OPEN ACCESS
Haya: The Saudi Journal of Life Sciences
Abbreviated Key Title: Haya Saudi J Life Sci
ISSN 2415-623X (Print) | ISSN 2415-6221 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Review Article

Advances and Applications of AI Modeling in Crop Science; A Comprehensive Review

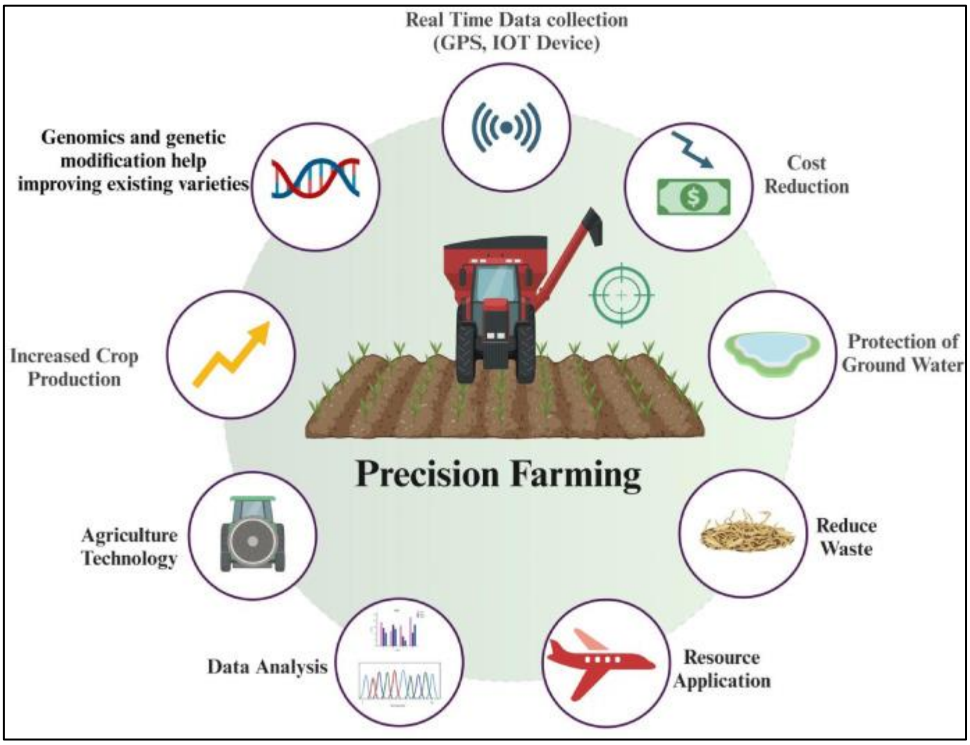
Muhammad Ali[1]*, Muhammad Anas[2], Usman M. Umar[3], Muhammad Saad ul Hasnain[4], Amna Younas[5], Adeeba Majeed[6], Sana Ashraf[7]

[1]Department of Botany, University of Agriculture Faisalabad, Punjab Pakistan
[2]Department of Crop Genetics and Breeding, Jiangxi Agricultural University, Nanchang China
[3]Department of Plant Production and Technology, Niğde Ömer Halisdemir University, Central Campus, Niğde 51240, Turkiye
[4]Department of Botany, Government College University Faisalabad, Pakistan
[5]Kunming Institute of Botany, Chinese Academy of Sciences
[6]Department of Botany, Lahore College for Women's University
[7]Department of Botany, University of Agriculture Faisalabad

DOI: https://doi.org/10.36348/sjls.2025.v10i10.002 | **Received:** 10.09.2025 | **Accepted:** 01.11.2025 | **Published:** 04.11.2025

***Corresponding author:** Muhammad Ali
Department of Botany, University of Agriculture Faisalabad, Punjab Pakistan

Abstract



Graphical Abstract

Artificial intelligence (AI) in crop science is redefining the agriculture issue by being accurate, scalable, and predictive. It is an overview of the recent developments in AI-based crop modeling in the context of its advancement, management, and sustainability. We criticize the application of machine learning (ML), deep learning (DL), reinforcement learning (RL) and computer vision to fields of high-throughput phenotyping, genomic prediction, yield forecasting and stress detection. Convolutional neural networks and vision transformers have assisted in new developments in image-based prediction of characteristics of UAVs, satellites, and ground sensors, and recurrent and graph neural networks to new developments in spatiotemporal modeling of crop-environment interactions. This is possible by combination of predictive modeling and crop simulation systems and enables dynamic decision support of the changing climatic conditions. Moreover, explainable AI (XAI) technique is also in progressive use to increase transparency of models and make them acceptable to breeders and farmers. However, there are still serious obstacles like the heterogeneity of the data, models transferability is not applicable across the regions, annotation bottlenecks, and the failure to incorporate the biological knowledge into the AI structures. The other fact, which we highlight, is the unavailability of AI to smallholder systems and the uniformity of standard and open-source datasets. Future directions It concentrates on the use of multi-omics, remote sensing, and on-farm data in individual AI systems, and physics-informed and hybrid modelling. Such integrative practices are necessary to make AI tools more powerful, decipherable and scalable. Ultimately, the strategic application of next generation AI models will be in sustainable increment, resultant reduction in environmental footprints, and crop production systems in a manner that will be resilient to the changing climatic conditions in order to feed the ever-growing world population which is increasing at an accelerated rate.

Keywords: Artificial Intelligence, Deep Learning, Computer Vision; Predictive Modeling, Explainable AI; Crop Phenotyping; Climate Resilience.

1. INTRODUCTION

Agriculture is on a crossroad as it must confront the rising food demands in the planet and the rising environmental stress as well as unpredictable changes in climate (Taheri Hossein Khani *et al.,* 2025). Since population is considered to grow to near 10 billion people by midcentury, there will be a need to boost crop production with a decline in ecological footprints such as soil erosion and water depletion. These problems are also enhanced by the variability of the climate that is realized via erratic weather conditions that disrupt the yields and enhance the intrusion of pests. The nexus introduces the necessity of more advanced, data-driven policies that will help in crop system efficiencies and flexibility ensuring that food security will not compromise the health of the planet (KUMAR *et al.,* 2025). The new digital agriculture has introduced a high level of transformation to the conventional paradigms of crop science. Nowadays, with the proliferation of sensor networks, satellite information, and data analytics of big data, researchers can now apply the massive stream of data to inform cultivation practice. Computational modeling also contributes to this change, as it is a simulation of the complex biological processes and interactions with the environment that are more precise than could be previously observed (Kumar *et al.,* 2023). Artificial intelligence (AI) is at the center of this development because it unites heterogeneous sources of data in singular predictive tools and propels precision farming, and it becomes possible to take action based on the management of resources (Indu *et al.,* 2024).

The AI systems are replacing the old empirical models and mechanistic simulations and introduce novel accuracy and scalability in crop science (Peng *et al.,* 2020). Early models were rule-based and statistical regression-based and often limited by assumptions of linearity and small sets of data. Machine learning on the other hand is applied in AI to discover patterns in high dimensional data which is intricate and has information that is resilient to variability in the real world. Integrating the genomic sequences with the phenotypical characteristics, the environmental indicators and the remote sensing data, such systems generate actable intelligence by optimizing the breeding activities and field operations (Xu *et al.,* 2022). The uses of AI in crop science are very broad with each use intimating the bottlenecks in productivity (Aijaz *et al.,* 2025). Computer vision is applied in high-throughput phenotyping of traits, which is faster in the analysis of large populations of plants. Genomic prediction models are used to predict the outcome of breeding by studying genetic markers, which hastens the progression of variety. The yield forecasting is an integration of time-based data of weather forecasts and soil sensors to calculate the quantity of harvest, which comes in handy when planning the supply chain. With the help of spectral analysis of images, it is possible to identify both biotic and abiotic risks (drought or fungal infections) and respond in time (Dhaliwal *et al.,* 2024). That can be supported by the fact that machine learning, deep learning, and computer vision can make dynamic decisions in the altering climatic conditions, whereby the models are continually refining their predictions as new data becomes available (Gupta *et al.,* 2024).

The more advanced neural architectures have led to the creation of AI that has addressed the complexity of crops (Wu *et al.,* 2025). CNNs are effective to deal with spatial hierarchy of pictures, and it enables them to recognize weeds correctly or map a disease in drone shots. Long-term memory variations of recurrent neural networks (RNNs) are time-dependent predictors of growth cycles and weather patterns, and can be used to improve time-series forecasting. The relational structure represented by the graph neural networks (GNNs) is able to reveal hidden biological pathways, such as a network of interactions between genes, or a network of relationships inside of a field. Transformers and their attention mechanisms are useful in dealing with multimodal and sequential data that can take into account text-based reports as part of visual inputs to produce full analyses (Xu *et al.,* 2023). Collectively, these architectures make spatial, temporal, and relational complexities available, and this results in additional models that capture the complexity of crop ecosystems. The effective application of AI to the already encountered crop simulation system and precision agriculture equipment increases its use in both small and large scale, on a single plant or on a region. The hybrid systems refer to the incorporation of the pattern recognition of AI with biophysical modeling resulting in a strong decision-making system of whether to irrigate or add fertilizers (Ajith *et al.*, 2025). This interoperability promotes multiscale knowledge where the information at the farm level is utilized to formulate policy at the global level. Increasingly, explainable AI (XAI) techniques, such as visualizing feature importance and counterfactual explanations, are making model decisions more transparent, building trust with stakeholders and allowing modeling to be applied to regulations in the agricultural context (Mathew *et al.*, 2025).

Despite these measures, AI in crop science is experiencing tremendous challenges. Data heterogeneity also arises because of the inconsistency of sensor and region formats and lacks the ability to train the models (Kathuria *et al.*, 2024). The absence of standardization of protocols has a negative impact on reproducibility, and the absence of transferability affects the applicability of the model to new contexts or crop species. The outcome of the inability to integrate biological priors is usually the simplification of representations at the cost of delicate physiological responses. The issues may be aggravated by socio-economic factors; the resource poor smallholder farmers in developing nations must face the high implementation costs, ineffective infrastructure and incompetencies, which increases the inequality in the technological uptake (Smith *et al.*, 2025). Later combinations of multi-omics datasets in the shape of genomics, transcriptomics, and metabolomics will be needed in order to seal these gaps in the future which incorporate remote sensing and AI paradigms. The hybrid modeling approaches that imply the combination of the two types of modeling, the mechanistic simulations, and the data-driven AI, have opportunities to provide resilient structures predicting the impacts of climate. It should direct its studies towards scaling and tools that can be interpreted and democratize access empowering the various farming communities. This convergence finally conceptualizes sustainable systems of crop production to balance productivity and ecological care, and introduces adaptive farming to a precarious future.

2. Neuro-Symbolic Hybrid Architectures for Integrative Crop Modeling

Artificial intelligence applications to crop science have evolved in two major divergent directions, each being data-driven, i.e. deep learning, which is competent in identifying patterns in high-dimensional data, and symbolic reasoning, which encodes explicit agronomic knowledge in a formal logic and rule system. Even though deep learning models, in particular, convolutional and transformer-based models have demonstrated impressive results in agroecosystems, such as prediction of yields and stress detection, these models lack transparency and require dependence on data, thus being less interpretable scientifically and less applicable to real agroecosystems (Aman *et al.*, 2025). Crop-physiological or soil-scientific based symbolic systems are on the other hand easier to offer transparency and causal structure but fail to offer the capacity to adjust to the noisy reality information of the real world. Neuro-symbolic hybrid architectures are a synthesis intersection which entails a combination of these paradigms and enables AI systems to learn data and pay tribute, instantiate and reason agronomic domain principles (Aman *et al.*, 2025).

Neuro-symbolic AI in crop modeling has the capability of synthesizing sub-symbolic neural representations with symbolic knowledge graphs, logic rules or agronomy, plant physiology and environmental science-based ontologies. The synthesis also allows models to not only predict consequences, such as grain yield during the drought, but also underpin predictions using intelligible series of elucidations that are congruent with what biological processes are known to do (Kumar *et al.*, 2024). By way of example, differentiable logical constraints (e.g. nutrient-yield response curves), changing point between phenological stages or irrigation thresholds can be cast as a training objective of neural training. This form of integration ensures the model behavior to be agronomically consistent when the training data are infrequent or biased that is of paramount importance in data-deficient regions or when applied to new climatic regimes.

In the recent developments, several emerging technical structures have been used to operationalize this vision. The differentiable logics programming can be applied to neural networks to be trained to adhere to the rules of first-order logic coded in a language like Prolog or Answer Set programming, allowing crop growth steps or the existence of pests to condition inference of the model (Zhao *et al.*, 2024). Transformers based on knowledge rely on structured ontologies of agriculture, such as the Crop Ontology or Soil Taxonomy in their attention processes, favoring attributes that are related to biologically significant variables. Probably the most promising are graph neural-symbolic models, where farms, fields or experimental plots are modeled as graphs, with nodes corresponding to entities (e.g., cultivar, soil type, weather event) and there are causal or associative edges. These graphs are then subjected to graph neural networks, the message-transmission mechanics of which are constrained by symbolic rules, permitting the joint acquisition of both statistical rules and causal programs and patterns between genotype × environment × management (G×E×M) interactions (Ding *et al.*, 2024).

This approach overcomes a major weakness of the older AI in agriculture namely that there is no capability of distinguishing between correlation and causation. Neuro-symbolic systems have the capacity to model the counterfactual state of affairs, examine the trade-offs among management decisions, and give evidence-based and scientifically-grounded suggestions since they plan the causal prior, such as: over-application of nitrogen to crops will lead to lodging, and not yield gain. Such capabilities are required to do regulatory applications, where traceable reasoning is required to certify or satisfy policy requirements, and farmer adoption, where comprehensible logic is required rather than incomprehensible results of algorithms.

Nevertheless, scaling neuro-symbolic crop models has still serious problems. An interdisciplinary collaboration between AI researchers, crop scientists, and knowledge engineers is required to encode agronomic knowledge in machine-readable logic formalized form, which is a bottleneck in those areas where tacit or context-specific knowledge is the most common. Besides this, to achieve a balance between the rigidity of symbolic rules and the plasticity of neural learning will demand a complex engineering of the architecture to make sure that the model does not over-constrain its expressivity. Current implementations are generally founded on manually built rule sets that only allow limited automation, intercrop and interregion transferability (Suprem *et al.,* 2013).

The neuro-symbolic AI will continue to develop and require maturation in crop science to create dynamic bodies of knowledge, which are updated with the introduction of scientific literature, via automated rule creation, with standardized frameworks to articulate agronomic causality. These systems combined with digital twin systems and decision-support systems could enable a new generation of intelligent agronomy in which AI does not simply predict, but also elucidates, justifies and co-designs sustainably sustainable management courses together with human stakeholders. This interdisciplinary amalgamation of cognitive science, formal logic, and information-based agronomy has resulted in neuro-symbolic model being one of the essential providers of transparent, reliable, and scientifically reliable AI of global food systems (Bhuyan *et al.,* 2024).

Table 1: A comparative discussion of neuro-symbolic hybrid architectures that analogy crops by shining light on their mechanisms, uses, and scientific benefits, and future prospects of research

Architectural Paradigm	Core Mechanism (neural ↔ symbolic fusion)	Application in Crop Science (representative use cases)	Scientific Advantages (why use neuro-symbolic here)	Technical / Practical Challenges (critical limitations)	Future Prospects (research & integration trajectories)
Differentiable Logic Programming (e.g., Neural-LP, DeepProbLog variants)	Logic rules (Horn clauses, probabilistic facts) are embedded as differentiable constraints; neural nets provide parameterized predicates or perceptual grounding; end-to-end gradient flow aligns symbolic satisfaction with predictive loss.	Phenotype classification grounded by agronomic rules (e.g., phenology stages → management actions); constrained yield estimation where physiological constraints must hold.	Enables learning while enforcing domain constraints → better generalization under sparse labels; supports soft logical explanations and constrained counterfactuals.	Formalizing domain knowledge as rules is time-consuming; brittle if rules are overly rigid; training can be unstable when symbolic loss conflicts with empirical signal.	Automated rule induction from data; hybrid training schedules that alternate symbolic regularizers and data loss; scalable solvers for large rule sets.
Knowledge-Guided Transformers (symbolic priors + attention)	Transformers ingest multimodal inputs; symbolic knowledge encoded as prompts, attention masks, or learned embeddings that bias self-attention toward known causal relations (e.g.,	Remote-sensing + weather → stress detection and temporal risk forecasting; contextualized recommendations that respect crop-specific constraints.	High capacity for multimodal fusion while preserving structured priors; flexible to temporal sequences and large datasets; improved sample efficiency when priors align.	Injected knowledge can be diffuse (hard to audit); over-biasing the model risks ignoring novel patterns; interpretability depends on how priors are represented.	Dynamic, contextual knowledge injection (time-aware priors); hybrid attention heads explicitly tied to symbolic modules for provenance.

Architectural Paradigm	**Core Mechanism (neural ↔ symbolic fusion)**	**Application in Crop Science (representative use cases)**	**Scientific Advantages (why use neuro-symbolic here)**	**Technical / Practical Challenges (critical limitations)**	**Future Prospects (research & integration trajectories)**
	crop calendars, nutrient hierarchies).				
Graph Neuro-Symbolic Models (KGs + GNNs)	Knowledge graphs represent entities (fields, varieties, pests) and relations; GNNs operate on KG subgraphs and raw sensor/node features; symbolic reasoning applied as graph constraints or symbolic query layers.	Trait×environment interaction modeling; pest/pathogen spread simulation across landscape graphs; recommendation systems linking genotype, management, and outcome.	Naturally encodes relational, hierarchical agronomic knowledge and enables relational generalization; supports explainable subgraph retrieval as justification.	KG curation and ontology alignment are labor intensive; inference on large graphs is computationally heavy; noisy or missing relations degrade reasoning.	Automated KG population from structured/unstructured agronomic sources; integration with spatiotemporal digital-twin graphs.
Neuro-Symbolic Pipeline (sequential modules: perception → symbolic planner/verifier)	Modular design: neural modules handle perception (images, spectra); outputs feed symbolic planners or rule engines that perform high-level reasoning, verification, and decision generation. Communication via structured intermediate representations (IRs).	Field-level scouting: neural detection of symptoms → symbolic diagnosis + management plan (fertilizer, irrigation scheduling).	Clear separation of concerns improves interpretability and auditability; easier to inject curated agronomic expertise and update rules without retraining perception.	Module interface mismatch (error propagation); non-differentiable modules complicate joint optimization; latency in real-time systems.	Differentiable surrogates for symbolic planners; hybrid debugging tools to localize failures across pipeline.
Probabilistic Programming Hybrids (Bayesian symbolic models + neural likelihoods)	Probabilistic programs specify causal/biophysical generative models; neural networks parameterize complex likelihoods or latent processes; inference integrates symbolic causal structure with learned components.	Yield decomposition into physiological components; modeling uncertainty in fertilizer response or water stress under scenario simulation.	Explicit uncertainty quantification and causal interpretability; principled integration of prior mechanistic knowledge with flexible data-driven submodels.	Computationally intensive inference; model misspecification of causal structure yields biased conclusions; requires careful prior elicitation.	Scalable variational/memory-efficient inference; automated structure learning to discover causal relations from observational and experimental data.

3. Self-Supervised and Foundation Models for Cross-Crop Phenomics

The scale and the unbiasedness of AI-based crop phenomics have been limited by task-specific models requiring to be trained on immense amounts of labeled data materials, which are common to the huge commercial crops, including maize, rice, and wheat. The same paradigm would not fit in the broad spectrum of under-resourced or so-called orphan drugs which would support the marginal and low-income regions. Self-supervised learning and production of crop foundation models (CFMs) large pre-trained models are now starting to change the world by being able to learn universal representations on unlabeled multi-modal agricultural data across the species and across the environment and sensing platforms (Luo *et al.,* 2024). In contrast to supervised learning, which can only be limited to the considerations of raw field imagery, hyperspectral, time-series weather, or even genomic sequences, these models use the inherent structure of raw field imagery, hyperspectral, time-series weather, or even genomic sequences to produce transferable feature spaces that can be adapted to new crops, traits, or agroecosystems (zero-shot or few-shot) with little or no fine-tuning.

The main principle of this paradigm is the un-annotated representation learning. Unlabeled drone, satellite, or ground-based sensor streams can therefore be directly utilized to obtain a self-supervised algorithm -based predictor of latent biological and environmental data (e.g., masked autoencoding, contrastive learning, temporal forecasting). In this case, vision transformers (ViTs) have also been beneficial, which absorb long-range spatial statistics in the structure of canopy and long-range temporal statistics in the vegetation structure development cycle with attention mechanisms trained on very large collections of field images. The model trained with high-level priors on plant morphology, growth stage and stress imaging during the unlabeled condition with strong priors when trained on masked image models (random patches are masked and uncovered). In a similar fashion, contrastive models that had been trained on multi-temporal UAV data are capable of identifying subtle phenotypic changes due to learning an invariant representation of light and viewing angles and seasonal changes (Yang *et al.,* 2025).

The biological boundaries are the capability of CFMs to generalize across the biological boundaries which is the real innovation of the CFMs. Through pre-training on a large range of species, such as (but not limited to) model crops, but also neglected staples such architectures generate an overlapping semantic space in which the phenotypic properties of leaf rolling, canopy temperature, or root architecture can be cross-taxonomically comparable. This makes interspecies knowledge transfer possible, e.g. maize prediction using drought-response signatures trained on accomplished experiments using well-labeled maize can be made with maize, where lack of labelled data is a deficiency (Kakoulidou *et al.,* 2021). Not only is this transfer an analogical transfer but it is based on physiologically conserved responses augmented by multi-modal fusion architectures to project visual, spectral and genomic embeddings on to a shared latent space. The initial signs are the fact that, hyperspectral reflectance/RNA-seq models can identify stress-response pathways conserved to a greater extent, which improve cross-crop generalizability as well. The connectivity of digital twin ecosystem assists in increasing the CFM utility that is scale-based, with real-time adaptive phenotyping. In its implementation as a farm-level digital twin, a foundation model can constantly take in new sensor measurements in a continuous and updating way, modifying its internal representations and making predictions more accurately without necessarily having to re-train the model as a unit. Such dynamic ability assists in making timely management decisions, including modifying the irrigation, depending on the first symptoms of water stress in unmarked images, even those crops, the characteristics of which were not identified by the time of pre-training (Sun *et al.,* 2025).

Despite the promise, CFMs possess several issues that do not permit their popularization. Normalization techniques, as well as domain-adaptation techniques, are highly developed since the agricultural data are highly diverse when it comes to the variety of different types of sensors, different geographies, and different growth stages. Besides that, the intentional selection of pre-training goals that have biological relevance (not outcomes of data gathering bias) must consider learned representations; in that regard, agronomic priors are coded into pre-training goals (Jubair *et al.,* 2023). The issue of computer expenses and data management is also there, especially where a cloud is unavailable, and the policy on open-data is not being pursued. The future work will necessitate the creation of future agricultural data commons of open multi-species and pre-training benchmarks. The concept of a democratization of the phenomics of preciseness and conversion of all spheres, despite their crop, or where they are located, into a world of scientific discovery and sustainable management, can be applied by CFMs as they reach the plane of real universality. The section thereby closes the gap in AI and agricultural innovation which is inclusive therefore rendering it feasible to possess equitable, scalable intelligences of global crop system in the future (Ozor *et al.,* 2025).

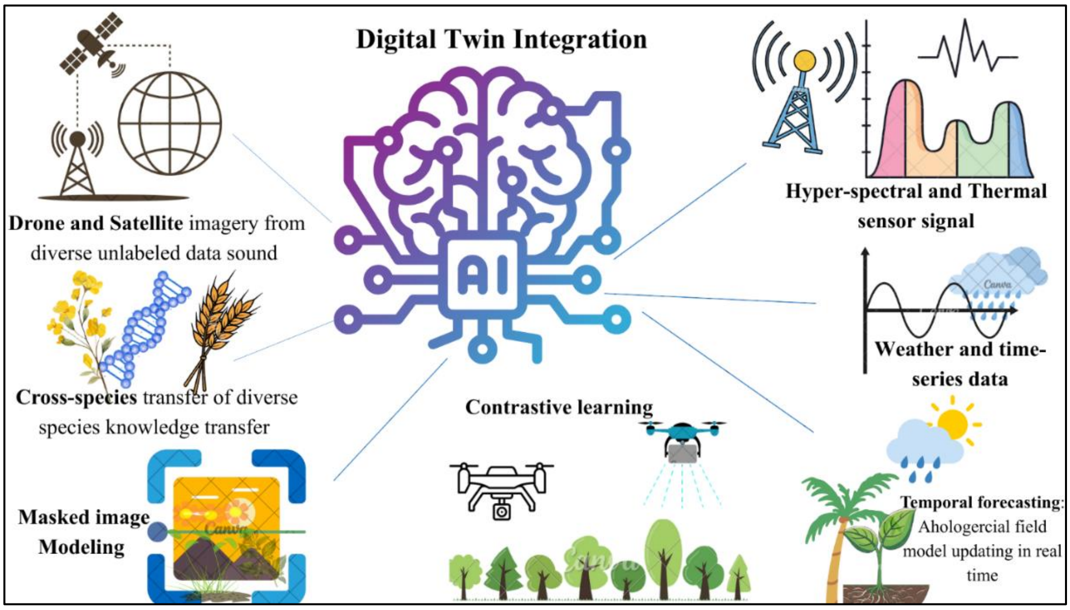


Fig 1: Cross-crop phenomics can be achieved with self-supervised and foundation models based on multimodal integration of data and cross-species transfer of knowledge. The central neural model bridges various streams of data to real-time digital twin systems on adaptive and scalable crop intelligence.

4. Causal Representation Learning for Genotype–Phenotype Decoding Under Environmental Perturbations

Statistical correlation of molecular markers and phenotypic performance has long been the basis of genomic prediction in crop science, in which case environmental variation is taken to be a noise to mean, and not a dynamic differentiation of genetic expression. Though these forms of correlation-guided breeding approaches have reduced breeding periods in stable characteristics within controlled environments, these do not work in case of an environmental perturbation drought, heat or nutrient stress when genotype phenotype relationships are nonlinear, context-dependent and confounded by spurious correlations (Malik *et al.*, 2024). The second frontier is the causal representation learning: a paradigm that cannot be based only upon associative mapping, but instead attempts to learn how genetic variants operate in the form of different environmental regimes. The approach can also decompose the actual genetic impacts of the theory of causal inference and deep representation learning on the ecological confounders to enable the contemporary process of enhancing the robust crop and climate adaptive modification.

The crux of such change is that phenotypic expression is not a deterministic role of genotype rather a contingent outcome of environmental situations (Burga *et al.*, 2012). This is formalized in causal AI models structural causal models (SCM) where directed acyclic graphs are used to indicate proposed relationships between genes, environment, management and traits. These SCMs are learnable in a neural network parameterization structure, and possess a causal meaning of the learned response surfaces. Most importantly, they also make possible do-calculus computations that allow scientists to explore counterfactual phenotypes, which were not possible using the old-fashioned regression or genomic best linear unbiased prediction (GBLUP) models. This counterfactual is the clue to the evaluation of genetic performance under the conditions of changing climates and to identify alleles that will produce the same action under all conditions (Brown *et al.*, 2016).

Recent methodology advances have adopted causal learning in genomics through various new structures. Causal variational autoencoders (CVAEs) are constructed on the prior latent-space models and add extra constraints that make the genetic and environmental latent factors be disentangled such that a perturbation of one does not cause perturbation of the other (Leeb *et al.*, 2022). IRM is also useful in enhancing generalizability since genetic predictor effects that are observed to be similar in many environments are useful in removing context-dependent noise and isolating sound causal information. The techniques prove to be particularly useful in solving complex genetic designs: IRM can learn to differentiate between true pleiotropic interactions (a single gene conditioning a high number of phenotypes) and spurious relationships caused by the shared environment response, and neural SCMs can compute epistatic interactions as conditional dependencies on temperature or soil humidity.

This is a causal prism parametrizing the genomic selection process into a mechanistic design technology. The breeders may then choose gene editing targets with uniform gains in the diverse stress situations by simulating counterfactual phenotypes in the condition of targeted environmental perturbations. In the example, disabling a regulator gene may be slightly useful in the optimal situation and utterly drought resistant in counterfactual simulations that are not observable with the correlation-based models (Camps-Valls *et al.,* 2024). Moreover, dynamic genotype phenotype maps based on causal representation can also be updated in real time when new climate data are available so that adaptive breeding predicts and does not respond to environmental change.

Nonetheless, causal genomics are still challenged by problems. Valid SCMs are built on substantial assumptions of causal structure often based on domain knowledge, which is not always complete. High-dimensional genomic data also increases the identifiability issue and necessitates regularization measures between leeway and causal plausibility. Furthermore, the absence of multi-env, multi-year phenotype data and correct environmental metadata of the study does not allow empirical testing of the causal claims (Sarzaeim *et al.,* 2023).

The adoption of causal representation learning in the future can be combined with transcriptomics, metabolomics and epigenomics layers of causal representation to enable hierarchical models of causal effects of DNA sequence on the molecular mediators of whole-plant phenotypes. These frameworks, with climate projection models, could be used to execute next-generation genomic selection pipelines which are accurate as well as causally robust, equitable, and future-proof. Here it is that genomic prediction comes back into the spotlight with a new element of pattern recognition with a new twist of mechanistic knowledge which determines causality as the basis of the robust crop design in a more environmentally unpredictable world (Riaz *et al.,* 2025).

5. Edge-AI–Enabled Sustainable Precision Agriculture Systems

The transformation of agricultural system to sustainable intensification is not only algorithmically sophisticated but also needs a smart system that is not only accurate but also combined, functional, and responsible towards the environment. Despite the fact that the farming sector has been finding it extremely efficient in terms of crop monitoring, aiding decision-making based on the feedback given by cloud-based AI systems, they rely on the uninterrupted flow of information, processing it on a centralized level, and computing it through energy-consuming means, which is unsuitable in resource-strained farms and fails to align with the principles of low-impact agriculture (Taheri Hosseinkhani *et al.,* 2025). A new paradigm is being in turn being developed: sustainability-conscious edge intelligence on-device artificial intelligence which will execute agronomic reasoning on the occasion of data collection, will optimize inputs and will be actively reducing the carbon, water, and chemical footprint. This approach renders AI performance-centric no longer, but the provider of planetary stewardship, and thus environmental constraints to the computational structure of precision agriculture.

This can be done using edge-AI in the form of both hardware and algorithm co-designing to execute at ultra-low-power on field-deployable machines (e.g., drones, soil sensors, autonomous tractors, etc.). The application of TinyML (Tiny Machine Learning) current edge architectures can be used to scale down deep neural networks to kilobyte scale models that can be run on microcontrollers in milliwatt-scale power consumption. It can also be more efficient when biological neurons models respond to salient event-driven variations in sensor inputs (e.g. sudden change in canopy temperature or spectral changes by pests) so they can avoid unnecessary computation and achieve better battery life (Barrios-Avilés *et al.,* 2018). The software-hardware synergies are capable of being utilized to allow the continual on-site optimization of crop stress, nutrient status or irrigation needs, without necessarily using cloud infrastructure, enabling precision agriculture to be employed even in off-grid or remote areas.

More significantly, the sustainability-conscious edge intelligence is more than energy efficiency can suggest that the integration of explicit ecological objectives into the decision rationality. Multi-objective reward functions are currently being conditioned on reinforcement learning agents distributed to the edge devices that maximize yield and environmental outcomes such as negative reward of activities that exceed the nitrogen leaching or water withdrawal goals under local sustainability of the aquifer. Integrating the concept of planetary boundaries into the loss landscape directly, these actors learn a policy that complies with the ecological carrying capacities without decreasing productivity (Steffen *et al.,* 2015). This is a structural break to the traditional precision agriculture which focuses on producing as much as possible without taking into account the externality.

In internet of things networks with decentralized farms, federated learning is applied to deal with data governance and model evolution. Instead of transmitting crude field measurements to central servers, edge devices can cooperate to optimize common models by exchanging model updates that preserve privacy of the farmers and enable joint learning with heterogeneous agroecosystems. More to the point, this decentralized paradigm significantly reduces the amounts of information exchange and carbon footprints and predisposes the models improvement to be closer to green AI. Another element of life cycle assessment (LCA), such as embodied carbon in sensors or irrigation energy usage, is also implemented in new structures as a training goal, as it is important not to only evaluate AI recommendations by their agronomic effectiveness, but by the total environmental price (Mohammadi Kashka *et al.,* 2023).

Despite these developments, issues related to the standardization of green AI metrics in agriculture, the model stability in case of hardware constraints, and assistance in bridging the digital divide to ensure that the smallholders without technical infrastructure can access green AI remain. The next-generation development is built on the significance of open hardware, inter-institutional comparison of models conscious of sustainability, and policy framework encouraging the use of low-footprint AI. It is with this that by pushing intelligence to the periphery, both physically and ethically, the paradigm makes precision agriculture ecologically responsible. It does not put AI in a remote layer of analysis, but as a part and parcel of the agroecosystem itself, a constituent of the system that is sustainable. Thus, the section is a practicalization of the larger vision of the review, which is that the future of AI in crop science must not only be smart, but also be frugal, fair, and be fundamentally tied to the biophysical limitations of the Earth (Kumari *et al.,* 2025).

6. Climate-Resilient Digital Twins with Generative AI and Uncertainty Quantification

With the agroclimate extremes becoming more common and severe as heatwave gain rate accelerates with rising climate change, narrow and broadly dispersed rainfall, and prolonged droughts, dynamic or probabilistic crop system models are becoming less applicable to inform long-term adaptation. The new solution is climate-resilient digital twins: dynamic, probabilistic models of physical cropping systems which interact multi-source data, process-based knowledge and generative artificial intelligence to simulate, predict, and jointly design dynamic responses to deep uncertainty. The next-generation versions of digital twins are futuristic, generative, and explicitly uncertainty-aware and are able to analyze a range of plausible futures rather than predict one as compared to the traditional versions, which simply mirror reality (Durlik *et al.,* 2025). This paradigm shift is what transforms digital twins as useful monitoring tools and instead active resilience planning engines to the breeders, agronomist and policymakers.

The most important part of this development is that generative AI and climate science are combined with stochastic systems modeling. In the absence of observational data, diffusion models and generative adversarial networks (GANs) are now being trained to generate high-fidelity and physically realistic datasets of crop responses in hypothetical conditions of climate change conditions when such data is unobservable. These models can generate unnaturally, but also realistically, yield, phenology, or stress curves with new combinations of temperature and CO 2 and precipitation based upon the historical data of joint resistance of climate variables and agronomy (Zhu *et al.,* 2025). Such forms of synthetic data do not just cause the size of the training sets to predictive models, but enable the management strategies to be tested against a black swan event to stress-test the adaptive envelope of the agricultural planning.

It is also important to quantify the uncertainty in a direct manner. There are climate predictions, non-homogeneity of the soil and biological variation, and their uncertainty is both aleatoric (randomness as such) and epistemic (lack of knowledge in the models). Digital twins are now capable of generating predictive distributions calibrated to prediction intervals not just with point estimates that can be deployed to make more risky suggestions (Zhang *et al.,* 2025). Using a twin as an illustration could be to say that a specific cultivar had a likely probability 70 to achieve target yield in the presence of moderate warming, and 40 in the presence of stress of compound heat-drought with measured confidence limits. Such openness to probabilities is required to take good judgments in extreme cases such as the implementation of a seed system or the concept of national food security.

The interactive and stakeholder-oriented design is also incorporated in these twins to increase their power of operation. Large language models (LLMs) embedded on emerging platforms can also be utilized as natural-language interfaces allowing farmers, extension agents, or policymakers to pose queries that take the form of a what-if query e.g., How would we spend an additional two weeks of no planting with RCP 4.5 and obtain interpretable, scenario-based responses on the basis of the generative engine of twins? The interactions facilitate the co-formation of climate-intelligent practices to overcome the gap between the complex-modeling and action-on-the-ground (Karol Mohan *et al.,* 2025). Also, physics-informed generative models, where neural networks are conditioned by conservation laws or crop growth equations, can ensure that synthetic situations are biophysically reasonable to enhance scientific plausibility and user trust.

Nevertheless, establishing generative twins in various agroecologies, as well as a broad range of agroecologies, remains challenging, and the equitable access to simulation infrastructure and counterfactual validation without the ground truth remains a challenge. This ought to be considered in the future through the open twin, standard uncertainty reporting, and participatory design with the smallholder communities (Lee *et al.,* 2025).

Digital twins that have climate resilience represent a paradigm shift towards anticipatory, adaptive and inclusive food systems driving the very fabric of agricultural modelling by incorporating generative foresight and extreme quantification of uncertainty. This section thus leads to the climax of the review of interpretable, generalizable and causal AI towards holistic visionary architecture of negotiating the deep uncertainties of agriculture in the 21st century (Pérez-Ortiz *et al.,* 2025).

CONCLUSION

Artificial intelligence has also become a game changer in the field of crop science and it has fundamentally changed the way we manage crops, predict crop yield, and make agricultural systems more sustainable. It is now possible to achieve unprecedented accuracy in real-time crop phenotyping, stress detection and yield forecasting using machine learning and deep learning models especially when combined with remote sensing, IoT-enabled field sensors, and high-resolution environmental data. These developments are driving the transformation of reactive to predictive and prescriptive agronomy and forming the basis of the next generation of precision farming maximizing the use of resources and reducing the ecological footprints. In the future, the convergence of AI and genomics, digital twins and edge computing will provide access to dynamic and genotype-informed management mechanisms that are resistant to climate variability. This potential can only be actualized on a massive scale through joint efforts; to guarantee interoperability of data across heterogeneous farming systems, mitigate bias in algorithms used, protect the sovereignty of farmer data and create lightweight, interpretable models that can be implemented in environments with low resources. It is only through interdisciplinary efforts through computer science, agronomy, ethics, and policy that AI-based crop science can live up to its hype of equitable, resilient, and sustainable food systems in the changing planet.

REFERENCES

- Aijaz, N., Lan, H., Raza, T., Yaqub, M., Iqbal, R., & Pathan, M. S. (2025). Artificial intelligence in agriculture: Advancing crop productivity and sustainability. *Journal of Agriculture and Food Research*, 101762.
- Ajith, S., Vijayakumar, S., & Elakkiya, N. (2025). Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms. *Discover Food*, *5*(1), 1-23.
- Aman, M., Khan, Z. U., Khan, J., Mashori, A. S., Ali, A., Jabeen, N., ... & Li, F. (2025). A Comprehensive Review on Crop Stress Detection: Destructive, Non-Destructive, and ML-Based Approaches. *Frontiers in Plant Science*, *16*, 1638675.
- Barrios-Avilés, J., Rosado-Muñoz, A., Medus, L. D., Bataller-Mompeán, M., & Guerrero-Martínez, J. F. (2018). Less data same information for event-based sensors: A bioinspired filtering and data reduction algorithm. *Sensors*, *18*(12), 4122.
- Bhuyan, B. P., Ramdane-Cherif, A., Tomar, R., & Singh, T. P. (2024). Neuro-symbolic artificial intelligence: a survey. *Neural Computing and Applications*, *36*(21), 12809-12844.
- Brown, J. L., Weber, J. J., Alvarado-Serrano, D. F., Hickerson, M. J., Franks, S. J., & Carnaval, A. C. (2016). Predicting the genetic consequences of future climate change: The power of coupling spatial demography, the coalescent, and historical landscape changes. *American Journal of Botany*, *103*(1), 153-163.
- Burga, A., & Lehner, B. (2012). Beyond genotype to phenotype: why the phenotype of an individual cannot always be predicted from their genome sequence and the environment that they experience. *The FEBS journal*, *279*(20), 3765-3775.
- Camps-Valls, G., Fernández-Torres, M. Á., Cohrs, K. H., Höhl, A., Castelletti, A., Pacal, A., ... & Williams, T. (2024). AI for Extreme Event Modeling and Understanding: Methodologies and Challenges. *arXiv preprint arXiv:2406.20080*.
- Dhaliwal, S. S., Sharma, V., Shivay, Y. S., Gupta, R. K., Verma, V., Kaur, M., ... & Hossain, A. (2024). Assessment and detection of biotic and abiotic stresses in field crops through remote and proximal sensing techniques—evidence from earlier findings. *Arabian Journal of Geosciences*, *17*(6), 188.
- Ding, J., Liu, C., Zheng, Y., Zhang, Y., Yu, Z., Li, R., ... & Li, Y. (2024). A Comprehensive Survey on Artificial Intelligence for Complex Network: Potential, Methodology and Application. *arXiv preprint arXiv:2402.16887*.
- Durlik, I., Miller, T., Kostecka, E., Kozlovska, P., & Ślączka, W. (2025). Enhancing Safety in Autonomous Maritime Transportation Systems with Real-Time AI Agents. *Applied Sciences*, *15*(9), 4986.
- Gupta, D., Kumar, P., Shukla, M. M., & Mahapatra, S. (2024). Enhancing climate change prediction and risk assessment with deep learning: Architectural approaches and data challenges. In *AI for climate change and environmental sustainability* (pp. 19-36). CRC Press.
- Indu, P. V., Nanjundan, P., & Thomas, L. (2024). AI for Optimization of Farming Resources and their Management. In *AI in Agriculture for Sustainable and Economic Management* (pp. 42-52). CRC Press.
- Jubair, S., & Domaratzki, M. (2023). Crop genomic selection with deep learning and environmental data: A survey. *Frontiers in Artificial Intelligence*, *5*, 1040295.
- Kakoulidou, I., Avramidou, E. V., Baránek, M., Brunel-Muguet, S., Farrona, S., Johannes, F., ... & Maury, S. (2021). Epigenetics for crop improvement in times of global change. *Biology*, *10*(8), 766.
- Karol Mohan, A., & Muraleedharan, G. (2025). Exploring co-production in redirecting climate urbanism. *Climate and Development*, *17*(2), 134-152.
- Katharria, A., Rajwar, K., Pant, M., Velásquez, J. D., Snášel, V., & Deep, K. (2024). Information Fusion in Smart Agriculture: Machine Learning

Applications and Future Research Directions. *arXiv preprint arXiv:2405.17465*.

- Kumar, A., Gill, A. S., Sharma, A., & Kumar, V. (2024, May). Enhancing the Explainability and Interpretability of Crop Yield Prediction Models Through Precision Agriculture. In *International Conference on Agriculture-Centric Computation* (pp. 218-226). Cham: Springer Nature Switzerland.
- Kumar, S., Guruparan, D., Aaron, P., Telajan, P., Mahadevan, K., Davagandhi, D., & Yue, O. X. (2023). Deep learning in computational biology: Advancements, challenges, and future outlook. *arXiv preprint arXiv:2310.03086*.
- KUMAR, S., RAVISANKAR, N., CHARY, G. R., PRUSTY, A., SHAMIM, M., & SINGH, R. (2025). Transforming food, land and water systems under global climate change: A review. *Indian Journal of Agronomy*, *70*, 1-10.
- Kumari, K., Mirzakhani Nafchi, A., Mirzaee, S., & Abdalla, A. (2025). AI-driven future farming: achieving climate-smart and sustainable agriculture. *AgriEngineering*, *7*(3), 89.
- Lee, T., Ramp, D., & Bless, A. (2025). Unlocking digital twin planning for grazing industries with farmer centred design. *Agriculture and Human Values*, 1-21.
- Leeb, F., Bauer, S., Besserve, M., & Schölkopf, B. (2022). Exploring the latent space of autoencoders with interventional assays. *Advances in neural information processing systems*, *35*, 21562-21574.
- Luo, Y., & Yao, T. (2024, December). Remote-sensing Foundation Model for Agriculture: A Survey. In *Proceedings of the 6th ACM International Conference on Multimedia in Asia Workshops* (pp. 1-7).
- Malik, A., Kumar, K., Kumari, G., Kumar, N., & Singh, H. (2024). Application of functional traits in modelling productivity and resilience under climate change. In *Plant Functional Traits for Improving Productivity* (pp. 77-96). Singapore: Springer Nature Singapore.
- Mathew, D. E., Ebem, D. U., Ikegwu, A. C., Ukeoma, P. E., & Dibiaezue, N. F. (2025). Recent emerging techniques in explainable artificial intelligence to enhance the interpretable and understanding of AI models for human. *Neural Processing Letters*, *57*(1), 16.
- Mohammadi Kashka, F., Tahmasebi Sarvestani, Z., Pirdashti, H., Motevali, A., Nadi, M., & Valipour, M. (2023). Sustainable systems engineering using life cycle assessment: application of artificial intelligence for predicting agro-environmental footprint. *Sustainability*, *15*(7), 6326.
- Nwaigbo, J. C., Sanusi, A. N., Akinode, A. O., & Cyriacus, C. (2025). Artificial Intelligence in Smart Cities: Accelerating Urban Sustainability through Intelligent Systems. *Global Journal of Engineering and Technology Advances*, *24*(03), 051-073.
- Ozor, N., Nwakaire, J., Nyambane, A., Muhatiah, W., & Nwobodo, C. (2025). Enhancing Africa's agriculture and food systems through responsible and gender inclusive AI innovation: insights from AI4AFS network. *Frontiers in Artificial Intelligence*, *7*, 1472236.
- Peng, B., Guan, K., Tang, J., Ainsworth, E. A., Asseng, S., Bernacchi, C. J., ... & Zhou, W. (2020). Towards a multiscale crop modelling framework for climate change adaptation assessment. *Nature plants*, *6*(4), 338-348.
- Pérez-Ortiz, M. (2024). From Prediction to Foresight: The role of AI in designing responsible futures. *Journal of Artificial Intelligence for Sustainable Development*, *1*(1), 1-9.
- Riaz, M., Yasmeen, E., Saleem, B., Hameed, M. K., Saeed Almheiri, M. T., Saeed Al Mir, R. O., ... & Gururani, M. A. (2025). Evolution of agricultural biotechnology is the paradigm shift in crop resilience and development: a review. *Frontiers in Plant Science*, *16*, 1585826.
- Sarzaeim, P., Muñoz-Arriola, F., Jarquin, D., Aslam, H., & De Leon Gatti, N. (2023). CLIM4OMICS: a geospatially comprehensive climate and multi-OMICS database for Maize phenotype predictability in the US and Canada. *Earth System Science Data Discussions*, *2023*, 1-35.
- Smith, A. (2025). Examining Gender-Inclusive Approaches to Green Technology Deployment in Agricultural Policy Frameworks: A Global Perspective. *Transdisciplinary Advances in Social Computing, Complex Dynamics, and Computational Creativity*, *15*(2), 1-9.
- Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., ... & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *science*, *347*(6223), 1259855.
- Sun, H., Chu, H. Q., Qin, Y. M., Hu, P., & Wang, R. F. (2025). Empowering Smart Soybean Farming with Deep Learning: Progress, Challenges, and Future Perspectives. *Agronomy*, *15*(8), 1831.
- Suprem, A., Mahalik, N., & Kim, K. (2013). A review on application of technology systems, standards and interfaces for agriculture and food sector. *Computer Standards & Interfaces*, *35*(4), 355-364.
- Taheri Hosseinkhani, N. (2025). Artificial Intelligence Applications and Economic Impacts in Sustainable Agriculture. *Available at SSRN 5474048*.
- Taheri Hosseinkhani, N. (2025). Global Food Security Amid Geopolitical Tensions and Climate Risk: Trade Governance and Adaptive Strategies. *Available at SSRN 5448314*.
- Wu, K., Ji, Z., Wang, H., Shao, X., Li, H., Zhang, W., ... & Bao, X. (2025). A Comprehensive Review of AI Methods in Agri-Food Engineering:

Applications, Challenges, and Future Directions. *Electronics*, *14*(20), 3994.

- Xu, P., Zhu, X., & Clifton, D. A. (2023). Multimodal learning with transformers: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(10), 12113-12132.
- Xu, Y., Zhang, X., Li, H., Zheng, H., Zhang, J., Olsen, M. S., ... & Qian, Q. (2022). Smart breeding driven by big data, artificial intelligence, and integrated genomic-enviromic prediction. *Molecular Plant*, *15*(11), 1664-1695.
- Yang, X., Chen, J., Lu, X., Liu, H., Liu, Y., Bai, X., ... & Zhang, Z. (2025). Advances in UAV Remote Sensing for Monitoring Crop Water and Nutrient Status: Modeling Methods, Influencing Factors, and Challenges. *Plants*, *14*(16), 2544.
- Zhang, Q., & Wang, T. (2024). Deep learning for exploring landslides with remote sensing and geo-environmental data: Frameworks, progress, challenges, and opportunities. *Remote Sensing*, *16*(8), 1344.
- Zhang, X., Wang, T., Ma, L., & Mahadevan, S. (2025). Reliability engineering, risk management, and trustworthiness assurance for AI systems. *Journal of Reliability Science and Engineering*, *1*(2), 022001.
- Zhao, X., Chen, B., Ji, M., Wang, X., Yan, Y., Zhang, J., ... & Lv, C. (2024). Implementation of large language models and agricultural knowledge graphs for efficient plant disease detection. *Agriculture*, *14*(8), 1359.
- Zhu, P., Abramoff, R., Makowski, D., & Ciais, P. (2021). Uncovering the past and future climate drivers of wheat yield shocks in Europe with machine learning. *Earth's Future*, *9*(5), e2020EF001815.