



AI Meets Agriculture-Remote Sensing-Driven Decision Support for Crop Health: A Comprehensive Review on Case Studies and Technology Applied

Deepak Lal^a, Mukesh Kumar^a, Rishabh Chaudhary^b, Shashi Prabha^b,
Ajaz Ahmad^b, Neeraj Kumar^b

^aCentre for Geospatial Technologies

^bDepartment of Computer Science and IT

^cPh.D. Research Scholars

Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj-211007, U.P.

DOI : <https://doi.org/10.5281/zenodo.15856781>

ARTICLE DETAILS

Research Paper

Accepted: 25-06-2025

Published: 10-07-2025

Keywords:

Remote sensing · Machine learning · Precision agriculture · Edge AI · Federated learning · Data fusion · India · Crop stress detection

ABSTRACT

The accelerating challenges of feeding a growing population under climate stress have driven rapid advances in AI-enabled remote sensing for crop health monitoring. This review synthesizes peer-reviewed research from 1995–2025, examining Satellite, UAV, and proximal-sensor platforms and their spectral/structural capabilities, Classical (Random Forest, SVM, GBM) and deep-learning (CNN, U-Net, ResNet) methods for stress detection and yield prediction, Data-fusion strategies that integrate spectral, thermal, LiDAR and textural inputs, Emerging paradigms—including edge AI for on-farm inference, federated learning for privacy-preserving collaboration, and decision-support systems such as AgroDSS, Cross-cutting challenges in scalability, interoperability, explainability and cost–benefit trade-offs. In the Indian context, national initiatives like the Digital Agriculture Mission (2021–2025) and pilot studies by CEEW demonstrate that AI-driven geospatial advisories can boost yields by 12–15% (≈ 0.4 – 0.6 t/ha), reduce input costs by 20–25%, and achieve benefit–cost ratios of

1.6–2.2. We identify five key research gaps—model generalization, concept-drift management, synthetic data augmentation, data-sharing policy frameworks, and standardized benchmarks—and propose a roadmap emphasizing open-science, farmer-centric design, and interdisciplinary collaboration.

i. Introduction

1.1 Context & Motivation

Agriculture faces unprecedented pressure: the global population is set to exceed 9.7 billion by 2050, demanding a 60 % boost in food production amid dwindling arable land and mounting water stress [1–3]. Climate extremes—heat waves, droughts, and pest outbreaks—already cause 20 %–30 % yield losses in vulnerable regions, underscoring the need for early stress detection to curb losses and optimize input use.

1.2 Why AI + Remote Sensing?

Digital crop monitoring originated with pixel-level image-processing techniques [4] and rigorous radiometric/geometric corrections for multisensor data [5]. Tucker’s Normalized Difference Vegetation Index (NDVI) provided the first quantitative proxy for canopy vigor and stress [6]. Over the last decade, smart-farming architectures have fused big-data pipelines with satellite, UAV, and proximal sensors—delivering sub-decimetre, field-scale insights and near-real-time analytics [7]. Concurrently, AI-driven machine-learning algorithms—from ensemble classifiers and support-vector machines to deep convolutional networks—automate feature extraction and achieve stress-detection accuracies above 90 % in diverse field trials [8].

1.3 Objectives & Structure of This Review

Despite rapid advances, a consolidated synthesis of AI-enabled remote sensing for crop health is lacking. This review aims to:

- Survey sensing platforms (satellite, UAV, ground) and their spectral capabilities.
- Evaluate machine-learning and data-fusion methods for stress detection, yield prediction, and precision interventions.
- Highlight real-world case studies, performance metrics, and adoption pathways.



- Examine emerging paradigms—edge AI for in-field inference and federated learning for privacy-preserving collaboration.
- Synthesize cross-cutting challenges (scalability, interoperability, trust).
- Propose a roadmap for future research, emphasizing open benchmarks and farmer-centric design.

2. Literature Search Methodology

We ran a reproducible, multi-database search in Web of Science, Scopus, IEEE Xplore and AGRICOLA using Boolean queries such as “crop stress” AND “remote sensing” AND (“machine learning” OR “deep learning” OR “edge AI” OR “federated learning”). The timeframe spanned January 1995 through March 2025, and we restricted results to peer-reviewed articles or book chapters from Springer, Taylor & Francis, Elsevier, Wiley and similar publishers.

Inclusion criteria:

- i. Detailed description of remote-sensing platforms and preprocessing pipelines.
- ii. Application of at least one AI/ML algorithm following the deep-learning survey [9].
- iii. Quantitative validation against field measurements or high-resolution reference data.
- iv. Reporting of standard performance metrics (accuracy, RMSE, F1-score).

Exclusion criteria:

- i. Proprietary or commercial studies lacking methodological transparency.
- ii. Reviews or opinion pieces without original data or algorithmic contributions.
- iii. Non-English publications.

3. Remote-Sensing Platforms and Data Modalities

3.1 Satellite-Based Systems

Satellite sensors remain the backbone of broad-scale crop monitoring. Moderate-resolution platforms such as Landsat and MODIS have enabled multi-decadal vegetation analytics, with Mulla (2013) [10] synthesizing key algorithmic advances and persistent gaps in precision-agriculture applications from 1990 to 2013. The Normalized Difference Vegetation Index (NDVI), established the critical link between red/NIR reflectance contrasts and canopy vigor[6]. More recently, Sentinel-2’s 10–20 m spatial resolution and 5-day revisit cycle—especially when fused with high-resolution UAV mosaics—have unlocked near-real-time crop surveillance at field scales.

3.2 UAV/UAS Imaging



Unmanned Aerial Vehicles deliver sub-decimeter resolution imagery on demand, bridging the gap between satellites and ground sensors. For instance, UAV-based hyperspectral imaging has been used for early detection of powdery mildew in wheat, achieving classification accuracies above 90 %.

3.3 Ground-Based and Proximal Sensing

Proximal platforms capture leaf- and soil-scale signals at very high resolution. Jensen (1986) [4] laid the foundation with pixel-level image-processing workflows for ground scanners, while Campbell (2002) [5] formalized radiometric and geometric corrections to ensure multisensor comparability. Jones & Vaughan (2010) [11] consolidated best practices for linking canopy reflectance to leaf biochemistry and stress physiology, guiding the design of tractor-mounted multispectral arrays and gantry phenotyping stations. Airborne LiDAR further enriches these insights: Popescu et al. (2003) [12] demonstrated that canopy-height models derived from discrete-return LiDAR strongly correlate with biomass and structural metrics, supporting sub-field vigor mapping and yield estimation.

4. Machine-Learning Models & Data Fusion

4.1 Classical ML Approaches

Before deep architectures dominated, classical algorithms laid the groundwork for crop-health analytics. Random Forests [13] build ensembles of decision trees to capture nonlinear relationships between spectral features and stress indicators, offering robustness to overfitting and ease of interpretation. Support Vector Machines [14] find optimal hyperplanes in high-dimensional feature spaces, excelling on small-to-medium datasets common in proximal sensing studies. Gradient Boosting Machines [15] construct sequential learners to minimize prediction error, though they require careful tuning and can be sensitive to noisy inputs.

4.2 Deep Learning & CNNs

Deep convolutional neural networks (CNNs) automate feature extraction by learning hierarchical filters directly from imagery data [16]. Architectures such as U-Net [17] and ResNet variants [18] enable pixel-level segmentation of stressed vs. healthy canopy zones, outperforming classical methods when ample labelled data exist. For instance, Liu et al. [19] used UAV-based hyperspectral imaging to detect powdery mildew in wheat, achieving classification accuracies above 90 %.

4.3 Hybrid & Multimodal Fusion

Combining data modalities—spectral, thermal, LiDAR, textural—can boost model accuracy and resilience. Feature-level fusion integrates handcrafted and learned embeddings, enabling models to



leverage complementary information without overwhelming the learning process. Barbedo [20] reviews agricultural data-fusion strategies and shows that feature-level approaches often strike the best balance, reducing yield-prediction RMSE by up to 20 % compared to single-sensor models.

5. Emerging Trends in Real-Time Decision Support

5.1 Edge AI for In-Field Inference

Deploying AI on field hardware “edge AI” eliminates cloud-round-trip delays and eases use in connectivity-poor areas. Lightweight models on mini-computers like the NVIDIA Jetson Nano can process UAV or proximal-sensor inputs on-site, delivering stress alerts in fractions of a second. For example, Zhang et al. (2022) [21] deployed a YOLOv4-Tiny network on a Jetson Nano to detect strawberry diseases from UAV imagery in real time, achieving 15 FPS inference and reducing end-to-end latency by over 90 % compared to cloud workflows.

5.2 Federated Learning for Privacy-Preserving Models

Federated learning trains a shared model across multiple farms without exchanging raw data. Local nodes compute weight updates on proprietary data; a central server aggregates them into a global model. This preserves privacy while leveraging diverse datasets. Li et al. (2020) [22] review core challenges—non-IID data, communication overhead, secure aggregation—and propose FedAvg with compression and differential-privacy extensions for robust performance in agricultural networks.

5.3 Integration with Advisory Systems

Real-time analytics must feed into farmer-centric advisories. AgroDSS [23] is a comprehensive decision support system that integrates sensor-derived stress indices, weather forecasts, crop calendars, and market data through a web-based and mobile interface. Field trials in Slovenia demonstrated a 12 % increase in yield and improved resource-use efficiency when farmers followed its tailored recommendations.

6. Cross-Cutting Challenges & Synthesis

6.1 Scalability

Translating promising field-scale pilots to regional or national deployments remains a key hurdle. Variations in sensor availability, network infrastructure, and farm management practices demand adaptable workflows. Pierpaoli et al. (2013)[24] review the sociotechnical drivers that influence farmers’ willingness and ability to adopt precision-agriculture technologies at scale, highlighting the need for flexible, context-sensitive architectures.



6.2 Interoperability

Data silos across agritech platforms hinder seamless multi-source fusion. The Farm Foundation's 2021 issue report [25] identifies lack of standardized data models, metadata inconsistencies, and proprietary API restrictions as key barriers to integration. It recommends adoption of open data frameworks (e.g., AgGateway ADAPT, ISO 19156 Observations and Measurements), establishment of data governance policies, and deployment of middleware that translates heterogeneous formats into common schemas—enabling plug-and-play analytics and reducing integration costs.

6.3 Trust and Adoption

End-user confidence hinges on transparent, explainable AI outputs and targeted capacity building. Pauzi et al. (2025) [26] underscores that opaque models and lack of interpretability remain significant barriers to adoption; it recommends integration of explainable-AI techniques (e.g., SHAP values, attention heatmaps) and participatory training workshops to build stakeholder trust and long-term engagement.

6.4 Cost-Benefit Balance

A robust business case accelerates uptake. Pay-as-you-go sensing services, tractor-mounted sensor rentals, and subscription-based advisory apps lower entry barriers. Wolfert et al. (2017) [27] argue for rigorous ROI analyses—benchmarking yield uplift, input savings, and labor reductions against capital and service costs—to persuade agribusinesses and policymakers to invest in precision-agriculture infrastructure.

7. Research Gaps and Future Directions

Despite significant progress, several critical gaps must be addressed to propel AI-driven, remote-sensing decision support from pilots to practice.

- i. Generalization across agro-climatic zones

Most stress-detection models are trained and validated within narrowly defined biomes, limiting transferability. Domain-adaptation and transfer-learning techniques—surveyed by Kamilaris & Prenafeta-Boldú [9] offer promising pathways, but robust evaluation on independent agro-ecological zones remains rare.

- ii. Longitudinal model maintenance and concept drift

Crop phenology and management practices evolve over time, causing “concept drift” that degrades model performance. Continuous monitoring frameworks that flag performance decay—and trigger automated retraining or few-shot fine-tuning—are still nascent.



- iii. Synthetic data generation via GANs for rare stress scenarios
Severe stress events (e.g., disease outbreaks, extreme drought) are underrepresented. Generative Adversarial Networks can augment training corpora, but balancing fidelity and diversity without introducing artifacts is challenging [29].
- iv. Policy and regulatory enablers for data sharing
Data-ownership concerns, inconsistent privacy laws, and lack of benefit-sharing frameworks discourage cooperative model training. Future work should co-design policies that align incentives across farmers, service providers, and policymakers—potentially leveraging blockchain-based smart contracts.
- v. Standardized benchmark datasets and challenge platforms
The absence of widely adopted, large-scale benchmark datasets hinders fair algorithm comparison. Community-driven platforms—with open leaderboards and harmonized annotations for stress types, yield metrics, and practices—will accelerate iterative improvements and transparency.

By systematically tackling these gaps—through interdisciplinary collaboration, open-science practices, and sustained field engagement—future research can deliver scalable, resilient decision-support systems that improve farmer livelihoods and environmental outcomes.

8. AI, ML and Geospatial Technologies for Crop Stress Management in India

Over the last five years, more than 120 field-validated studies have shown that fusing remote sensing with machine-learning classifiers—Random Forests, Support-Vector Machines and Convolutional Neural Networks—can detect nitrogen, water and pest stresses in rice, wheat and soybean with accuracies above 85 percent [30].

National and state programs have unlocked these capabilities through open-data portals and geospatial platforms. Initiatives such as India's Digital Agriculture Mission (2021–2025) stream real-time Sentinel-2, Cartosat and meteorological layers—powering developer APIs and mobile dashboards that deliver plot-level stress alerts via SMS and smartphone apps [31].

On-farm pilots now integrate UAV fleets, proximal sensors and cloud-hosted AI. For example, Nampally et al. (2023) deployed a deformable-CNN + attention-LSTM model on UAV multispectral mosaics to classify maize water stress in Indian trial fields, achieving 91.3 percent accuracy and generating sub-field stress maps within 45 minutes of flight data acquisition [32].



8.1 Economic Outcomes in an Indian Context

Precision-agriculture pilots across India deliver compelling per-hectare returns when AI/ML is integrated with geospatial data [33] and [34]:

i. Yield uplift

Farms using variable-rate application and guided by UAV- or satellite-derived stress maps see 12–15 % higher yields (0.4–0.6 t/ha). At ₹ 18 000–20 000/tonne, that equates to an extra ₹ 7 200–12 000 / ha.

ii. Input-cost savings

Precision fertilizer and pesticide application reduces chemical use by 20–25 %, saving ₹ 2 000–2 500 / ha, while soil-moisture-based irrigation control cuts water and energy costs by ₹ 1 500–2 000 / ha.

iii. Benefit–Cost Ratios for UAV Services

Annual UAV-survey costs average ₹ 5 000–7 000 / ha. Spreading capital and operating expenses over two cropping cycles yields benefit–cost ratios of 1.8–2.2, with Punjab pilot clusters reaching break-even in 2 seasons.

iv. Community-Scale Impact

Cooperatives of 20–30 smallholders (100–150 ha total) can collectively generate ₹ 1.2–1.8 million extra income per season, supporting local drone-survey enterprises and advisory services.

v. Environmental and economic sustainability

Deploying geospatial decision support reduces off-site nitrogen runoff by ~30 %, avoiding remediation costs of ₹ 1 000–1 500 / ha over five years. Life-cycle analyses show these practices cut GHG emissions by 15–20 % relative to conventional management.

These outcomes establish a robust economic case for AI-powered geospatial decision support in Indian agriculture—informing investment by farmers, AgriTech providers, and state agencies.

9. Conclusions

This review highlights how the fusion of remote-sensing technologies with AI/ML algorithms has matured into a versatile toolkit for early stress detection, yield optimization, and precision interventions.

The following can be concluded:

- Platform synergy: Satellite (Landsat/MODIS/Sentinel-2), UAV and proximal sensors each contribute unique spatial, spectral and temporal insights; strategic data-fusion unlocks synergies.



- Model evolution: Classical methods (Random Forest, SVM, GBM) remain valuable for small datasets, while deep architectures (CNNs, U-Net, attention networks) excel when ample labeled imagery is available.
- Emerging innovations: Edge-AI deployments on NVIDIA Jetson and TinyML microcontrollers deliver real-time on-farm inference; federated learning frameworks safeguard privacy across cooperative networks; and decision-support systems like AgroDSS demonstrate measurable yield gains in pilot regions.
- Cross-cutting challenges: Scaling from plots to regions demands adaptable workflows; data-silo fragmentation calls for middleware and open standards; transparent, explainable AI fosters trust among farmers and extension agents; and rigorous cost–benefit analyses underpin investment decisions.

This study also examined the technological advancements and economic impact of AI, machine learning, and geospatial technologies in the Indian agricultural context. Initiatives such as Digital Agriculture Mission and CEEW-documented pilots underscore the economic viability of these innovations: typical yield uplifts of 12–15% (₹ 7 200–12 000/ha extra revenue), input savings of ₹ 2 000–2 500/ha, and benefit–cost ratios approaching 2.0 have catalysed adoption in Punjab, Maharashtra and beyond.

Overall, it may be concluded that transitioning from promising pilot initiatives to large-scale adoption will require future research to:

- i. Rigorously test models across diverse agro-climatic zones and cropping systems
- ii. Develop automated drift-detection and few-shot retraining pipelines
- iii. Leverage GANs and simulation frameworks for rare-event data augmentation
- iv. Co-design data-governance frameworks and smart-contract mechanisms that align stakeholder incentives
- v. Establish community-driven benchmark datasets and open-leaderboard challenges

By embracing open-science, fostering interdisciplinary partnerships, and focusing farmer needs, AI-powered geospatial decision support can scale sustainably enhancing productivity, resource efficiency and resilience in Indian agriculture and beyond.

References



- United Nations, Department of Economic and Social Affairs. (2022). World Population Prospects 2022. <https://population.un.org/wpp/>
- Food and Agriculture Organization. (2017). The Future of Food and Agriculture – Trends and Challenges. <https://www.fao.org/3/a-i6887e.pdf>
- Intergovernmental Panel on Climate Change. (2019). Special Report on Climate Change and Land. <https://www.ipcc.ch/srccl/>
- Jensen, J. R. (1986). Introductory Digital Image Processing. Prentice Hall. https://archive.org/details/introductorydigi0000jens_o3p5
- Campbell, J. B. (2002). Introduction to Remote Sensing (3rd ed.). Guilford Press. https://archive.org/details/introductiontore0000camp_q7v6
- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8, 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming—a review. *Agricultural Systems*, 153, 69–80. <https://doi.org/10.1016/j.agsy.2017.01.023>
- Gao, Z., Luo, Z., Zhang, W., Lv, Z., & Xu, Y. (2020). Deep learning application in plant stress imaging: A review. *AgriEngineering*, 2(3), 430–446. <https://doi.org/10.3390/agriengineering2030029>
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
- Mulla, D. J. (2013). Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, 114(4), 358–371. <https://doi.org/10.1016/j.biosystemseng.2012.08.009>
- Jones, H. G., & Vaughan, R. A. (2010). *Remote Sensing of Vegetation: Principles, Techniques, and Applications*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199563459.001.0001>
- Popescu, S. C., Wynne, R. H., & Nelson, R. F. (2003). Measuring individual tree crown diameter with LiDAR and assessing its influence on estimating forest volume and biomass. *Canadian Journal of Remote Sensing*, 29(5), 564–577. <https://doi.org/10.5589/m03-025>



- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32. <https://link.springer.com/article/10.1023/A:1010933404324>
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297. <https://doi.org/10.1007/BF00994018>
- Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 1189–1232. <https://projecteuclid.org/euclid.aos/1013203451>
- Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, 61, 85–117. <https://doi.org/10.1016/j.neunet.2014.09.003>
- Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention (MICCAI 2015)*, LNCS 9351, 234–241. <https://arxiv.org/abs/1505.04597>
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778. <https://doi.org/10.1109/CVPR.2016.90>
- Liu, Y., Ma, X., An, L., Sun, H., Zhao, F., Yan, X., Ma, Y. and Li, M. (2025). Exploring UAV narrow-band hyperspectral indices and crop functional traits derived from radiative transfer models to detect wheat powdery mildew. *International Journal of Applied Earth Observation and Geoinformation*, Volume 141. <https://doi.org/10.1016/j.jag.2025.104627>
- Barbedo, J. G. A. (2022). Data Fusion in Agriculture: Resolving Ambiguities and Closing Data Gaps. *Sensors*, 22(6), 2285. <https://doi.org/10.3390/s22062285>
- Zhang, Y., Yu, J., Chen, Y., Yang, W., Zhang, W. and He, Y. (2022). Real-time strawberry detection using deep neural networks on embedded system (rtsd-net): An edge AI application. *Computers and Electronics in Agriculture*, Volume 192, <https://doi.org/10.1016/j.compag.2021.106586>.
- Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. *IEEE Signal Processing Magazine*, 37(3), 50–60. <https://doi.org/10.1109/MSP.2020.2975749>
- Rupnik, R., Kukar, M., Vračar, P., Košir, D., Pevec, D. and Bosnić, Z. (2019). AgroDSS: A decision support system for agriculture and farming. *Computers and Electronics in Agriculture*, Volume 161, Pages 260-271, <https://doi.org/10.1016/j.compag.2018.04.001>



- Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M. (2013). Drivers of precision agriculture technologies adoption: A literature review. *Procedia Technology*, 8, 61–69. <https://doi.org/10.1016/j.protcy.2013.11.010>
- Pauzi, N.A.M., Mustaza, S.M., Zainal, N., Zaman, M.H.M., and Moubark, A. M. (2025). Artificial Intelligence in Precision Agriculture: A Review. *Jurnal Kejuruteraan* 37(2) 2025: 1025-1047 [https://doi.org/10.17576/jkukm-2025-37\(2\)-38](https://doi.org/10.17576/jkukm-2025-37(2)-38)
- Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming—a review. *Agricultural Systems*, 153, 69–80. <https://doi.org/10.1016/j.agsy.2017.01.023>
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems*, 27, 2672–2680. <https://arxiv.org/abs/1406.2661>
- Pokhariyal, S., Patel, N. R., & Govind, A. (2023). Machine learning-driven remote sensing applications for agriculture in India—A systematic review. *Agronomy*, 13(9), 2302. <https://doi.org/10.3390/agronomy13092302>
- Bagwan, W. A. (2024). Revolutionizing agriculture: Geospatial technologies and precision farming in India. In K. Pandey, N. Vaidya & S. Sen (Eds.), *Advances in Geographical and Environmental Sciences* (pp. 43–59). Springer. https://doi.org/10.1007/978-981-97-0341-8_3
- Nampally, T., Kumar, K., Chatterjee, S., Pachamuthu, R., Naik, B., & Desai, U. B. (2023). StressNet: A spatial-spectral-temporal deformable attention-based framework for water stress classification in maize. *Frontiers in Plant Science*, 14, 1241921. <https://doi.org/10.3389/fpls.2023.1241921>
- Council on Energy, Environment and Water. (2021). Precision Farming: Sustainable Agriculture in India. <https://www.ceew.in/publications/sustainable-agriculture-india/precision-farming>
- Singh, A., Kumar, P., & Mehta, S. (2024). Economic assessment of digital agriculture adoption in smallholder farms in India. *Computers and Electronics in Agriculture: Regional Studies*, 5, 100046. <https://doi.org/10.1016/j.cear.2024.100046>