A Systematic Review of Spectral Temporal Approaches for Crop Yield Prediction across Multiple Fields

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Abstract:

Crop yield forecasting plays a vital role in sustainable food security, easing the burden of agricultural management, and supporting data-driven decision making. The development of spectral and temporal data integration has shown encouraging results of enhancing prediction accuracy in different agricultural settings. Our study provides a broad review of the spectral–temporal approach used in crop yield forecasting, while our findings from the last few years are based on remote sensing data-the multispectral to hyperspectral imagery merged with time-period information gained from satellite platforms, unmanned aerial vehicles (UAVs), and ground-based sensors. The study looked at a variety of machine learning and deep learning techniques, such as regression models, Random Forests, Support Vector Machines, or neural networks to show how well they could yield results when establishing the relationship of complicated interaction between plant replicate pattern and environmental factors. Further, the review reported on a variety of data fusion techniques and feature extraction methods, which have been prepared to refine predictive performance. A special look was given at the spatial variability of multi-fields including soil properties, climate conditions and crop types that greatly impact the generality of the model. Additional challenges such as data heterogeneity, low temporal resolution, substantial computational capacity, and the requirement for vast annotated datasets were highlighted. Emerging trends are also discussed that involve hybrid models, transfer learning, and advanced spatiotemporal techniques to combat limitations. Ultimately, the strong, statistically competitive methodology used in this review provided an overall understanding of the state-of-the-art spectral-temporal methods for aiming toward crop yield prediction. The intended function of these findings was supposed to guide researchers and practitioners in selecting the correct methods for estimating high-precision yields throughout different agricultural disciplines.

Keywords: *Crop Yield Prediction, Spectral–Temporal Integration, Remote Sensing, Machine Learning, Time-Series Analysis, Precision Agriculture*

I. INTRODUCTION

Crop yield prediction has become the area of utmost importance to agricultural informatics. It has a direct impact on global food security, economic stability, and sustainable farming practices amid climate change and increased population pressure. The expected world population of over nine billion over the next decades has brought intense demand for productive agricultural systems, thus necessitating an accurate means of yield estimation, a focus of paramount researchers, policymakers, and agribusiness stakeholders. Many decades ago, the practice of manual agricultural estimation, based on farmers' observations, started to get rudimentary with time. Of the three popular yield estimation methods, manual field surveys are becoming less regarded upon regarding knowledge-creating mechanisms and for other factors such as constraints within spatial coverage, low efficiency, and high labor cost. Conventional statistical methodologies usually have an assessment period of one year and may be less able to document environmental variations putting spatially-based information into sight. However, these traditional methods do not take advantage of considerable flexibility when presented with massive datasets [1]. This is a shortfall perceived with rising adoption of spectral and temporal analysis in agricultural monitoring as a quicker and scalable solution. Given the right setup, the integration of spectral and temporal data seems to be most promising in the context of crop yield estimation. Thus, while spectral data derived from mult to hyperspectral sensors facilitate the measurement of physiological and biochemical traits of vegetation, such as chlorophyll level, leaf area index, and water stress, temporal data allows one to analyze those traits over time and, subsequently, supports phenological tracking and stress detection throughout the growing season.

Integrating information over two dimensions as such successfully models spatial heterogeneity and temporal past in the cropping operation, hence the final conclusion is that combining two closely spaced data dimensions significantly enriches the agricultural landscape compared to a single data source [2]. A myriad of methodologies for integrating spectral and temporal data have been suggested over recent years, such as statistical models, machine learning techniques, and deep learning architectures. These methods have yielded highly promising results for yield estimation from various crop types, geographies, and environmental conditions. But with such great developments, the realm remains divided given the

peculiarities prevalent in the datasets, preprocessing strategies, feature evaluation mechanisms, and output metrics used, which makes life tough for cross-study comparisons and consensus building. Posing extra challenges are noise, consequently missing on the temporal counterpart, atmospheric interferences, and sensor calibration differences, among others. The availability of high-spatial-resolution satellite imagery from current systems and UAVs (Sentinel, MODIS, and Landsat/UAV) has opened new potentials for advanced observation while imposing greater problems related to data complexity. Moreover, assertive AI steps, mainly machine learning and deep learning, toward modeling high-dimensional data containing a plethora of nonlinear relationships could render enhanced predictive performance, contributing to the development of higher-yield estimation models [3].
It is necessary for multi-field analysis, given that agro-ecosystems vary greatly with regard to soil compositions, irrigation practices, climatic conditions, and crop management, which all have direct impacts on model generalizability [4]. Thus, there is a need for a comprehensive review to consolidate available studies and compare methods constituting points of strength and weakness, thereby suggesting future recommendations in research. This systematic review work accentuates evaluating published research in spectral and temporal techniques for crop yield prediction with a focus on data sources, modelling framework, engineering approach to special consideration to features and performance evaluation metrics; it further discusses how new technologies such as cloud computing, big data analytics, and AI contribute to making agricultural prediction systems more scalable and efficient [5]. Thus, by combining across several studies, we would achieve a holistic overview of what has been going on and even suggest the building of sturdier and more accurate models to support the objectives of precision agriculture and global food security. Figure 1 illustrates how satellite or UAV-based spectral bands are processed to extract vegetation information for estimating crop yield across agricultural fields.

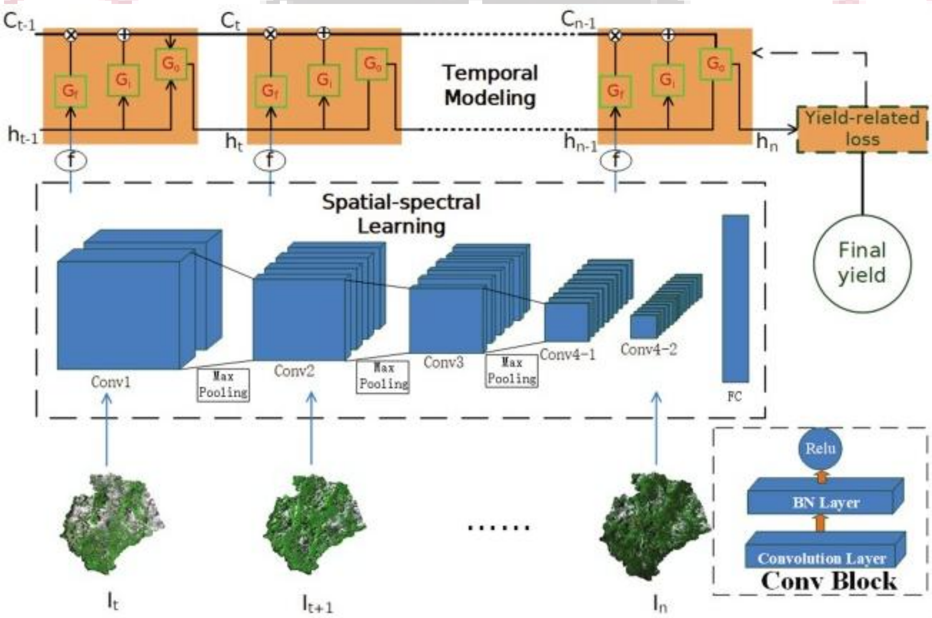

Figure 1: Crop yield prediction from multi-spectral [5]

II. BACKGROUND AND CONCEPTUAL OVERVIEW

The watershed of agrometeorology, remote sensing, and data science stands as the backdrop to crop yield estimation-a conceptual framework that quantifies agricultural output in relation to environmental, biological, and management determinants. Soil characteristics, weather conditions, genotypes, irrigation systems, and pest and disease attacks usually play out as mosaic scenarios in terms of spatial and temporal variability, which again affect from time to time in different genotypes and years, all of these fall through to supreme control of a design on the components implicit in water management (crop yield). Propelled by land sensors from satellites and low-orbit aircraft in its backdrop of crop development, one side of remote sensing technology itself could keep an eye directly or indirectly on the same crop under observation. Measurement of the absorption and reflection of vegetation light carried by spectral data from satellite and airplane sensors at widely separated electromagnetic wavelengths from the visible range to near-infraredd to the short life infrared band of the electromagnetic spectrum provides a reflection of the vigor, green biomass, chlorophyll content, etc., of the host plant actively addressing the level of water stress [6].

Hyperspectral imaging extends this leap ahead by capturing hundreds of narrow spectral bands useful for harvesting very accurate low-resolution biochemical information about the host plant. Another set of data that supports the raw spectral characteristics of crop properties is indeed temporal information whereby sequential observations of crop conditions over time sympathetically follow the progression of growth trajectories, phenological transitions, and response to stress during the growing season []. A perfect blend of spectral and temporal dimensions potentially forms a basis for spectral–temporal analysis aiming at capturing spatial heterogeneities with the added aspects of capturing their temporal evolution within agricultural systems during any specific growing season. Essentially, this is based on the premise of crop yield being a concentrated expression of all interactions within a cropping system over time and, therefore, distributed within and through the season rather than never produced from a single momentary image.

Temporal patterns of growth dynamics have received primary attention for the analysis of vegetation-related information by modeling, prediction, etc. through time-series analytics; both linear and nonlinear variants of autoregressive moving-average (ARMA) models and recurrent neural networks model the temporal dependencies in the crop data [8]. For the spatial analysis (SA), various techniques are applied to guard against the inherent transferability of the study results between different area cases. Data-fusion techniques will reinforce effectively combining SMs with satellite imagery, soil measurements, meteorological data along with local soil management data expected in bioannex. With the emergence of BigData, new engineering principles and computational mechanics have evolved. The use of Earth Observation (EO) data, in particular the advent of Google Earth Engine, has increased over time. Concurrently, the employment of processing large numbers of images generated by the new controversial satellite systems has reduced considerably. All these improvements are contradicted by various conceptual challenges among them, namely, data inconsistency from different instruments, atmospheric distortion, temporal missing data due to cloud cover, and the critical challenge of multi-source datasets having varying spatial and temporal resolutions [9].

Furthermore, agricultural systems change greatly from one region to the next, complicating generalization of models; key factors of crop growth patterns are the differences in localized environmental conditions and agronomic practices. All these conceptual challenges show the necessity for a truly reliable modeling framework capable of handling noisy, incomplete, and heterogeneous data while preserving the predictive power. Consequently, the conceptual framework of crop yield prediction has been forced to transition from simple statistical modeling to far more data-intensive approaches, since that is the way to handle crop growth dynamics in the context of the spatio-temporal assessment of spectral data. This transition certainly fits within the bigger context of making cheap but substantial use of all data available to enhance crop productivity, optimize soil productivity, and reduce general agriculture stresses. Understanding these conceptual bases is critical when it comes to reflecting the methods used such as those discussed earlier and setting the next strategic guidelines for spectral–temporal estimation in crop yield prediction [10].

III. SPECTRAL–TEMPORAL APPROACHES FOR CROP YIELD PREDICTION

The spectral - temporal approach in predicting the crop yield is an advancement in agricultural monitoring by conceiving the spectral reflectance data into the time-series observations capturing the spatial and temporal variability of crop growth. These strategies use multisource remote sensing data that are acquired by a combination of satellite, UAV, and ground sensors to form comprehensive datasets on crop health dynamics through the growing season. The spectral information, through which studies are made into characteristics of vegetation in its reflectance patterns across varying wavelength bands, for the temporal data reflects change in these spectral signa1res over time, making it possible to establish phenology, stress conditions, development stages of a crop.

One common practice in spectral - temporal strategy is constructing a series of vegetation indices, for instance NDVI from time-series data [11]. These NDVI trajectories once established are then analyzed to get growth patterns and yield prediction. This time-series data is processed via smoothening techniques, interpolation methods, assessing phenological features from noise, and then essentially polishing the signal. In recent times, the application of data fusion to spectral - temporal integration has started to gain ground. It blends multiple types of information, namely optical imagery, radar products, weather variables, and soil moisture observations into one developing prediction frameworks. With such integrations of multimodal information, the feature model seems to greatly increase effectiveness from its comportment. Spatial-temporal fusion models like STARFM and ESTARFM have been generally used to produce high-resolution temporal data set because combining high-resolution spatial data with periodic temporal observations [12].

Concomitants on the issue, deep learning-based fusion techniques have surfaced as powerful alternative ways to perform automatic feature extraction and hierarchical representation and learning with complex datasets. Another significant contribution to this area is feature engineering, where relevant variables like vegetation indices, texture features, and phenological markers are drawn out to improve model interpretability and performance. Machine learning models like RandomForest, Gradient Boosting, and Support Vector Regression are commonly applied to such engineered features. Diversity implies that they are efficient in yield-prediction tasks when compared to other regression models not used in practice. However, the process demands extensive preprocessing and manual feature selection. CNNs perform well in extracting spatial patterns from spectral imagery, while LSTMs work excellently in modeling temporal dependencies in sequential data. A combination of two models has been seen to outperform with respect to the single-model performance. Further, it has come to the forefront that attention mechanisms can be blended into those models to weight features based on importance and thus enhance prediction accuracy.

Nevertheless, with the advent of technological progressions, some current challenges in spectral-temporal modeling exist, arising from the scale of application of the same; among these are data heterogeneity, computational complexity, limited labeled datasets, and variability across farm fields [13]. These challenges include not having a transferability mechanism for field prediction, owing to magnitudinal effects varying with the specific types of crops, soil types, and climatic factors. Furthermore, satellite imagery always comes with clouds on a spatio- temporal basis, thereby inducing missing temporal observations that require addressing through some more advanced gap filling techniques. Notwithstanding these hurdles, recent advancement is aimed at reshaping spatio-temporal fusion toward more sophisticated techniques using advanced machine learning algorithms, fusion of multisource data, and high-performance computing frameworks promising the viability of spectral-temporal models as a cornerstone of next-generation crop yield prediction systems [14].

IV. MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

Machine learning and deep learning methods have become essential aspects of contemporary crop yield predictions. These have been applied to spectral–temporal data integration, where large-sample, high-dimensional datasets require advanced computational modeling that captures complex nonlinear relationships. Classical machine learning approaches like Linear Regression, Support Vector Machines, Decision Trees, and Random Forests have been widely used due primarily to the simplicity, interpretability as well as adepts in handling structured agricultural data. Random Forest has been a star performer in the prediction of crop yields with ensemble decision trees reducing variance and generalization power. In terms of high performance on high-dimensional feature spaces when nonlinear relationships are in existence between the inputs and crop yield, SVM is another star performing machine learning model [15]. However, the recent Gradient Boosting methods such as XGBoost and LightGBM are more explored as the sequential optimization of weak learners had exhibited a huge improvement in prediction accuracy. Nonetheless, these traditional models are more focused on manual feature engineering, which minimizes their ability to exploit all the raw spectral–temporal data. This figure 2 shows how multiple data sources (weather, chemical, pesticides, and yield) are integrated, processed, and analyzed to generate features for machine learning-based yield prediction.

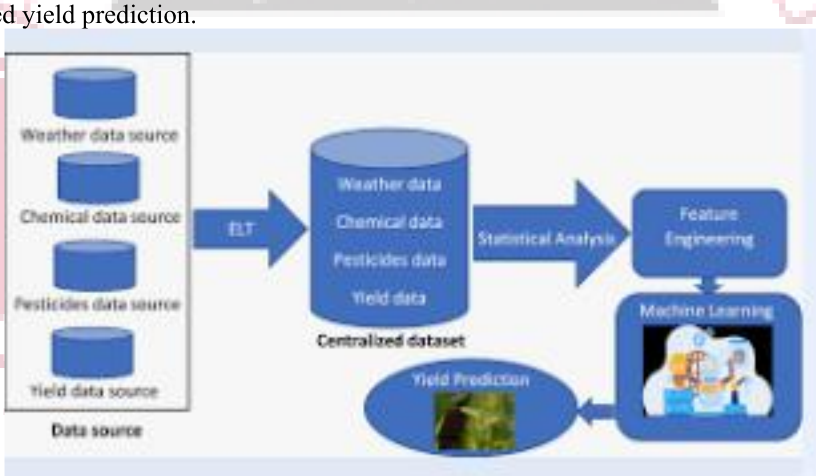

Figure 2: Data Pipeline for Crop Yield Prediction Using Machine Learning [15]

With this constraint, deep learning has attracted wide attention due to its ability to learn multiple levels of hierarchical features from massive amounts of data automatically. CNNs are particularly useful in the domain of extracting spatial features from spectral imagery, enabling the detection of vegetation patterns, field boundary detection, and stress indicators [16]. RNNs, particularly LSTM-RNNs, are designed to grasp temporal dependencies on sequential data, making them a very good choice for all the models of the dynamics of crop growth across time. The hybrid CNN-LSTM architecture combines spatial feature extraction and temporal sequence modeling to improve yield prediction accuracy. Most recently, Transformer-based models have been presented to agriculture with an attention mechanism to learn long-range dependencies in spectral–temporal datasets without the overhead of needing to process sequentially as seen in RNNs [17]. These models show potential in dealing with large-scale remote sensing data with complex temporal relationships.

Graph Neural Networks (GNNs) are also undergoing research for modeling spatial relationships in the agricultural fields to attain better multi-field yield prediction. Deep learning models can also benefit heavily from transfer-learning techniques, where pre-trained models are fine-tuned with agricultural datasets to address the problem of limited labeled data. However, in general, despite all the benefits that deep learning methods have to offer, agricultural applications prevent the model from being olammable, due to the large training data and high amount of computational expenses. Also, model interpretation, overfitting, and class imbalance still exist as great troubles. In response to these challenges, researchers make gradual incorporation with explainable AI (XAI) techniques to improve transparency and trust associated with model predictions. Altogether, the integration of machine learning and deep learning methodologies has rapidly propelled crop yield forecasting far beyond provision of more accurate, scalable and strong models which take due advantage of spectral–temporal data across vastly different agricultural settings [18]. Figure 3 shows the classification of machine learning into supervised learning (classification and regression) and unsupervised learning (clustering) based on the presence or absence of labeled data.

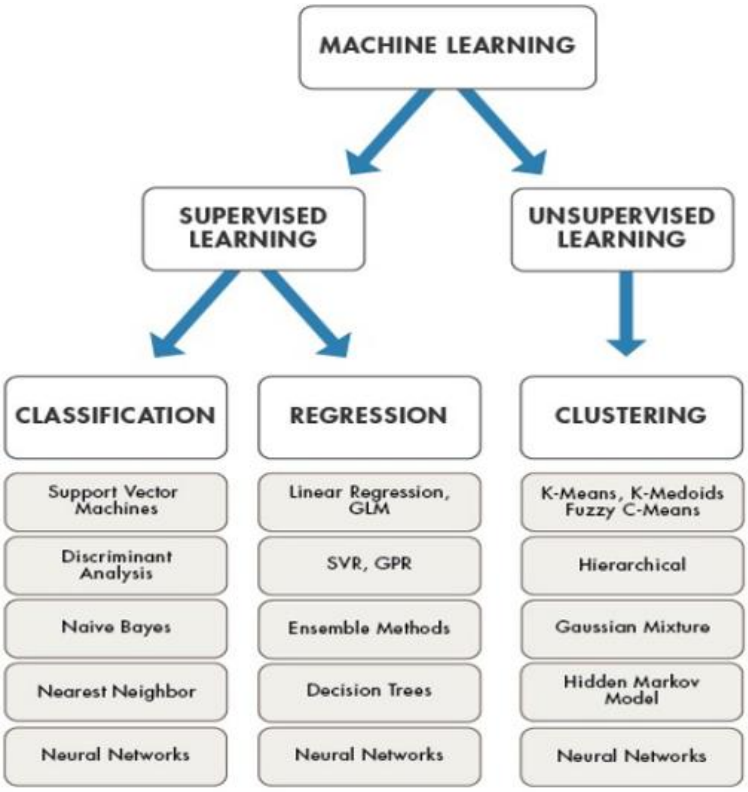

Figure 3: Classification of Machine Learning Techniques

V. COMPARATIVE ANALYSIS OF EXISTING STUDIES

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Table 1: Challenges and Limitations

Challenge / Limitation	Description	Impact on Crop Yield Prediction Models
Data Heterogeneity	Spectral–temporal data comes from multiple sources such as satellites, UAVs, and ground sensors with different resolutions and formats.	Causes inconsistencies in data fusion and reduces model reliability.
Missing Temporal Observations	Cloud cover, sensor failure, and irregular satellite revisit cycles lead to gaps in time-series data.	Affects continuity of crop growth monitoring and reduces prediction accuracy.
Limited Ground Truth Data	Accurate field-level yield data is often scarce and expensive to collect.	Restricts model training and validation, especially for deep learning models.
High Computational Complexity	Deep learning and multi-source fusion models require significant processing power and memory.	Limits scalability and real-time deployment in resource-constrained environments.
Poor Model Generalization	Models trained on one region or crop type often fail in different environmental conditions.	Reduces applicability across multiple agricultural fields.
Variability in Agricultural Practices	Differences in irrigation, fertilization, and farming techniques across regions.	Introduces noise and reduces prediction consistency.
Sensor and Atmospheric Noise	Satellite images are affected by atmospheric interference, shadows, and radiometric distortions.	Degrades quality of spectral features and increases prediction error.
Feature Selection Complexity	Large number of spectral indices and temporal features can lead to redundant or irrelevant inputs.	Causes overfitting and reduces model efficiency.
Lack of Standardized Datasets	No unified benchmark dataset for crop yield prediction exists.	Makes comparison of different studies difficult.
Model Interpretability Issues	Deep learning models operate as “black boxes” with limited explainability.	Reduces trust and adoption in real-world agricultural decision systems.
Spatial Scale Variability	Differences between field-level, regional, and global-scale datasets.	Leads to inconsistency in model performance across scales.
Temporal Resolution Limitations	Satellite revisit times may not align with critical crop growth stages.	Misses important phenological events affecting yield estimation.

VI. EMERGING TRENDS

In recent years, there was a drastic change in the area of crop yield prediction using spectral–temporal integrations due to the improvements made in remote-sensing technology, artificial intelligence, and high-performance computing methods. A look at the emerging trends reveals that there is a clear movement off the traditional, single-source, static approaches to multitiered, dynamic, intelligent modeling that captures the real-time complexities of agricultural processes within. An important transformation in this hue is the greater adoption of the use of deep learning architectures, particularly transformers, which have revolutionized the processing of sequential data by overcoming the constraints of recurrent frameworks, thereby capturing long-distance dependencies. Unlike RNN or LSTM structures, the transformer architecture uses self-attention mechanisms that enable the model to focus simultaneously on real temporal and spectral characteristics, which increases crop yield estimation predictive accuracy [22].

Another key trend involves the merging of multi-modal data fusion, where spectral image data is inculcated within meteorological data, soil parameters, topographic factors, and various on-farm management practices to capture the profounder, true meaning of the farming system. This fusion of myriad modes mitigates the weakness of various sources and enhances model strength in the face of much-welcome uncertainty. To this aspect, the increasing proliferation of higher-resolution satellite imagers such as Sentinel-2, Landsat-9, and other commercial Earth observation systems has greatly enhanced the spatial and temporal resolutions of data pertinent to agricultural monitoring, especially to the level of far-field cases [23]. The steadily acquiring availability of imagery from UAV sources has further upside on the hyperresolution analysis, particularly for small farming units, yet is cut by the bottleneck of scalability due to issues related disadvantages.

Transfer learning in combination with domain adaptation is expected to be a breakthrough development, indeed having an appreciable effect on enhancing the generalization of models over different geographical regions and crop types. Such an approach lets us recycle the models trained on extensive datasets in one region over a completely new environment without requiring much labeled data. This, indeed, is one of the emerging directions concerning all the hurdles in applying machine learning in agriculture [24]. The self-supervised learning method is currently being pursued as a method to push on voluminous remote-sensed unlabeled data for yielding good results in field and scene awareness in remote-sensing experiments with minimal dependency on expensive ground truth annotations. Modern high-tech gadgets such as edge computing and cloud-hosted geospatial engine like Google Earth Engine are reshaping the way such data is processed and analyzed in agriculture, by handling both real-time data processing and the deployment of models at a broader geographical scale. These technologies are mainly of help for practical functioning of near-real-time crop agricultural systems that may provide prompt editing for decision-making in precision agriculture.

Another big trend is the work with explainable artificial intelligence (XAI) that can explain the indefensibilities associated with deep learning models by succeeding in explaining and shedding light on feature importances and the path through which the model made a decision the net result being transparency and trust among those in the agricultural sectors. In other words, such agriculture is making things more feasible. Hybrid-modeling strategies combining process-oriented crop growth models with machine learning methods also seem to be among the latest trends as they are marrying the essential aspects of domain knowledge with data-driven learning, hence increasing the robustness of model accuracy and interpretability. Slightly deviating from it, there is spatial-temporal graph neural network development, which presents a very cutting-edge precedent by creating models that incorporate relationships between various fields as interconnected nodes [25]. This allows capturing of spatial dependencies that more traditional models tend not to consider. Another emerging area of study contributing to research on crop yield prediction is climate-smart agriculture. It is a research domain where models are developed with respect to climate variability as a framework to address extreme weather events and, consequently, to upbring resilience and impacts adaptation. Of recent concern is the development of real-time yield forecasting systems, employing Internet of Things (IoT) devices that constantly generate data from sensors in the field, recording every data bit into predictive algorithms as a base for real-time decision support. Checking how an invention utilises blockchain technology may be one area of interest with regard to the proper management of secure agricultural data and traceability issues that greatly enhance the authenticity of data across supply chains.

A healthy trend is toward models centred around sustainability, whereby yield prediction is further in collaboration with an environmental impact assessment such as estimations of carbon footprints and water use efficiency [26]. The endeavor coincides with global efforts promoting sustainable agriculture and climate change mitigation. Despite this progress, several challenges remain in deploying in this space: for example, privacy of data issues, excessive computational costs, and classification benchmarks-notwithstanding, these challenges continue to be mitigated with ongoing research to produce more sleek algorithms and models, lightweight architectures, and collaborative data-sharing frameworks. Altogether, forthcoming trends relating to spectral–temporal crop yield prediction chart the manifesto of committed, scalable, immensely integrated agricultural systems that make the most of artificial intelligence, remote sensing, and big data analytics toward the realization of several opportunities of relevance in precision agriculture systems, promising greater accuracy in forecasting, better management of resources, and enhanced global food security [2]. Table 2 presents a comparative summary of recent research highlighting methodologies, key contributions, results, and limitations of spectral–temporal and machine learning-based approaches for crop yield prediction.

Table 2: Review of Crop Yield Prediction Studies

Ref. No.	Methodology / Approach	Key Contribution	Results	Limitations
[1]	UAV multispectral + DNN	Phenology-aware yield estimation	High accuracy in in-season prediction	Limited scalability across regions
[2]	Prithvi encoder regression	Satellite foundation model for yield	Improved prediction over classical ML	High computational cost
[3]	Sentinel-2 + CANbus + regression	Maize yield estimation integration	Better temporal representation	Limited sensor compatibility
[4]	Transfer learning + DSSAT + PROSAIL	Hybrid physical-ML model for canola	Improved field-scale accuracy	Complex model integration
[5]	Sentinel-2 + vegetation indices	Potato yield estimation	Good performance using spectral indices	Sensitive to atmospheric noise
[6]	R2U-Net deep learning	Satellite + agro-environmental fusion	High predictive accuracy	Requires large training data
[7]	Foundation model benchmarking	AlphaEarth evaluation	Strong generalization capability	Limited agricultural fine-tuning

[8]	UAV + ML models	Spatial generalization study	Moderate-to-high accuracy	UAV data not scalable
[9]	Synthetic images + ML	Soil texture prediction	Improved field-level prediction	Synthetic data bias
[10]	Neural ODE + LLM + optimization	Advanced yield forecasting model	High predictive performance	Very high complexity
[11]	Review study	Pest detection systems	Identified strong sensing techniques	Not yield-specific focus
[12]	Chemometric modeling	Pre-harvest yield prediction	Good quality estimation	Limited to specific crop
[13]	Transfer learning models	Model transfer in low-data regions	Improved adaptability	Reduced accuracy in extreme climates
[14]	UAV + satellite fusion	Wheat yield prediction	High accuracy with limited samples	Data fusion challenges
[15]	Multi-task transformer	Soil + crop trait prediction	Strong multi-task performance	Requires large datasets
[16]	Sentinel-2 + Landsat ML	Potato field detection	High classification accuracy	Seasonal dependency
[17]	Literature review	Precision agriculture overview	Identified key ML trends	No experimental validation
[18]	Spatio-temporal modeling	EO-based yield prediction	Improved temporal understanding	Computationally intensive
[19]	Systematic review	Satellite-based yield prediction	Comprehensive synthesis	Lack of uniform comparison metrics
[20]	Spatial-temporal modeling	Wheat canopy spectral analysis	Good predictive trends	Limited dataset diversity
[21]	Hyperspectral + DL	EnMAP wheat yield prediction	High accuracy using hyperspectral data	High cost of data acquisition
[22]	Deep learning time-series	Crop protection forecasting	Strong temporal learning	Overfitting risk
[23]	Time-series ML	County-scale wheat prediction	Reliable regional prediction	Poor cross-region transferability
[24]	UAV + ML fusion	Corn yield optimization	Improved prediction accuracy	UAV data dependency
[25]	Meta-analysis NDVI	NDVI-based yield prediction review	NDVI effective indicator	Saturation in dense vegetation
[26]	Representation learning	Multi-spectral classification	Improved feature learning	Requires high compute power
[27]	CNN + RNN + Sentinel-2	Crop mapping with deep learning	High classification accuracy	Limited interpretability

VII. CONCLUSION AND FUTURE DIRECTIONS

This systematic review attempts to investigate both spectral–temporal approaches for looking into crop yield prediction encompassing several agricultural fields, focusing especially on the considerable strides of depicting remote sensing (RS) data with state-of-the-art machine learning and deep learning systems. From our perspective as authors of this synthesis, merging spectral descriptors from multispectral and hyperspectral imagery together with references to temporal time-series observation shows an enhanced prediction accuracy when Traditional Regressions are compared. These are Machine learning models with certain established baselines of performance that include Random Forest and Support Vector Machines and deep learning models that are CNNs, LSTM, and other hybrid models that have pushed the predictive power by linking with spatial and temporal features which, being inherently complex, need to be learned automatically. Despite many advancements, there remain several drawbacks. These include differences in geographical locations where training data exists, temporal observations, variety of yields, and generalization in models amongst varied regions. Countless research gaps reflect, as several complex possibilities related to yield estimation models remain open for research. Likewise, though deep learning models need a lot of computing time and memory because of the high dimensionality of input data, these limitations confine the wide-scale adoption of very complicated and poorly interpretable machine learning models which cannot be confidently trusted for practical application in agriculture. Future research requests creation of slightly more general models with more transference capability, capable of adapting over varied environmental conditions and farming practices.

REFERENCES

[1] Athar, Usama, et al. "Phenology-aware in-season crop yield estimation through UAV multispectral imagery and deep neural networks." *Computers and Electronics in Agriculture* 240 (2026): 111210.
[2] Nejadshamsi, Shayan, et al. "FARM: Crop Yield Prediction via Regression on Prithvi's Encoder for Satellite Sensing." *AgriEngineering* 8.1 (2026): 2.
[3] Miralles, G. Stefanescu, et al. "Maize yield estimation from Sentinel-2 multi-temporal imagery and CANbus data integration: a non-parametric regression approach." *Biosystems Engineering* 264 (2026): 104401.
[4] Du, Ruiqi, et al. "TrSC2Y: A transfer-learning-based model from UAV hyper-spectra imagery for field-scale canola yield prediction by integrating DSSAT with PROSAIL." *European Journal of Agronomy* 174 (2026): 127926.
[5] Amin, Mohamed ES, et al. "Exploitation of sentinel-2 spectral bands and vegetation indices in potato yield estimation." *Journal of the Indian Society of Remote Sensing* 54.1 (2026): 13-31.
[6] Gawade, Sushopti Dashrath, et al. "Optimizing crop yield prediction with R2U-Net-AgriFocus: A deep learning architecture with leveraging satellite imagery and agro-environmental data." *Expert Systems with Applications* 296 (2026): 128942.
[7] Ma, Yuchi, et al. "Harvesting AlphaEarth: Benchmarking the geospatial foundation model for agricultural downstream tasks." *International Journal of Applied Earth Observation and Geoinformation* 149 (2026): 105258.
[8] Sankara, Wilfried. *Spatial Generalization of Crop Yield Prediction Models Using UAV Imagery and Machine Learning*. Diss. University of Ottawa, 2026.
[9] Wang, Yiang, et al. "Spatial Prediction of Soil Texture at the Field Scale Using Synthetic Images and Partitioning Strategies." *Remote Sensing* 18.2 (2026).
[10] Alduailij, Mai, et al. "Agricultural Yield Forecasting Using LLM-Informed Preprocessing and Neural ODE Models Optimized via the Football Optimization Algorithm." *Potato Research* 69.1 (2026): 11.
[11] Chen, Tianhua, et al. "Detection technologies and sensing systems for crop pest identification and infestation severity prediction: a review." *Frontiers in Plant Science* 17 (2026): 1765363.
[12] Tang, Yidan, et al. "Predicting Faba bean yield and grain quality Pre-Harvest using chemometric modelling." *Precision Agriculture* 27.1 (2026): 6.
[13] Tiwari, Ashutosh, et al. "Transferability of spatial and temporal learning models for winter wheat mapping in data-scarce environments: A case study in Armenia." *Remote Sensing Applications: Society and Environment* (2026): 101885.
[14] Xiong, Yuan, et al. "Improved prediction of winter wheat yield at regional scale with limited ground samples by unmanned aerial vehicle and satellite synergy." *Remote Sensing of Environment* 335 (2026): 115271.
[15] Sun, Guangyao, et al. "Soil knowledge-guided multi-task transformer model for predicting soil properties and crop traits with early warning alerts." *Artificial Intelligence in Agriculture* (2026).
[16] Tokluoğlu, Emre, et al. "Detection of Potato Fields Using Sentinel-2 and Landsat 8 Data-Based Machine Learning Models in Semi-arid Region of Central Anatolia, Türkiye." *Potato Research* 69.1 (2026): 14.
[17] Saha, Sarmistha, et al. "Precision agriculture for improving crop yield predictions: a literature review." *Frontiers in Agronomy* 7 (2025): 1566201.
[18] Ofori-Ampofo, Stella, et al. "On the strategy of exploring spatio-temporal information from Earth observation data for crop yield prediction." *Smart Agricultural Technology* (2025): 101540.
[19] Radočaj, Dorijan, et al. "Satellite remote sensing for crop yield prediction: A review." *Agriculture* 16.4 (2026): 417.
[20] Zhang, Donghui, et al. "Precision agriculture: temporal and spatial modeling of wheat canopy spectral characteristics." *Agriculture* 15.3 (2025): 326.
[21] Mucsi, László, et al. "Assessment of the Effectiveness of Spectral Indices Derived from EnMAP Hyperspectral Imageries Using Machine Learning and Deep Learning Models for Winter Wheat Yield Prediction." *Remote Sensing* 17.20 (2025): 3426.
[22] He, Tao, Meijin Li, and Dong Jin. "Deep learning-based time series prediction for precision field crop protection." *Frontiers in Plant Science* 16 (2025): 1575796.
[23] Zhu, Guocan, et al. "Winter wheat yield prediction at a county scale using time series variation features of remote sensing spectra and machine learning." *European Journal of Agronomy* 170 (2025): 127751.
[24] Zhang, Huihui, et al. "Optimizing corn yield prediction: Integrating multi-temporal UAS data and machine learning." *Smart Agricultural Technology* (2025): 101344.
[25] Fuentes, Ignacio, et al. "The normalised difference vegetation index as an analytic tool for wheat crop yield prediction: A review and meta-analysis." *Precision Agriculture* 26.4 (2025): 55.
[26] González-Ramírez, Andrea, et al. "Representation learning of multi-spectral earth observation time series and evaluation for crop type classification." *Remote Sensing* 17.3 (2025): 378.
[27] Tufail, Rahat, Patrizia Tassinari, and Daniele Torreggiani. "Deep learning applications for crop mapping using multi-temporal Sentinel-2 data and red-edge vegetation indices: integrating convolutional and recurrent neural networks." *Remote Sensing* 17.18 (2025): 3207.