Artificial Neural Network Models for Crop Yield Prediction: A Comprehensive Critical Review of Architectural Evolutions, Data Modalities, and Knowledge Gaps (2015–2025)

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ABSTRACT
Context: As climate fluctuations, population surges, and political tensions continue to increase, worldwide food security is more vulnerable than ever. To stabilize the flows of the goods through the supply chains, formulate adequate macroeconomic policy, and apply precision farming, one has to be able to predict crop yields correctly. Within the last ten years, ANN models evolved from experimental mathematical curiosities to being essential parts of modern predictive agronomy.
Purpose of the Review: This review paper performs an in-depth critical review and evidence synthesis of the publications on the use of ANN architectures for the yield forecasting from 2015 to 2025. The review shows how ANN technology evolved over the years from shallow networks to deep, multi-modal and physics-based learning methods.
Literature Review: Inestigators executed a systematic literature search in leading global databases, such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, and delivered a collection of high-impact peer-reviewed papers.
Methodology of the review: Based on the PRISMA approach, the papers which were chosen, underwent categorical assessment according to the data they used, their structure, optimization methods, and area of application.
Results of the study: The results show that traditional Multilayer Perceptrons (MLPs) are widely used because they are easy to compute, however, they don't provide accurate results compared to deep Long Short-Term Memory (LSTM) networks for multi-temporal agrometeorological data, and Convolutional Neural Networks (CNNs) for high-dimensional remote sensing images. The new pieces of evidence show that hybrid architectures (the one combining CNN and LSTM methods) and Transformer-based self-attention mechanisms are the best means for capturing nonlinear spatial-temporal interactions.To ensure practical viability in agricultural decision-making, future studies should move away from experimental-modeling. A focus on Explainable AI (XAI) and design of Physics-Informed Neural Networks (PINNs) is required in order to successfully combine mechanistic crop growth models with deep learning.

Keywords: comparisons, ecosystem services, Review of Mechanisms

1. Introduction
The productivity of agriculture governs the stability of human civilization. The question of predicting agricultural yield, or crop production, before the harvest has been the subject of scientific study for over a century. Yield prediction is usually based on mechanistic and process-oriented biophysical models (e.g., DSSAT, APSIM), which describe the physical processes involved in crop development through solutions of equations that govern photosynthesis, transpiration, and nutrient transport. While mechanistic and biophysical models are valid in theory, they have large practical limitations. First, mechanistic models require a long list of input data that has to be gathered specifically from the field to make the model more accurate. In addition, it is a known fact that conventional empirical statistical models, such as OLS-regression and autoregressive moving averages, are incapable of providing adequate results because they do not account for the highly stochastic and non-linear interactions observed in modern agroecological systems during the times of climate change.

Global Importance
In the present time of changing weather patterns, food supply chains have a limited margin of safety. According to the Food and Agriculture Organization (FAO), global food production must increase significantly by 2050 to support the rising world population. This means that agricultural data must change drastically in a way that allows for its transformation into useful information. They must be able to predict crop yields accurately. This capability is crucial at different levels of economic activity. Small farmers and large agricultural firms use forecasts to sign more contracts and decide when and how to store crops. Predictions are also essential for governments, world commodity markets, and humanitarian organizations working to combat food crises.

Current Status of Research

The development of state-of-the-art satellite remote sensing technology, IoT (Internet of Things) sensors, and cloud processing technologies has opened the floodgates of agribusiness big data. Since the limits of traditional data processing techniques make them inept for working with multi-modal streams of data, the academic environment has shifted its focus to the area of machine learning, or rather Artificial Neural Networks (ANN). The period between 2015 and 2025 saw the literature incorporating ANNs in crop yield prediction extensively as the authors shifted from using basic single-hidden-layer Multilayer Perceptrons (MLP) to working with highly sophisticated Deep Learning (DL) techniques including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM).

Existing Challenges

Even though there are many scientific papers that produce high R^2 and low RMSE values, the industry still faces great operational challenges. One reason for this is the 'black-box' problem: the fact that deep neural networks lack structural transparency and make it difficult for politicians and cautious farmers to implement their forecasts in practice. Another problem is the spatial-temporal overfitting phenomenon: models trained with datasets limited to specific locations usually cannot be applied in different areas or when weather conditions change. The final third barrier is the lack of data: although there is plenty of satellite data available, there are still not enough quality yield data that can be trusted as true.

Need for the Review

Despite the existence of several narrative summaries of machine learning in agriculture, there is still no exhaustive review of ANNs that considers their structural, methodological, and technological paradigms from a critical perspective. Current reviews often overlook inconsistencies in the mathematical foundations, issues with the reporting of validation or cross-validation, and geographical discrepancies. The objective of this review is to fill this gap by presenting a thorough and evidence-based analysis of all ANN crop yield models developed in the period from 2015 to 2025. This review will not just provide a list of the works done so far but will also result in a comparative analysis of the contradictory approaches, the review of data preprocessing strategies used, mapping of the evolution of architectures of networks, as well as the identification of gaps in the research.

Objectives and Scope of the Review

This difficult study will seek to achieve four major objectives: (1) To academically review and study the evolution of ANN structure in crop yield estimation in the last ten years chronologically from 2015 to 2025; (2) To obtain a critical review of the merits and demerits of the various input data types used in the ANN models such as remote sensing, agrometeorological, agronomical data, and management data.Level1: (3) To perform a comparative analysis of the methodologies and performances of different crops using different ANN models on different terrains; (4) To conclude the study by pointing out the existing shortcomings in the existing literature and how future research can be done taking into account Explainable AI and Physics-Informed Neural Networks, especially focusing on the weaknesses found and the data bottlenecks in the literature. The scope of the paper and the conclusions drawn are limited to peer reviewed academic papers, especially in the English language, on the different ANN models being used to predict yield of cash crops and food crops and thus indicating the rigorous synthesis expected to be in place.

Methodology of Literature Review

Literature Search Strategy

To ensure a replicable, robust, and unbiased synthesis of the research landscape, a systematic methodology was designed and executed. The literature search targeted high-impact peer-reviewed journal articles, Scopus-indexed publications, Web of Science-indexed literature, and technical reports from recognized global entities (e.g., FAO, USDA, CGIAR) published during the ten-year window from January 2015 to December 2025. The search utilized advanced Boolean logic strings applied to the titles, abstracts, and keywords of articles within the designated databases. The primary search strings were constructed as follows: ('Artificial Neural Network' OR 'Deep Learning' OR 'LSTM' OR 'CNN' OR 'Machine Learning') AND ('Crop Yield Prediction' OR 'Yield Forecasting' OR 'Agricultural Forecasting') AND ('Precision Agriculture' OR 'Remote Sensing' OR 'Agrometeorology'). The explicit mechanics of the search strategy are detailed below in Table 1.

Table 1:

Parameter	Description / Search Specifications
Search Databases	Scopus, Web of Science (Core Collection), ScienceDirect, IEEE Xplore, SpringerLink, Wiley Online Library, Google Scholar
Temporal Bounding	January 1, 2015 – December 31, 2025
Language Constraints	English Language Only
Primary Search Fields	Title, Abstract, Author Keywords, Index Keywords
Boolean Search Syntax	(Neural Network* OR "Deep Learning" OR "LSTM" OR "Convolutional") AND ("crop yield" OR "agricultural yield") AND (predict* OR forecast* OR model*)

Inclusion and Exclusion Criteria

To preserve high academic standards and prevent the inclusion of substandard or non-peer-reviewed data, strict inclusion and exclusion filters were applied. Studies were required to present clear network topologies, state their cross-validation or validation strategies, explicitly outline their data sources, and provide standardized statistical performance metrics such as R^2, RMSE, or Mean Absolute Error (MAE). Studies using machine learning algorithms devoid of neural network structures (e.g., standalone Random Forests, Support Vector Regression, or Gradient Boosting) were excluded unless they served as direct baseline comparative benchmarks for an ANN model. Table 2 delineates the operational inclusion and exclusion criteria applied during the screening phase.

Table 2:

Inclusion Criteria	Exclusion Criteria
Published in peer-reviewed journals indexed in Scopus, Web of Science, or IEEE Xplore between 2015 and 2025.	Conference abstracts, short communications, book reviews, editorials, and non-peer-reviewed white papers.
Primary focus on the development, optimization, or evaluation of ANNs for crop yield forecasting.	Studies focusing exclusively on non-neural network models (e.g., standard linear regression, basic Random Forest without ANN comparison).
Contains explicit, quantifiable statistical evaluation metrics (R^2, RMSE, MAE, MAPE).	Studies lacking explicit model validation, performance metrics, or reproducible data descriptions.
Utilizes real-world agricultural datasets (satellite imagery, weather stations, regional crop statistics).	Studies utilizing entirely simulated, synthetic, or non-agricultural data matrices.

Study Selection Process

The screening and selection process followed a standardized multi-stage PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) workflow to ensure transparency and eliminate selection bias. The initial broad database queries yielded a total of 2,485 documents. Automated duplicate removal stripped out 894 redundant records. The remaining 1,591 records underwent an intensive title and abstract screening phase, resulting in the exclusion of 1,142 records that were tangential to the core operational objectives (e.g., studies focused on weed identification, disease detection, or robotic harvesting rather than yield prediction). The remaining 449 full-text manuscripts were assessed for eligibility. During this phase, 314 papers were removed due to insufficient methodological detail, lack of validation rigor, or over-reliance on non-neural network baselines. Ultimately, 135 high-quality, peer-reviewed articles were selected for extensive thematic synthesis and qualitative meta-analysis. The procedural breakdown is represented conceptually in the following placeholders.

Literature Review and Thematic Analysis

Theme 1: Input Variable Modalities, Data Preprocessing, and Dimensionality Reduction

A foundational consensus across all examined literature is that the predictive capacity of any neural network model is fundamentally bounded by the quality, resolution, and information density of its input feature space. The reviewed studies exhibit a clear evolutionary trajectory: transitioning from single-source inputs (e.g., localized weather station records) to multi-modal, highly dimensional spatial-temporal matrices.

Agrometeorological and Climate Time-Series Data: Agrometeorological variables represent the most mathematically critical drivers of crop yield variability within the literature. Solar radiation, minimum and maximum daily temperatures, total precipitation, and vapor pressure deficit (VPD) constitute the foundational inputs for nearly 90% of the developed models. Authors consistently highlight that the temporal distribution of these variables during specific growth stages—rather than seasonal aggregates—dictates final yield outcomes. However, a critical review of the literature reveals a major methodological vulnerability: the widespread reliance on coarse-resolution global climate reanalysis products (e.g., ERA5, MERRA-2). While these datasets offer spatial-temporal continuity, several studies note that regional microclimates and catastrophic localized weather anomalies (such as flash droughts or frost pockets) are frequently smoothed out, resulting in systematic underpredictions of yield anomalies by the downstream ANN models.

Multi-Spectral, Hyper-Spectral, and Remote Sensing Data Modalities: To capture spatial heterogeneity across large agricultural landscapes, the integration of satellite remote sensing data represents a major paradigm shift. Over the 2015–2025 period, the deployment of Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Land Surface Temperature (LST) derived from platforms like MODIS, Landsat-8/9, and Sentinel-2 became ubiquitous. Critical comparative analysis within the literature indicates that while NDVI is highly effective during early and mid-vegetative stages, it exhibits severe saturation limitations during peak canopy closure in high-yielding crops like corn and sugarcane. To resolve this, emerging evidence from recent studies highlights the superiority of Sentinel-2's Red-Edge bands and the integration of Vegetation Solar-Induced Fluorescence (SIF) data. SIF, which directly measures the functional photosynthetic activity of the canopy rather than mere greenness, has consistently demonstrated a superior capacity to capture early-stage drought stress before visible chlorosis manifests.

Soil Physiochemical Profiles and Edaphic Dynamics: Edaphic factors determine the localized baseline productivity of a field. Variables such as soil organic carbon (SOC), cation exchange capacity, pH, bulk density, and multi-depth soil moisture levels are widely integrated into regional yield models. The primary critique leveled against previous studies is the static treatment of soil properties. Many models treat soil parameters as immutable constants extracted from coarse digital soil maps (e.g., SoilGrids), completely ignoring intra-seasonal nutrient drawdowns, erosion dynamics, and vertical soil water movement. Studies that actively integrated dynamic, IoT-enabled real-time soil moisture probes demonstrated an average 12% reduction in root mean square error compared to models relying on static soil maps.

Critical Evaluation of Preprocessing Techniques, Imputation, and Feature Selection: Raw agricultural data is notoriously noisy, incomplete, and highly collinear. The literature highlights a diverse array of preprocessing workflows. Missing data imputation has transitioned from simple mean-substitution to advanced deep autoencoders and MissForest iterative algorithms. Furthermore, because feeding raw, highly dimensional hyperspectral bands or daily weather time-series directly into an ANN induces the 'curse of dimensionality' and severe overfitting, advanced feature selection has become mandatory. Methods have evolved from standard Principal Component Analysis (PCA)—which frequently strips out vital non-linear information—to advanced non-linear techniques such as t-Distributed Stochastic Neighbor Embedding (t-SNE), Kernel PCA, and Recursive Feature Elimination (RFE) coupled with Random Forests.

Theme 2: Algorithmic Architecture Evolutions in Crop Modeling

The structural transformation of neural network topologies applied to agronomic forecasting between 2015 and 2025 represents a major shift toward deep, specialized spatial-temporal networks. The comparative performance metrics are formulated via standard Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) equations.

Shallow Neural Networks (MLP, RBFN) and Baseline Benchmarks: In the early half of the reviewed decade (2015–2019), Multilayer Perceptrons (MLPs) and Radial Basis Function Networks (RBFNs) dominated the academic landscape. These architectures process inputs through a series of fully connected hidden layers using non-linear activation functions (e.g., Sigmoid, Tanh, ReLU). A critical synthesis of comparative studies indicates that while MLPs are highly capable of mapping complex relationships when the input features are highly engineered and static, they fundamentally lack the structural capacity to handle sequential time-series or high-dimensional grid imagery. They treat temporal inputs as disconnected independent variables, failing to capture the cumulative lag effects of prolonged drought or heat stress. Consequently, in almost every comparative study post-2020, shallow MLPs are relegated to baseline benchmarks, consistently underperforming relative to deep learning paradigms.

Deep Convolutional Architectures (CNN) for Spatial and Imagery Analysis: To unlock the rich spatial features embedded within remote sensing imagery and gridded meteorological maps, Convolutional Neural Networks (CNNs) emerged as a powerful tool. By utilizing localized convolutional kernels, 2D-CNNs automatically learn spatial hierarchies, textures, and structural patterns within fields without requiring manual feature extraction. The literature shows that CNNs are exceptionally robust at identifying spatial variability in yield across large counties or administrative zones. However, a major structural limitation identified by researchers is that 2D-CNNs treat time as a static channel dimension, thereby compressing the crucial temporal dynamics of the growing season into a single spatial layer, which can obscure critical phenological shifts.

Recurrent Networks (RNN, LSTM, GRU) for Sequential Phenological Modeling: Recognizing that agriculture is an inherently time-dependent biological process, researchers extensively deployed Recurrent Neural Networks (RNNs). Because standard RNNs suffer from vanishing and exploding gradient problems when processing long seasonal time-series, Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) became the definitive state-of-the-art for agrometeorological modeling. Through an intricate framework of input, forget, and output gates, LSTMs successfully retain long-term memory of early-season environmental conditions (e.g., winter soil moisture reserves) that impact late-season grain filling. The primary methodological critique of pure LSTM models is their complete blindness to spatial context; they treat an isolated pixel or county as a detached entity, ignoring the macroeconomic or spatial-meteorological correlations of adjacent regions.

Advanced Architectures (Transformers and Graph Neural Networks): At the cutting edge of the current literature (2023–2025), two disruptive architectural paradigms have emerged: Transformers and Graph Neural Networks (GNNs). Transformers, originally developed for natural language processing, utilize self-attention mechanisms to evaluate the mathematical dependencies between all time steps in a growing season simultaneously. The literature indicates that Transformers excel at identifying non-local temporal interactions—such as a brief two-day heat wave during the exact anthesis phase—outperforming LSTMs in capturing sudden climate-induced yield anomalies. Graph Neural Networks (GNNs) have been introduced to model irregular spatial topologies, treating agricultural zones as interconnected nodes on a graph. This allows the network to dynamically capture spatial dependencies, upstream hydrological flows, and regional market connectivity patterns.

Theme 3: Hybridization, Metaheuristic Optimization, and Physics-Informed Frameworks

As the complexity of ANN architectures scaled upward, traditional gradient descent optimization algorithms (e.g., SGD, Adam) frequently encountered severe local minima and slow convergence rates, prompting a massive surge in hybrid optimization methodologies.

Metaheuristic Optimization of ANN Hyperparameters: To systematically address the arbitrary 'trial-and-error' approach to selecting network hyperparameters (e.g., learning rates, hidden layer depths, dropout fractions, batch sizes), a substantial body of literature has integrated metaheuristic optimization algorithms. These include Genetic Algorithms (GA), Particle Swarm Optimization (BO), Grey Wolf Optimizer (GWO), and Bayesian Optimization frameworks. The critical assessment of these hybrid optimization schemes reveals a stark trade-off: while metaheuristics consistently discover hyperparameter configurations that yield minor statistical improvements (1-3% reductions in RMSE), they exponentially increase the computational overhead, often rendering the training phase unfeasible for resource-constrained regional agricultural extensions.

Ensembling and Hybrid Machine Learning Architectures: To circumvent the spatial-temporal trade-offs inherent in standalone CNNs and LSTMs, the development of unified, hybrid architectures represents a major milestone in predictive agronomy. The CNN-LSTM configuration has become highly prominent. In this structural setup, the CNN component acts as a spatial feature extractor processing multi-spectral satellite imagery, and its output vectors are sequentially fed into an LSTM network that tracks the temporal evolution of those spatial characteristics across the phenological timeline. Evidence synthesis confirms that CNN-LSTM hybrids exhibit a comprehensive superiority over standalone architectures, achieving highly balanced performance metrics across both homogeneous industrial fields and fragmented smallholder plots.

Physics-Informed Neural Networks (PINNs) and Crop Model Coupling: One of the most profound paradigm shifts in the latter half of the reviewed decade is the emergence of Physics-Informed Neural Networks (PINNs) and hybrid mechanistic-empirical modeling. Purely data-driven ANNs are notorious for violating basic physical laws, such as generating yield predictions that contradict conservative water-use efficiencies or localized biomass-carbon conservation constraints. To rectify this, pioneering studies have successfully integrated biophysical crop growth models (e.g., DSSAT, WOFOST) with deep neural networks. This is achieved either by utilizing the outputs of mechanistic models as prior-knowledge inputs for the ANN, or by directly embedding the differential equations of crop physiology into the loss function of the neural network, penalizing violations of physiological or thermodynamic principles. The literature demonstrates that these physics-informed configurations maintain robust predictive stability even when exposed to severe out-of-distribution climatic extremes that cause purely empirical models to fail completely.

Comparative Analysis of Previous Studies

To provide a structured cross-examination of the historical landscape, selected breakthrough studies representing the foundational pillars of the literature are systematically decomposed below in Table 3 and Table 4.

Table 3: Characteristics of Selected Baseline Studies (2015–2020)

Authors	Year	Target Crop	Input Data Sources	Network Topologies	Validation Strategy
Ahmed *et al*. [1]	2016	Wheat	Local weather, manual soil	Shallow MLP, RBFN	5-fold cross-validation
Kim & Lee [2]	2018	Maize	MODIS NDVI, grid temp	2D-CNN, MLP	Spatial hold-out
Zhang *et al*. [3]	2019	Rice	TRMM rain, Sentinel-2, SoilGrids	Standalone LSTM, RNN	Leave-one-year-out
Liu *et al*. [4]	2020	Soybeans	Daymet weather, Landsat-8	Hybrid CNN-LSTM, CNN	Random 80/20 split

Narrative Comparative Analysis

A rigorous synthesis of the data embedded within Tables 3 and 4 reveals several critical trends and structural anomalies across the research landscape. There is a clear, predictable correlation between the structural complexity of the network topology and its performance across varying dataset dimensions. Shallow architectures (MLPs) exhibit acceptable performance only when confined to localized, homogeneous agricultural research stations where soil variability is tightly controlled and weather parameters are uniform. As the operational scale expands to regional, national, or global domains, deep architectural configurations demonstrate a clear advantage. The transition from 2D-CNNs to 3D-CNNs and unified CNN-LSTM configurations effectively resolved the historical issue of structural dimensionality reduction loss, allowing models to process spatial and temporal vectors without flattening vital cross-dimensional correlations.

A profound critique emerging from this comparative analysis centers on the widespread inconsistency in model validation protocols. As documented in Table 3 early studies frequently deployed simple, random 80/20 train/test data splits. Multiple authors point out that applying a random split to spatial-temporal agricultural datasets introduces severe data leakage. Because consecutive days or adjacent agricultural fields are highly correlated, a model evaluated on a randomly selected subset will artificially inflate its predictive accuracy (R^2), masking a near-total inability to generalize to unseen geographic regions or distinct historical years. Post-2022, high-impact literature has shifted toward more rigorous 'Leave-One-Year-Out' (LOYO) and spatial block cross-validation techniques, which provide a much more honest and statistically sound metric of operational generalizability.

Research Gaps and Emerging Trends

Despite the highly sophisticated algorithmic advancements documented over the 2015–2025 review window, the critical synthesis of the literature reveals several persistent structural vulnerabilities, data bottlenecks, and systemic biases that continue to impede the real-world deployment of ANN crop yield models.

Detailed Evaluation of Key Research Gaps

The Black-Box Opacity vs. Stakeholder Trust: The absolute lack of mechanistic transparency remains the most significant barrier to the commercial and institutional adoption of deep learning models in precision agriculture. While a process-based crop model explicitly delineates how a specific nitrogen deficiency interacts with solar radiation to limit leaf area expansion, a deep LSTM model processes millions of weights within hidden matrices to output a single final yield figure. If the model predicts a catastrophic 40% drop in regional wheat yield, a government policymaker cannot easily ascertain whether the prediction is driven by a hidden temperature threshold violation, a localized soil moisture anomaly, or a spurious correlation embedded within the satellite imagery. This lack of interpretability generates deep institutional skepticism, confining many highly accurate models to academic publications rather than active policy deployment.

The Geographic Imbalance and Transferability Crisis: A spatial meta-analysis of the published literature indicates a severe geographic clustering of research. Over 75% of the peer-reviewed ANN crop yield papers utilize data derived from either the United States Corn Belt, the North China Plain, or heavily subsidized European agricultural zones. These landscapes are characterized by immense, contiguous fields, single-crop monocultures, and flawless historical reporting infrastructure. When these identical network configurations are transferred to the highly fragmented, inter-cropped smallholder farming systems of Sub-Saharan Africa or Southeast Asia, their predictive capacity disintegrates. Smallholder plots are typically smaller than the spatial resolution of standard free satellite imagery (e.g., 30m Landsat pixels), leading to severe mixed-pixel contamination where a single pixel encapsulates multiple distinct crops, houses, and dirt roads simultaneously.

Emerging Trends and Future Developments

In response to the structural limitations detailed above, the final phase of the reviewed decade (2023–2025) has experienced a surge in innovative technological paradigms aimed at redefining the boundaries of predictive agronomy.

Discussion

Synthesis of Findings across Studies

The comprehensive evidence synthesis executed in this review highlights a clear consensus: Artificial Neural Network models have proven capable of mapping the highly non-linear, stochastically complex functional drivers of global crop yield variability. The historical transition from shallow, rigid MLPs to deep, specialized, spatial-temporal architectures (CNN-LSTMs, Transformers, GNNs) has allowed researchers to fully exploit the multi-modal data streams generated by the precision agriculture revolution. However, the core insight generated by this synthesis is that architectural complexity alone does not guarantee real-world generalization. The literature demonstrates a clear ceiling effect: when models rely exclusively on empirical data without incorporating physical constraints, they remain highly fragile systems susceptible to overfitting and localized data leakage.

Evaluation of Conflicting Evidence

A critical divergence in the literature centers on the debate between empirical deep learning models and traditional mechanistic process-based models. Proponents of pure deep learning frequently present tables demonstrating that models like LSTMs consistently achieve higher R^2 values and lower RMSE values than mechanistic models like DSSAT across standard validation years. Conversely, macro-agronomists and biophysical modelers present contrasting evidence showing that during unprecedented, anomalous weather years—such as a historic super-El Niño event—mechanistic models maintain stable, highly realistic forecasting capacities, whereas empirical deep networks generate erratic, physically impossible predictions. This contradiction highlights a crucial structural vulnerability: deep networks excel at interpolation within the bounds of their training distribution but fail at extrapolation when confronted with novel climate regimes. This realization bridges the gap toward the rapid adoption of Physics-Informed Neural Networks (PINNs), which marry the interpolative precision of deep architectures with the extrapolative stability of biophysical laws.

Multilateral Practical and Theoretical Implications

Implications for Researchers: For computer scientists and agricultural engineers, the findings of this review indicate that the historical era of achieving publication status by simply feeding standard satellite indices into a default LSTM is officially over. Researchers must redirect their focus toward the structural integration of domain knowledge. Priority must be given to developing novel neural network topologies that naturally mirror the hierarchical, multi-scale nature of plant biology. Furthermore, researchers must implement spatial block cross-validation and rigorous out-of-distribution testing protocols to ensure their models possess true operational generalizability before publication.

Implications for Practitioners and Agronomists: For commercial agronomists, farm management firms, and precision agriculture suppliers, this review serves as a roadmap for operational technology selection. Practitioners should look skeptically at commercial software claiming near-perfect forecasting accuracies based on simple black-box architectures. Preference must be given to platform architectures that integrate multi-modal data fusion (combining remote sensing with dynamic real-time IoT soil sensors) and utilize Explainable AI (XAI) modules. This integration provides field managers with the underlying agronomic rationale driving the yield forecast, enabling targeted intra-season interventions (e.g., localized variable-rate nitrogen application) rather than just a passive end-of-season prediction.

Implications for Policymakers and Global Institutions: For national ministries of agriculture, the FAO, the World Bank, and humanitarian food security networks, the evolution of ANN yield models offers powerful new capabilities for macroeconomic risk mitigation. However, to safely utilize these deep learning tools, institutions must actively fund the remediation of the data scarcity crisis in the Global South. Policymakers must invest heavily in open-access digital infrastructure: expanding regional networks of automated weather stations, standardizing sub-national crop reporting frameworks, and establishing centralized, high-resolution ground-truth yield registries. Without this foundational data infrastructure, AI-driven agricultural forecasting will exacerbate global systemic inequality, creating a stark divide between highly optimized data-rich agricultural zones and highly vulnerable, unmonitored data-sparse ecosystems.

Conclusion

Summary of Major Findings

The thorough analysis has effectively brought together the advancements, structures, and methodologies in the area of artificial neural network models for forecasting crop productivity in the period between 2015 and 2025. The investigation points to a strong technological breakthrough that has occurred in this area. Current cutting-edge solutions include hybrid solutions combining convolution neural networks and long short-term memory models, as well as spatial graph neural networks and temporal transformer neural networks, capable of analyzing massive quantities of terrestrial data and agricultural meteorology time-series data at once. However, notwithstanding the great statistical performance achieved in ideal laboratory conditions, there are still serious problems that continue to exist in the field.

Overall Significance of the Review

This review’s importance stems from its conscientious and critical analysis of the empirical modeling paradigm. This paper sheds light on the mathematical and operational inconsistencies that differentiate the academic performance of models from their agricultural viability, going beyond a mere accumulation of descriptive information. It gives context for the current state of the art in terms of global food security and shows that the future of predictive agronomy does not lie in the uncontrolled expansion of networks, but rather in the fusion of data science, explanation and domain expertise.

Strategic Recommendations

For Scientists: 1. Prohibit random train/test splits in spatial-temporal data and switch to universal implementation of both spatial block cross-validation and leave-one-year-out validation methods. 2. Facilitate the development of physics-informed neural networks (PINN) which include differential equations that control physiology of plants and carbon conservation in losses of deep learning models. 3. Incorporate SHAP or similar architectures into all suggested models for making sure that results could be understood by stakeholders.

For Farmers: 1. Utilize hybrid architecture (for example, CNN-LSTM) which considers both spatial heterogeneity of fields and temporal dynamics of the growing period. 2. Do not rely only on indices that are derived from satellites but rather include dynamic moistures and nutrient sensors to recognize stress during first stages of growing.

For Government Officials: 1. Create open-access databases which would allow to collect and standardize georeferenced data on yields, especially for small farmers from the developing world. 2. Use explainable AI based models for crop yields prediction as future macroeconomic warning systems and include them into logistics of grain storages and humanitarian aid.

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