAPE) is a normalised error metric. It is useful for making comparisons across different crops and regions.

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3}$$

Correlation-Based Metrics

Coefficient of Determination (R^2): Proportion of variance explained by the model.

$$R^2 = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}} \tag{4}$$

Where:
$SS_{res}=\Sigma(yi-\hat{y}i)2$ = Residual sum of squares
$SS_{tot}=\Sigma(yi-\bar{y})2$ = Total sum of squares
yi = actual observed yield

ŷi = predicted yield
$\bar{y}$ = mean of observed yields

Pearson's Correlation Coefficient (r): Captures the linear association between predicted and observed yields.

$$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}} \quad (5)$$

Where:
yi = actual yield, ŷi = predicted yield, $\bar{y}$ = mean of actual yields, $\bar{\hat{y}}$ = mean of predicted yields, n = number of samples

Classification Metrics (for suitability/yield category prediction)

This includes Accuracy, Precision, Recall, and F1-Score.

5 Comparative Analysis and Applications

Table 1 shows an estimation of different modelling approaches used in crop yield prediction, giving their key strengths and weaknesses. It gives an outline of how traditional machine learning, deep learning, and hybrid crop model–based approaches differ in terms of data requirements, interpretability, and modelling capabilities.

Table 1. Comparison of ML, DL, and Hybrid Approaches.

Approach	Strengths	Weaknesses
Machine Learning (RF, SVM, Gradient Boosting)	Robust to limited data; Interpretable feature importance; Good performance with multisource fusion	Depend heavily on handcrafted features (e.g., vegetation indices, temporal descriptors)
Deep Learning (MLP, CNN, LSTM)	Capture spatial–temporal dynamics directly from raw data; Reduce need for manual feature engineering; Often outperform ML when Large datasets are available	Require high-quality labelled datasets; Computationally intensive; Less interpretable
Hybrid Approaches (Crop Models + ML/RS)	Combine biophysical understanding with data-driven flexibility. Generalise better across regions	Require extensive calibration and integration of multiple data sources

5.1 Applications

Crop yield prediction has many important uses across modern agriculture and environmental management. Precision agriculture provides the accurate application of water, fertilisers, and pesticides by discovering the zones with different yield potential. Yield forecasts are also vital

for food security observation, helping governments and agencies forestall shortages, stabilise markets, and plan import export approaches. Additionally, these models support climate impact by assessing crop weakness to drought, flooding, and heat stress under changing climatic situations. From another point of view, correct predictions give important inputs for agricultural planning, subsidy distribution, and risk management plans. In breeding and agronomic research, UAV-based measurements and remote sensing indicators support in assessing genotypes and progressing crop improvement programs. Also, yield prediction plays an important role in sustainability and resource management by improving soil health, crop rotations, and nutrient cycles to promote long-term agricultural productivity.

6 Challenges and Future Directions

6.1 Challenges

Data availability and quality frequently limit how correctly we can foresee crop yields. Model tuning and justification rely on ground truth yield data, which is often not enough, defective, or collected at uneven times and places. These issues can decrease the precision of these well-trained models that work with different crops and regions. Additionally, there are still high-resolution, long-term remote sensing datasets, mostly in developing countries. Frequent data collection is also affected by reasons like cloud cover, low spatial resolution, and inconsistent revisit times. These problems reduce models' ability to capture detailed changes in crop growth over space and time, affecting their validity and adaptability. This creates the need for even yield reporting systems, better data collection methods, and open-access satellite records.
An important problem in the outline of yield prediction models is the fundamental heterogeneity of agricultural landscapes. Crop growth outlines are affected by differences in cropping systems, management techniques, and soil properties, which makes it difficult for models developed in one area to function steadily in another. Additional variability recorded by remote sensing data is shown by a variety of agronomic practices, including planting densities, irrigation plans, and fertiliser using rates. Also, satellite-based yield evaluation is made difficult by dynamic practices like crop rotation and intercropping, which change canopy reflectance and vegetation indices. In order to improve systematic accuracy, adaptive modelling methods and region-specific tuning policies are required, as this spatial and temporal heterogeneity reduces model transferability.

6.2 Model Limitations

Even though crop yield forecast accuracy has increased pointedly thanks to machine learning and deep learning techniques, there are still a number of model-related issues. For agronomists and policymakers who need a complete understanding of the variables influencing yield variation, deep learning architectures like CNNs and LSTMs are often viewed as "black-box" models, providing little clarity. The arrangement of such models in operational agricultural decision-making is behind by lack of clarity. Also, deep networks' flexibility is inadequate by their high systematic cost and need for large, well-labelled datasets, especially in areas with limited resources or data. To provide wider applicability and confidence in predictive agricultural systems, these limitations show the importance of creating explainable, computationally effective, and data-adaptive modelling frameworks.

6.2 Future Directions

To increase crop yield prediction, future studies should focus on making solid and clear data ecosystems. By developing high-quality, publicly available datasets, we can improve model transparency, reproducibility, and regional applicability. We can reach better time and space

resolution by using advanced remote sensing tools like CubeSats, hyperspectral UAVs, and geostationary sensors. This will allow real-time monitoring of crop dynamics. Also, tuning data collection methods and metadata frameworks will progress data sharing and model viability across research organizations and regions.

Future growth in crop yield prediction should focus on hybrid modelling frameworks that combine data-driven machine learning techniques with process-based crop models. Connecting these approaches can develop predictive and analytical studies and work while using the understanding of crop growth from biological models. This increases both model understandability and the ability to apply findings to different agroclimatic zones. Also, agronomists and policymakers can understand the effects of environmental and management factors by adding Explainable Artificial Intelligence (XAI) techniques in model decision-making.

To deal with rising variation and doubt caused by global climate change, future crop yield predicting systems need to move toward climate-resilient frameworks. It will be possible to calculate the long-term effects of warming temperatures, changed precipitation patterns, and changing growing seasons on agricultural productivity by joining climate model projections into yield prediction pipelines. Additionally, creating early warning systems for floods, droughts, and possible yield losses can help farmers and disaster management organizations make choices to improve agricultural systems' ability to respond and ensure long-term food security in changing environmental conditions.

7 Conclusion

This study examined the collaboration between remote sensing data and machine learning methods in predicting crop yields. By integrating spectral indices, weather data, and soil data with learning models like Random Forest, LSTM, and hybrid frameworks, studies have openly improved the correctness and scalability of agricultural forecasts. Current methods show this progress clearly. Multi-resolution and multi-temporal data from remote sensing platforms, including satellites and drones, help monitor screen crop growth dynamics better. However, several difficulties remain, such as the need for models that are easier to understand and transfer, the variety of the data, and the lack of ground-truth data. Even with these problems, the methods deliberated reveal how useful data-driven approaches can be in handling sustainable agriculture, food security, and climate flexibility. In conclusion, crop forecasting using remote sensing and machine learning is emerging as a vital tool for researchers and decision-makers. These systems will likely develop into reliable, farmer-focused decision-support tools as open datasets, explainable AI, and hybrid modelling.

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