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Crop Yield Prediction through Machine Learning Integration with Sentinel-2 Time Series Data in Irrigated Agroecosystems

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Abstract

Accurate, timely crop yield prediction is essential for food security, market stability, and precision agriculture, particularly in irrigated agroecosystems where spatial heterogeneity in water, nutrient, and management practices complicates forecasting. This review synthesizes recent advances in integrating high-resolution Sentinel-2 time-series data with machine learning (ML) models to achieve field-level yield estimation. Sentinel-2's 10–60 m multispectral bands, 5-day revisit frequency, and derived vegetation indices (NDVI, EVI, NDRE, SAVI, GNDVI) capture phenological dynamics, canopy development, and stress responses across growth stages. Key ML approaches include Random Forest, Support Vector Regression, Gradient Boosting Machines (XGBoost, LightGBM), deep learning architectures (CNN, LSTM, Transformer-based models), and hybrid frameworks combining vegetation indices with meteorological variables, soil properties, and crop management data. Studies demonstrate R^2 values of 0.75–0.95 and RMSE reductions of 15–40% compared to traditional statistical or coarse-resolution models, with superior performance in heterogeneous irrigated systems (rice, wheat, maize, cotton). Feature importance analyses consistently highlight mid-season red-edge and near-infrared bands for predictive power. Challenges such as cloud cover, data harmonization, model transferability, and ground-truth scarcity are addressed through gap-filling techniques, transfer learning, and data augmentation. The integration of Sentinel-2 with ML offers scalable, cost-effective yield forecasting, enabling proactive interventions and supporting climate-resilient agriculture in water-managed regions.

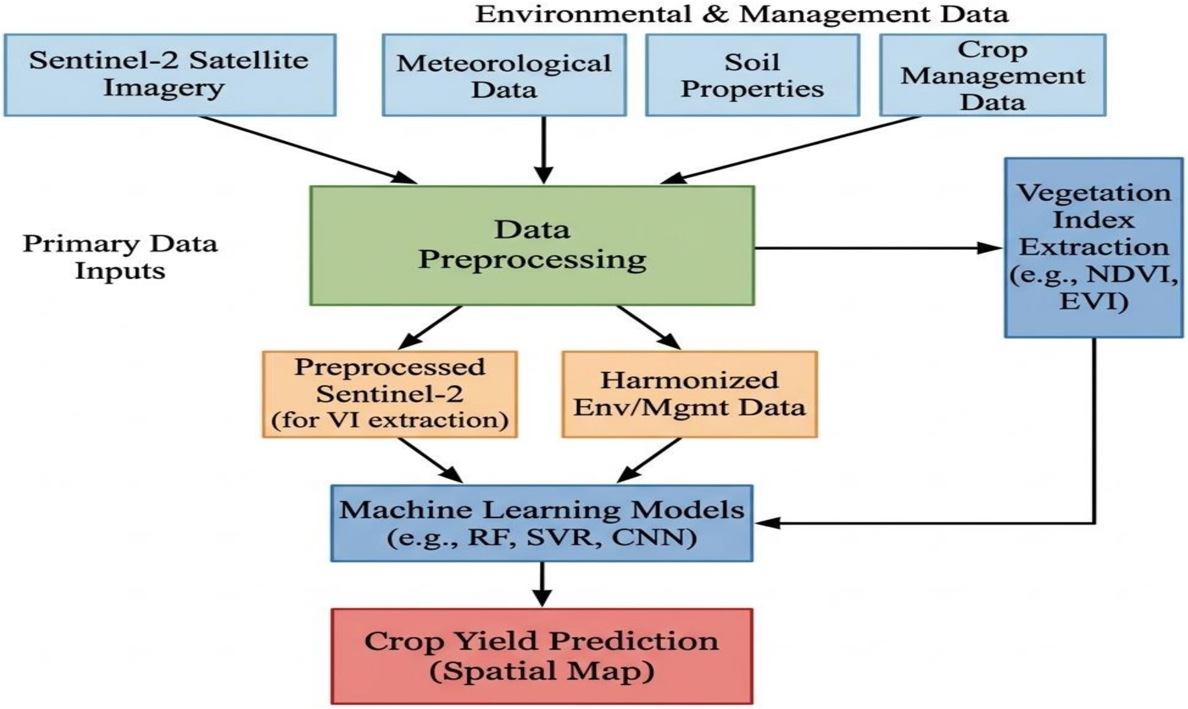
Keywords: Crop Yield Prediction, Sentinel-2, Machine Learning, Remote Sensing, Vegetation Indices, Precision Agriculture, Irrigated Agroecosystems, NDVI, EVI, Random Forest, Deep Learning, Phenology

1. Introduction

The global agricultural sector is currently navigating a period of profound transition, driven by the intersecting pressures of a burgeoning human population, climate-induced environmental volatility, and the finite nature of arable land and water resources (Li et al., 2023). As the population continues its upward trajectory, the demand for staple food products increases commensurately, exerting unprecedented stress on natural ecosystems (Lata et al., 2025). In this context, the concept of precision agriculture has evolved from a nascent technological trend into a fundamental necessity for ensuring global food security (Van Klompenburg et al., 2020). Precision agriculture focuses on the optimization of agricultural inputs such as water, fertilizers, and pesticides to maximize crop productivity while simultaneously minimizing environmental impact and resource wastage (Sindhushree et al., 2025). At the core of this optimization lies the ability to accurately predict crop yields well in advance of the harvest, providing critical information for market stability, logistical planning, and regional policy interventions (Saha et al., 2025).

The emergence of satellite remote sensing as a primary tool for agricultural monitoring has revolutionized the scale and frequency at which crop assessments can be conducted. Among the various satellite missions currently operational, the European Space Agency's Sentinel-2 constellation has become the gold standard for field-level monitoring due to its unique combination of high spatial, spectral, and temporal resolutions (Wu et al., 2023). By providing frequent, multispectral imagery at resolutions as fine as 10 meters, Sentinel-2 allows for the detailed observation of intra-field variability, which is essential for managing complex irrigated agroecosystems (Grich et al., 2026). These ecosystems, characterized by artificial water applications that often exhibit high spatial heterogeneity, present unique challenges for yield prediction that traditional, low-resolution sensors cannot adequately address (Quille-Mamani et al., 2024). The integration of remote sensing data and machine learning enables efficient crop monitoring and yield prediction. The overall workflow of this integrated framework is illustrated in Figure 1.

Figure 1: Conceptual Framework of Crop Yield Prediction Using Sentinel-2 and Machine Learning



2. The Evolution of Yield Prediction Methodologies

Historically, crop yield estimation relied on destructive field sampling or the extrapolation of historical statistical trends, methods that are inherently labor-intensive, costly, and limited in spatial scope (Chahbi-Bellakanji et al., 2025). These traditional approaches often fail to capture the dynamic responses of crops to sudden environmental stresses or variations in management practices. The integration of remote sensing data introduced the possibility of objective, non-destructive, and spatially continuous monitoring (Ashwani Kumar et al., 2021). However, early remote sensing models were frequently limited to simple linear regressions between vegetation indices and final yield, which often failed to account for the complex, non-linear interactions between soil properties, climatic variables, and crop physiology (Haseeb wt al., 2025).

The advent of machine learning and deep learning has provided the computational framework necessary to decode these complexities. Unlike traditional statistical models, machine learning algorithms can ingest vast quantities of multi-source data including satellite imagery, meteorological records, and soil property maps to identify subtle patterns that correlate with final productivity (Ed-Daoudi & El Haloui, 2025). In irrigated agroecosystems, where the relationship between water availability and yield is mediated by factors like evapotranspiration and nutrient leaching, the ability of machine learning to model non-linear dependencies is particularly advantageous (Ndagijimana et al., 2026).

Table 1. Comparison of Traditional vs. Machine Learning-Based Yield Prediction

Feature	Traditional Methods	Machine Learning/Remote Sensing
Data Acquisition	Destructive field sampling, surveys (Chahbi-Bellakanji et al., 2025)	Non-destructive satellite/UAV imaging (Chahbi-Bellakanji et al., 2025; Sindhushree et al., 2025)
Spatial Scale	Local, point-based observations (Chahbi-Bellakanji et al., 2025)	Continuous field-to-regional coverage (Sindhushree et al., 2025)
Temporal Frequency	Infrequent, often post-harvest (Chahbi-Bellakanji et al., 2025)	High frequency (5-day revisit) (Grich et al., 2026; Quille-Mamani et al., 2024)
Complexity	Linear statistical models (Ashwani Kumar et al., 2021)	Non-linear, multi-dimensional patterns (Ndagijimana et al., 2026; Sindhushree et al., 2025)
Cost	High (labor and time intensive) (Chahbi-Bellakanji et al., 2025)	Lower per-unit area for large scales (Sindhushree et al., 2025)
Predictive Window	Late season or post-harvest (Chahbi-Bellakanji et al., 2025)	Up to 3 months before harvest (Chahbi-Bellakanji et al., 2025)

The predictive power of these models is further enhanced by the use of time series data. Rather than relying on a single "snapshot" of the crop during the peak of the growing season, time series analysis captures the entire phenological trajectory of the plant (Varela et al., 2021). This temporal dimension allows models to differentiate between early-season vigor and late-season senescence, providing a more comprehensive understanding of the factors driving the final yield (Filippi et al., 2022).

3. Sentinel-2 Satellite System and Spectral Capabilities

The Sentinel-2 mission, a core component of the Copernicus program, consists of two identical satellites, Sentinel-2A and Sentinel-2B, positioned in the same sun-synchronous orbit with a 180 degree phase difference (Sudmanns et al., 2020). This configuration ensures a high revisit frequency of five days at the equator and even higher frequencies at mid-latitudes, which is critical for monitoring rapid changes in crop phenology and capturing cloud-free observations during the growing season (Segarra et al., 2020). The primary payload of each satellite is the Multi-Spectral Instrument (MSI), which samples 13 spectral bands covering the visible, near-infrared (VNIR), and shortwave infrared (SWIR) domains (Sindhushree et al., 2021).

Table 2. Detailed Spectral Characteristics of Sentinel-2 MSI Bands

Band Number	Purpose	Wavelength (nm)	Resolution (m)	Agricultural Relevance
B1	Coastal Aerosol	443	60	Atmospheric correction, aerosol detection (Sindhushree et al., 2021)
B2	Blue	490	10	Soil/vegetation differentiation, plant health (Sindhushree et al., 2021)
B3	Green	560	10	Chlorophyll reflection, biomass density (Sindhushree et al., 2021)

B4	Red	665	10	Chlorophyll absorption, growth assessment (Sindhushree et al., 2021)
B5	Red Edge 1	705	20	Early stress detection, nitrogen sensing (Clevers & Gitelson, 2012)
B6	Red Edge 2	740	20	Canopy chlorophyll content estimation (Clevers & Gitelson, 2012)
B7	Red Edge 3	783	20	Advanced biomass and N assessment (Clevers & Gitelson, 2012)
B8	NIR	842	10	Biomass content, plant vigor monitoring (Ashwani Kumar et al., 2021; Sindhushree et al., 2021)
B8A	Narrow NIR	865	20	Vegetation classification, moisture tracking (Quille-Mamani et al., 2024; Sindhushree et al., 2021)
B9	Water Vapor	945	60	Atmospheric monitoring (Sindhushree et al., 2021)
B10	Cirrus	1375	60	Cloud detection and masking (Sindhushree et al., 2021)
B11	SWIR 1	1610	20	Soil/vegetation moisture, water stress (Clevers & Gitelson, 2012; Sindhushree et al., 2021)
B12	SWIR 2	2190	20	Lignin/cellulose, drought monitoring (Clevers & Gitelson, 2012; Sindhushree et al., 2021)

The presence of three bands in the "red edge" region (Bands 5, 6, and 7) is perhaps the most significant feature of Sentinel-2 for agricultural applications. The red edge is the spectral region characterized by a sharp increase in reflectance between the visible red and the near-infrared, and its position and slope are highly sensitive to leaf chlorophyll and nitrogen concentrations (Clevers & Gitelson, 2012). Research has demonstrated that red-edge indices are more linear estimators of canopy chlorophyll than traditional NIR-Red indices and are less prone to the saturation effects observed in high-biomass crops (Segarra et al., 2021). In irrigated systems, where nitrogen fertilization and water application are often coupled, the ability to monitor nitrogen status through red-edge bands provides a direct link to the physiological drivers of yield (Sellami et al., 2022).

Furthermore, the SWIR bands (Bands 11 and 12) are indispensable for assessing water dynamics. These bands are sensitive to the liquid water content in plant tissues and the moisture levels in the topsoil (Billah et al., 2024). In arid and semi-arid regions, the integration of SWIR data allows for the calculation of moisture-sensitive indices like the Normalized Difference Moisture Index (NDMI), which can identify irrigation requirements and water stress before they become visually apparent (Ahmed & Hanane, 2025).

4. Data Preprocessing and Time Series Reconstruction

The transition from raw satellite imagery to a structured dataset suitable for machine learning requires a rigorous preprocessing pipeline (Moskolaï al., 2022). This process begins with atmospheric correction, which converts Top-of-Atmosphere (TOA) reflectance to Bottom-of-Atmosphere (BOA) surface reflectance, ensuring that the spectral signals represent the actual properties of the land surface rather than atmospheric interference (Shekar et al., 2026). For Sentinel-2, this is typically achieved using the Sen2Cor algorithm or similar atmospheric correction models (Gil Lerchundi, 2022).

Cloud cover remains the most significant obstacle to consistent time series monitoring. Even with a 5-day revisit cycle, persistent cloudiness can obscure critical growth phases, leading to significant gaps in the data (Zhu et al., 2021). To mitigate this, researchers employ several strategies. The first involves the use of advanced cloud masking products, such as Fmask or Cloud Score+, which identify and filter out pixels contaminated by clouds, cirrus, and shadows (Jain et al., 2025). However, simple filtering can result in a "sparse" time series, which is problematic for models that require regular temporal inputs. Gap-filling and data reconstruction techniques have evolved to address these missing values (Dronova & Taddeo, 2022). Spatial interpolation methods like Kriging and Inverse Distance Weighting (IDW) can estimate missing pixel values based on neighboring information, while temporal methods use linear or spline interpolation along the time axis (Middya & Roy, 2021). More recently, spatio-temporal deep learning and SAR-optical data fusion have emerged as robust alternatives. Sentinel-1 Synthetic Aperture Radar (SAR) data, which can penetrate clouds and provide consistent signals regardless of weather conditions, is increasingly used to guide the reconstruction of optical signals or to directly estimate vegetation health during overcast periods (Zahmatkesh et al., 2026). Deep residual neural networks have been successfully trained to remove even optically thick clouds by learning the relationship between multi-temporal optical imagery and co-registered radar data (Ahmed et al., 2026). Another essential step in the preprocessing pipeline for Sentinel-2 is spatial resolution harmonization. Because the bands are acquired at 10, 20, and 60-meter resolutions, they must be resampled to a common grid for multivariate analysis (Hung et al., 2025). Bicubic interpolation is widely preferred for this task as it generates smooth outputs and preserves spatial continuity better than simpler techniques like nearest-neighbor interpolation (Ullah et al., 2025)

5. Spectral Indicators and Phenological Modeling

Vegetation Indices (VIs) serve as the primary features in most yield prediction models. These indices are designed to enhance the signal of green vegetation while minimizing background noise from soil, water, and atmosphere (Zeng et al., 2022). While the Normalized Difference Vegetation Index (NDVI) remains the most common metric, its susceptibility to saturation in high-yielding, dense-canopy crops has led to the development of more robust alternatives (Ji et al., 2022).

Table 3. Formulas and Applications of Common Vegetation Indices

Index	Formula	Application
NDVI	(NIR - Red) / (NIR + Red)	General biomass monitoring, phenology (Quille-Mamani et al., 2023; Sindhushree et al., 2021)
NDRE	(NIR - RedEdge) / (NIR + RedEdge)	Chlorophyll/Nitrogen sensing, late-season health (Clevers & Gitelson, 2012; Singh, 2025)
EVI	2.5 * ((NIR - Red) / (NIR + 6 * Red - 7.5 * Blue + 1))	Saturation-resistant biomass, yield prediction (Singh, 2025)
NDMI	(NIR - SWIR) / (NIR + SWIR)	Water stress, soil moisture monitoring (Ahmed & Hanane, 2025)
PSRI	(Red - Blue) / NIR	Plant senescence, ripeness assessment (Tufail et al., 2025)
GNDVI	(NIR - Green) / (NIR + Green)	Chlorophyll sensitivity, early biomass (Chahbi-Bellakanji et al., 2025)
NDWI	(Green - NIR) / (Green + NIR)	Water body detection, flood monitoring (Ahmed et al., 2026)

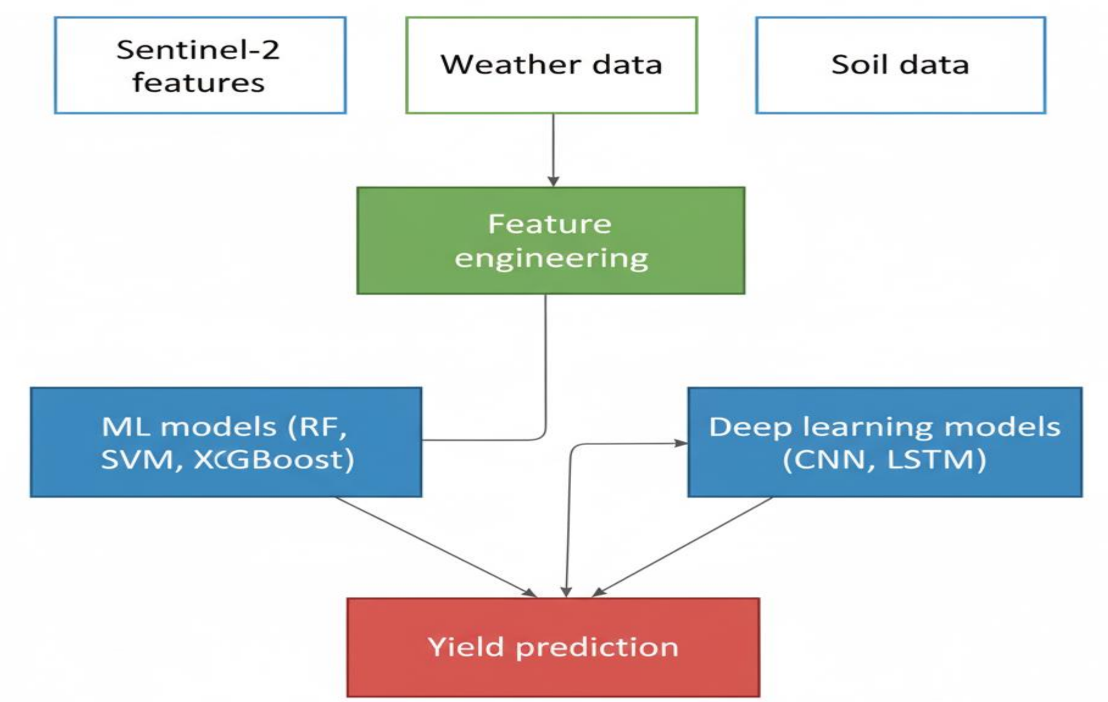
In irrigated agroecosystems, the EVI is often cited as a superior predictor of yield compared to NDVI, particularly for high-biomass crops like cotton or maize, because it remains sensitive to canopy structure even after the leaves have achieved full coverage (Singh, 2025). Furthermore, indices utilizing the red-edge bands, such as the Normalized Difference Red Edge (NDRE) or the Three Red-Edge Vegetation Index (NDVI3RE), have shown higher correlations with maize yield by effectively capturing the physiological vigor of the plant during advanced growth stages (Qiao et al., 2024).

Phenological modeling extends the utility of these indices by aligning spectral signals with key biological milestones. The life cycle of a crop from emergence and vegetative growth to flowering, grain filling, and maturity is characterized by distinct spectral patterns. Phenological metrics, such as the Start of Season (SOS), Peak of Season (POS), and End of Season (EOS), are calculated by analyzing the curvature of the VI time series (Quille-Mamani et al., 2023). For instance, the timing of the Peak of Season and the magnitude of the index at that peak are often the most influential features in yield models for maize and soybean (Diao, 2020). Without this phenological context, a model might misinterpret a high NDVI value in the early season as being equivalent to a high value in the late season, even though their impacts on final yield are very different (Pei et al., 2025).

6. Machine Learning Frameworks for Prediction

The integration of Sentinel-2 data with machine learning algorithms has transitioned yield prediction from a static observation into a dynamic forecasting process. Various algorithmic families have been evaluated for their ability to model the complex relationship between spectral inputs and harvest outcomes (Lata et al., 2025). Machine learning algorithms integrate multisource data to model complex crop–environment relationships. The general machine learning workflow for yield prediction is shown in Figure 2.

Figure 2: Machine Learning Workflow for Crop Yield Prediction



6.1 Traditional Supervised Learning Algorithms

Random Forest (RF) is frequently highlighted as the most versatile and high-performing algorithm for agricultural yield prediction. RF is an ensemble learning method that builds multiple decision trees during training and outputs the average prediction of the individual trees (Ashwani Kumar et al., 2021). Its popularity stems from several factors: it is robust to outliers, handles high-dimensional data without requiring extensive feature selection, and provides a built-in measure of feature importance (Njoku, 2026). In studies across diverse regions such as Tunisia and Rwanda, RF models have consistently achieved R2 values exceeding 0.90 for cereal crops, outperforming models like Support Vector Machines (SVM) and Linear Regression (LR) (Ndagijimana et al., 2026).

SVM is also widely used, particularly for classification and small-scale regression tasks. SVM works by finding the optimal hyperplane that separates data points in a high-dimensional space (Wang et al., 2024). While SVM can be more precise in certain low-sample scenarios, it generally lags behind RF in terms of accuracy and computational efficiency for large-scale yield forecasting (Abiodun et al., 2021). In the context of rice yield in Peru, SVM models achieved an R2 of 0.69 when combined with phenological metrics, demonstrating their utility for plot-level monitoring where data might be less abundant (Jarro-Espinal al., 2025).

Gradient Boosting Machines (GBM), including implementations like XGBoost and LightGBM, have also shown promising results. These models build trees sequentially, with each new tree attempting to correct the errors of the previous ones (Hajihosseinlou et al., 2023). While powerful, they are often more sensitive to hyperparameter tuning and noise than RF, sometimes leading to overfitting if the training dataset is limited or highly variable (Choudhury et al., 2024).

6.2 Deep Learning and Temporal Architectures

The emergence of Deep Learning (DL) has shifted the focus toward architectures that can natively process the temporal and spatial structures of satellite data. Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), are specifically designed to capture long-term dependencies in sequential data (Moskolaï et al., 2021). This is particularly relevant for agriculture, where the final yield is the cumulative result of environmental conditions throughout the entire growing season. LSTM models have demonstrated high performance in predicting yields for crops like jowar and ragi, reaching accuracies as high as 99.85% when integrated with multi-source satellite data (Singh et al., 2024).

Temporal Convolutional Networks (TCN) represent a more recent advancement in sequence modeling. Unlike RNNs, which process data sequentially, TCNs use dilated convolutions to capture information from long time horizons in parallel, making them more computationally efficient for large-scale satellite image time series (Mishra et al., 2022). Research has shown that TCNs can outperform classical RF and standard RNN models in yield forecasting, particularly due to their ability to handle variable-size inputs and their inherent robustness to cloud-induced noise (Peltonen-Sainio et al., 2022).

Hybrid architectures are also gaining traction, combining the spatial feature extraction of Convolutional Neural Networks (CNN) with the temporal sequence modeling of LSTMs or Gated Recurrent Units (GRU) (Aravinda et al., 2025). For instance, a hybrid CNN-RNN-Attention model was found to be the most effective for predicting yields in underrepresented crops like sweet potato, reaching an R2 of 0.64 by focusing the model's attention on the most critical spectral features and growth periods (Zhang et al., 2025).

Table 4. Comparative Performance of ML/DL Models Across Regions

Crop	Region	Model	Metric	Value	Source
Wheat	Tunisia	Random Forest	R2	0.91	(Chahbi-Bellakanji et al., 2025)
Maize	Rwanda	Random Forest	R2	0.957	(Ndagijimana et al., 2026)
Rice	Peru	SVM	R2	0.69	(Quille-Mamani et al., 2023)
Rice	Peru	RF	R2	0.44	(Quille-Mamani et al., 2023)
Cassava	Global	ETS-ANN	R2	0.80	(Ajay et al., 2026)
Cereals	Morocco	Hierarchical (RF+LSTM)	R2	0.77	(Ed-Daoudi & El Haloui, 2025)
Cotton	USA	Random Forest	R2	0.84	(Singh, 2025)

7. Dynamics of Irrigated Agroecosystems

The application of Sentinel-2 and machine learning in irrigated agroecosystems requires a nuanced understanding of water management and its spectral signature. Irrigation fundamentally alters the relationship between crop health and environmental variables by decoupling plant growth from immediate precipitation (Xing et al., 2025). However, inaccurate irrigation whether excessive or insufficient remains a major cause of yield loss and resource depletion (Ahmed & Hanane, 2025).

7.1 Water Stress and Soil Moisture Monitoring

Monitoring crop water stress is essential for optimizing irrigation schedules. The Normalized Difference Moisture Index (NDMI), calculated using Sentinel-2's NIR and SWIR bands, is a primary indicator for vegetation water content (Ibrahim et al., 2023). In maize crops, seasonal NDMI dynamics have been shown to perfectly reflect water-supply conditions; higher cumulative NDMI values occur in optimal years, while extreme water stress in dry years results in a collapse of the index (Gaznayee et al., 2023

In highly sophisticated systems, the integration of thermal remote sensing allows for the calculation of the Crop Water Stress Index (CWSI), which is based on the temperature difference between the plant canopy and the surrounding air (Lykhovyd & Sharii, 2024). Studies have shown that a canopy temperature increase is an early indicator of stomatal closure, which directly limits photosynthesis and final yield (Ihuoma et al., 2021).

7.2 Site-Specific Factors vs. Irrigation Volume

A critical insight from precision agriculture research is that irrigation volume alone is often not the primary driver of final yield variations. In a study of cotton production in semi-arid regions, it was found that while mid-season biomass was influenced by irrigation volume, the final yield was more strongly dictated by site-specific factors such as apparent soil electrical conductivity (ECa), slope, and elevation (Elhoseny et al., 2026). This suggests that a uniform water application across a heterogeneous field often leads to inefficient water use in certain zones and water stress in others (Kumar, 2022).

By using machine learning models (such as Random Forest) to account for these soil and topographic variables, researchers have developed site-specific irrigation strategies that can improve water use efficiency (WUE) by up to 21.4% and increase yields by 31% compared to conventional, uniform methods (Hammouch et al., 2024).

8. Feature Engineering and Model Interpretability

The "curse of dimensionality" is a significant challenge in processing multispectral time series. With 13 bands and multiple observation dates, a single growing season can generate hundreds of features for each pixel. Redundant features can lead to model overfitting and increased computational costs, necessitating effective feature selection and dimensionality reduction (Tufail et al., 2025).

8.1 Feature Selection Techniques

Techniques such as Principal Component Analysis (PCA) and Random Forest-based feature importance are commonly used to identify the most predictive variables (Centorame et al., 2025). For example, a comparative study in Italy found that the most effective feature set for crop mapping and yield assessment consisted of raw Sentinel-2 spectral bands selected by a Random Forest feature selection method, rather than pre-calculated vegetation indices alone (Kasarda et al., 2023).

Furthermore, ensemble feature selection (EFS) methods which aggregate the results of multiple selection algorithms like Boruta and RReliefF have been shown to provide higher prediction accuracy and more stable results than any single selection method (Paul et al., 2025). These methods ensure that the model focuses on the most physiologically relevant signals, such as the red-edge and SWIR reflectance, which are most sensitive to biomass and water content (Clevers & Gitelson, 2012).

8.2 Explainable AI (XAI) in Agriculture

As machine learning models become more complex, their "black-box" nature becomes a barrier to practical adoption by farmers and policymakers. Stakeholders require an understanding of *why* a model predicts a low yield to take corrective action (Ed-Daoudi & El Haloui, 2025). Explainable AI (XAI) techniques, such as SHAP (Shapley Additive exPlanations) and permutation importance, are being increasingly applied to yield forecasting workflows (Sindhushree et al., 2025).

In a hierarchical modeling approach applied to semi-arid Morocco, SHAP analysis was used to identify crop-specific critical thresholds that drove yield outcomes. For instance, the analysis revealed that maximum summer temperatures exceeding 40 degrees C were the primary driver of vegetable yield loss, while winter precipitation of less than 30mm was the critical threshold for cereal failure (Eck et al., 2020). This level of interpretability transforms the model from a simple prediction tool into a decision-support system that can inform climate adaptation strategies (Vogel et al., 2021).

9. Scalability, Transfer Learning, and Global Food Security

One of the ultimate goals of agricultural machine learning is the development of scalable models that can be applied across different regions and seasons without requiring massive amounts of local ground truth data (Mao et al., 2025). However, the spatial and temporal transferability of models is often limited by "domain shift" differences in soil types, climate patterns, and crop varieties between the training region and the target region (Zhang et al., 2025).

9.1 Transfer Learning Mechanisms

Transfer Learning (TL) has emerged as a key solution to this challenge. TL involves training a model on a data-rich "source domain" (e.g., North American agricultural fields) and then fine-tuning it on a "target domain" with limited data (Kakchingtabam et al., 2025). Studies in the Hexi Corridor demonstrated that while "naive" transfer yields moderate results, transfer learning strategies can achieve classification accuracies of over 90% even with minimal local samples (Mai et al., 2025).

Cross-crop transfer learning is another innovative approach, where a model trained on a major crop like potato is adapted for an underrepresented crop like sweet potato. This is effective when the crops share similar canopy structures or growth patterns (Yadav al., 2025). By identifying "robust predictors" features that maintain their relationship with yield across different species researchers can create more generalizable models that reduce the need for expensive, localized data collection (Jiang et al., 2025).

9.2 Implications for Developing Regions

The scalability of these technologies is particularly critical for developing regions where agricultural productivity is a primary driver of the economy but data is often sparse. The lack of formal reporting and the presence of fragmented, small-scale farming plots make traditional yield estimation nearly impossible (Qiao et al., 2024). Free, high-resolution data from Sentinel-2, combined with transfer learning-based machine learning, provides a cost-effective alternative for these regions (Njoku, 2026). By providing early warnings of crop failure and identifying underperforming areas, these tools can help mitigate famine risks and support the formulation of effective agricultural policies (Quille-Mamani et al., 2024).

10. Future Directions and Research Gaps

Despite the significant advancements in integrating Sentinel-2 with machine learning, several research gaps and future directions remain (Chahbi-Bellakanji et al., 2025).

10.1 Multi-Sensor Fusion and Hyper-Temporal Monitoring

The synergistic integration of optical (Sentinel-2), radar (Sentinel-1), and thermal (Landsat 8/9 or ECOSTRESS) data is a major frontier. While individual sensors provide valuable information, their fusion can overcome specific limitations, such as cloud occlusion or spectral saturation (Grich et al., 2026). Furthermore, the move toward "hyper-temporal" monitoring using constellations of small satellites (CubeSats) to provide daily sub-meter imagery will allow for the detection of even more rapid physiological changes, although this presents new challenges in terms of data volume and cross-sensor calibration (Singh, 2025).

10.2 Standardization and Interoperability

The current landscape of agricultural machine learning is characterized by a lack of standardization in methodologies. Researchers use different vegetation indices, preprocessing pipelines, and evaluation metrics, making it difficult to directly compare results across studies (Van Klompenburg et al., 2020). There is an urgent need for unified experimental frameworks and open-access benchmark datasets to facilitate the development of more robust and transparent models (Lata et al., 2025).

10.3 IoT and Ground-Sensor Integration

The integration of remote sensing with Internet of Things (IoT) sensors provides a multi-scale monitoring approach. Ground-based sensors can provide continuous, high-precision data on soil moisture, nutrient levels, and local weather conditions, which can be used to "anchor" satellite-based predictions (Ajay et al., 2026). In irrigated systems, real-time feedback from IoT-enabled irrigation valves and soil probes can be combined with satellite-derived yield forecasts to create truly autonomous precision farming systems (Ndagijimana et al., 2026).

11. Conclusion

The fusion of Sentinel-2 time-series imagery with advanced machine learning has fundamentally advanced crop yield prediction, delivering field-scale accuracy and temporal granularity unattainable with earlier methods. By leveraging high-frequency, multispectral observations to track vegetation dynamics, stress indicators, and phenological transitions, these models provide reliable forecasts that outperform conventional statistical approaches and coarse-resolution satellites, particularly in spatially variable irrigated systems. The demonstrated improvements in R^2, reduced prediction errors, and ability to integrate ancillary data (meteorology, soil, management) position Sentinel-2–ML frameworks as a cornerstone of modern precision agriculture. Future progress will hinge on overcoming persistent limitations cloud contamination mitigation, cross-region model generalization, incorporation of very-high-resolution commercial imagery, and real-time operational deployment through continued advances in cloud-native processing, explainable AI, and multi-sensor fusion. As climate variability intensifies and food demand rises, scaling these technologies will empower farmers, policymakers, and supply-chain actors with actionable intelligence, fostering more resilient, resource-efficient, and food-secure agroecosystems worldwide.

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