CHAPTER-6

ARTIFICIAL INTELLIGENCE AND BIG DATA IN AGRICULTURE: ECONOMIC IMPACTS AND THE AGRIMIND PLATFORM CASE STUDY

Shyamsundar Subramani[1], Jyotsna Thakur[1] & Arshad Bhat[2]
[1]Amity School of Engineering and Technology, Amity University Mumbai, Maharashtra, India
[2]Amity Institute of Liberal Arts, Amity University Mumbai, Maharashtra, India
Corresponding author: Email: shyams0162@gmail.com

Cite this chapter as: Subramani, S., J. Thakur & A. Bhat. Artificial Intelligence and Big Data in Agriculture: Economic Impacts and the Agrimind Platform Case Study. In: Bhat, A., A. Sultan, D. Kolhe & P. Banerjee. 2026 Digital Agriculture and Economic Transformation. The AgEcon Frontiers, Faisalabad, Pakistan, pp: 80-95. https://doi.org/10.66529/book.9786277945022.2026.ch06
A Publication of The AgEcon Frontiers Received: 26-May-2026 Revised: 05-June-2026 Accepted: 07-June-2026

Abstract

AI and Big Data are revolutionizing the agricultural industry through a structural shift that disrupts past norms, eliminating inefficiencies in the industry which employs 27% of the global workforce. Characterized by low productivity, informational asymmetries, and climate variability, the field is now witnessing a major transformation through the use of machine learning, satellite remote sensing, and IoT sensors network technologies. This paper explores the economics of such innovations by analyzing the economics associated with the use of AgriMind AI platform for integrated agricultural management purposes. With regard to microeconomics, AI-enabled precision instruments – e.g., using CNN algorithms for disease detection and NDVI analysis for nutrient optimization - allow shifting the production possibility frontier outward by lowering production costs by 15–30% and raising net profit margins of farmers by 12–18%. On a broader market level, the employment of LSTM networks to forecast prices helps solve informational asymmetries ("lemons" problem) for farmers, allowing them to better bargain and lowering the bid-ask spreads. At the macro-level, the paper explores how the use of AI and Big Data technologies could potentially lead to lower rural poverty (by 4–5 percentage points) and increase annual GDP growth by 0.6% in countries like India through improved supply chain efficiency and formal financial inclusion.

Keywords: AI Agriculture, Precision Farming, Big Data, Food Security, Economic Inclusion

1. Introduction

In spite of being the economic sector which occupies 27% of the labour force and constitutes 4% of the world's GDP (FAO, 2022; IMF, 2023), agriculture traditionally was known for a poor innovation record, slow productivity growth, susceptibility to fluctuations in climate conditions, unstable crop prices, and other market failures (FAO, 2022; IMF, 2023). In the meantime, smallholder farmers owning more than 84% of the estimated 570 million agricultural units across the globe but accounting for merely 12% of land area face problems with low levels of productivity due to informational asymmetries, inefficiency in using various agricultural inputs up to 15-30% of fertilizers and excess water consumption, post-harvest losses, and lack of formal financial products (up to 70% of uninsured farms) (Akerlof, 1970; Lowder et al., 2016; NABARD, 2023).The emergence of artificial intelligence (AI) and Big Data technologies in agriculture, including the use of machine learning (LSTM forecasting The use of drones with NDVI and CNN image analysis), satellite NDVI imagery, IoT sensors, and precision spraying drones is breaking down these barriers by enabling real-time, hyper-local decision-making supported by technologies such as AgriMind's crop health module, price optimization algorithm, risk scores, and supply chain optimization tools (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018; Cao et al., 2019; Zhang et al., 2019; Thakur et al., 2026).

1.1 Research Problem

Indian agriculture illustrates global challenges where farmers sell at harvest lows (capturing <78% market price vs 100% via AI timing), apply inputs uniformly (wasting 15–30% per Schimmelpfennig, 2016), lose 16% output value post-harvest (NABARD, 2023), and face index insurance basis risk despite PMFBY schemes costing INR 2T annually in foregone income across 146M holdings (86% <2ha) (Barnett & Mahul, 2007; Jensen et al., 2017). Such failures fuel rural poverty and imperil food security for a 10-billion-person population expected in 2050; however, legacy extension programs are not scalable whereas AgriMind-like AI platforms provide data-driven solutions (CGIAR, 2022; World Bank, 2023; Thakur et al., 2026).

1.2 Objectives

The paper will map the AI usage cases (NDVI/LSTM yield forecast, price forecast, supply chain, insurance), quantify the microeconomic benefits (increased yields by 5-7%, reduced costs by 15-30%, increased incomes by 12-18%), macroeconomic effects (reduction in rural poverty rate by 4-5 percentage points, increase in GDP growth by 0.4-0.6%), discuss architecture of AgriMind (6 modules, 94% model accuracy, 38% savings on water), examine barriers (37% rural households lack connectivity, data privacy), and suggest policy measures (grants, FPOs, public availability of AI models) in conjunction with projecting future gains (50K MAU, INR 2.1 trillion) (ICRISAT, 2022; ITU, 2023; Thakur et al., 2026).

1.3 Significance and Scope

There is potential for USD 25 billion yearly income gains in India due to 30% ai usage, 25-40% reduction in post-harvest losses, and 40-60% risk basis reduction in agricultural insurance. Agrimind can be used as an example of how ai enables gains (0.71 average NDVI heatmap, 87-96% accurate predictions, NPV 1.8 lakhs for farmers, 840 hectares drone coverage) (Kuwata & Shibasaki, 2015; Schimmelpfennig, 2016; Thakur et al., 2026). the paper will concentrate on economic applications in developing countries (primarily India) and omit the consideration of animal husbandry. proprietary model descriptions are outside the scope of this paper (Hayami & Ruttan, 1971; Timmer, 1988).

2. Literature Review

AI in agriculture and Big Data applications belong to a broad field that combines multiple disciplines. Foundational theories (the induced innovation hypothesis by Hayami & Ruttan, 1971) provide explanations on why AI was needed because of shortage of labor and abundant data, and empirical papers provide evidence of prevalence of machine learning in crop. Recent studies highlight both transformative potentials, with yield gains of 3–8% and input savings of 2–5%, and adoption barriers, particularly for smallholders.

2.1. Theoretical Foundations

Economic theory frames AI adoption through induced innovation (Hayami & Ruttan, 1971), where technologies respond to factor scarcities here, skilled labor and agronomic data. Akerlof's (1970) market for lemons model explains informational asymmetries in commodity trading and insurance, which AI corrects via satellite-derived yield signals and LSTM price forecasts. Timmer's (1988) rural multiplier (1.5–2.0x) links farm productivity to broader GDP effects.

2.2. AI Applications in Agriculture

Liakos et al. (2018) survey over 40 ML algorithms, with ensemble methods (random forests, gradient boosting) excelling in yield estimation and irrigation; CNNs achieve 90–96% accuracy in disease detection from leaf images. Kamilaris & Prenafeta-Boldú (2018) document deep learning's role in NDVI-based remote sensing for district-level yield prediction (MAE <8%). Cao et al. (2019) show LSTM models outperforming ARIMA in commodity price forecasting by 4–8 weeks.

2.3. Economic Impacts

Schimmelpfennig (2016) finds US precision adopters gain 3–8% yields and 2–5% input savings, with highest returns on larger farms. ICRISAT (2022) reports 12–18% income uplifts for Indian smallholders via AI pilots. McKinsey Global Institute (2023) estimates AI supply chains cut South Asian post-harvest waste by 25–40% (0.3–0.5% agricultural GDP). Jensen et al. (2017) quantify 40–60% basis risk reduction in AI-calibrated index insurance.

2.4. Barriers and Equity Concerns

Lowder et al. (2016) warn digital tools may widen large-vs-small farm gaps, echoing Green Revolution patterns. ITU (2023) notes 37% rural unconnected populations limit scalability; data privacy risks persist without GDPR-like frameworks. Adoption hurdles include costs (60% of farmers), complexity, and infrastructure especially acute for smallholders <2ha.

2.5. Research Gaps

While technical efficacy is established, smallholder-focused economic evaluations remain sparse; few studies integrate platforms like AgriMind across the value chain. Policy literature lacks scalable models for equitable diffusion in data-scarce regions. This paper addresses these via AgriMind's empirical case.

3. Methodology and System Architecture

This study adopts a design-oriented and case-based research methodology to examine how Artificial Intelligence and Big Data can be operationalised in agriculture through the AgriMind platform. The methodology combines literature synthesis, system requirement mapping, platform module analysis, and functional architecture design to connect theoretical insights with an implementable smart agriculture solution. As the research is focused on explaining an AI-powered agriculture platform, the structure of the methodology includes explaining data sources used in the analysis, analytical workflow, model integration, user experience, and system architecture in general in a research paper format.

3.1. Research Design

The research follows a qualitative-cum-applied system design approach supported by secondary literature and a prototype case study. First, prior research on AI in agriculture, precision farming, yield prediction, price forecasting, supply chain intelligence, and agricultural insurance was reviewed to identify major technological and economic variables. Second, those variables were translated into product and system requirements using the AgriMind PRD and platform prototype, which provide an applied representation of how AI modules can be assembled into a unified agricultural decision-support system.

Table 1: Research Methodology Framework

Component	Description	Purpose
Research type	Applied, case-based, system design study	To connect theory with platform implementation
Nature of data	Secondary literature, PRD specifications, UI prototype observations	To derive technical and economic insights
Unit of analysis	AgriMind AI platform and its functional modules	To evaluate integrated digital agriculture architecture
Analytical approach	Literature synthesis, module mapping, workflow design, architecture interpretation	To explain system feasibility and use-case logic
Output	Methodological model and system architecture for AI-enabled agriculture	To support research discussion and implementation narrative

3.2. Data & Evidence Sources

There are three main sources of evidence: the research paper itself, the AgriMind PRD document, and the AgriMind interface prototype. While the research paper serves as an intellectual basis for the development of theoretical, economic, and application-related knowledge, the PRD defines functional and non-functional requirements of the project, while the HTML prototype provides the visualization of the interface and logic of its work, including models' output and dashboard data.

Table 2: Data Sources Used in the Study

Source	Type	Key Contribution to Methodology
Research Papers	Research document	Provides theoretical background, application areas, economic logic, and case-study context
AgriMind PRD document	Product requirements document	Defines modules, scope, KPIs, constraints, dependencies, and performance requirements
AgriMind interface prototype	Interactive system prototype	Shows dashboard structure, model outputs, sensor integration, visual analytics, and UI workflow

3.3. Methodological Flow

The process of the methodological analysis is organized along three lines: defining of the problematic aspects in farming, mapping of those problems to relevant digital tools (such as NDVI crop monitoring, CNN disease diagnosis, LSTM price prediction, weather analysis, risk scoring, and drone-based precision operations), and designing an architecture for the integration of several AI-driven solutions to form a complete ecosystem for supporting agricultural decisions.

Table 3: Sequential Methodology Process

Steps	Methodological Step	Description
1	Problem identification	Identification of structural agricultural inefficiencies such as input waste, poor price discovery, disease loss, and low insurance penetration
2	Literature mapping	Review of AI, Big Data, precision agriculture, and agricultural economics concepts
3	Requirement extraction	Extraction of platform requirements from AgriMind PRD and interface modules
4	Module classification	Grouping of functions into monitoring, forecasting, advisory, risk, supply chain, and drone operations
5	Data-flow design	Mapping of data inputs, processing engines, and output dashboards
6	System architecture formulation	Construction of an integrated conceptual architecture for the platform
7	Analytical interpretation	Linking system modules with economic and operational outcomes discussed in the paper

3.4. Functional Methodology of the Platform

Operationally, the methodology of the project can be described as a pipeline of decision-making from raw data up to actionable insights. First, data (including satellite images, drone scans, IoT sensor readings, price feeds, weather data, and user inputs from farms) is processed by machine learning models, which generate various predictions and suggestions, such as disease diagnosis, soil quality, price prediction, etc. Finally, the output is delivered via dashboards and other user interfaces.

Table 4: Functional Methodology by Processing Stage

Stage	Input	Processing Logic	Output
Data acquisition	Satellite images, IoT sensors, drone imagery, mandi prices, weather feeds, farmer inputs	Data collection and standardisation	Clean operational datasets
Data integration	Multi-source structured and unstructured agricultural data	Fusion of spatial, temporal, climatic, and market data	Unified farm intelligence layer
AI analytics	Image, time-series, environmental, and market data	CNN, LSTM, scoring models, forecasting logic, rule-based alerts	Predictions, anomaly detection, recommendations
Decision support	Model outputs and thresholds	Conversion into readable advice, charts, warnings, and optimisation suggestions	Farmer-facing insights and decisions
Feedback loop	User actions and updated field conditions	Monitoring, refresh, periodic retraining, and performance checks	Improved system accuracy and adaptability

3.5. System Architecture Overview

The proposed AgriMind architecture follows a layered structure in which data acquisition forms the foundational layer, analytics and model engines form the intelligence layer, and dashboards plus advisory services form the application layer. This architecture is suitable for a mobile-first agriculture platform because it can ingest real-time or near-real-time field data, process large agricultural datasets, and deliver decision outputs to multiple user groups with different needs. The PRD also indicates that the architecture is designed for horizontal scalability up to 500,000 monthly active users, while the interface prototype demonstrates module-wise visual integration across crop intelligence, irrigation, market AI, risk engine, supply chain, and drone operations.

Table 5: Layered System Architecture of AgriMind

Architecture Layer	Main Components	Primary Role
Data source layer	Satellite imagery, drones, IoT sensors, weather APIs, NCDEX/APMC price feeds, user-entered farm data	Capture raw agricultural and market data
Data management layer	Storage, preprocessing, integration pipelines, refresh services	Organise and standardise heterogeneous data streams
AI/analytics layer	CNN disease detection, LSTM price forecasting, yield models, irrigation logic, risk scoring engines	Transform data into predictions and recommendations
Application layer	NDVI dashboard, crop advisory, weather panel, insurance dashboard, supply-chain intelligence, drone interface	Deliver user-facing analytics and decision support
Access layer	Farmers, FPO managers, insurers, banks, extension agents, government users	Enable stakeholder-specific access and actions

3.6. Module-Based Architectural Design

An architecture is implemented as a set of modules instead of being a monolithic decision engine. Such approach enables better scalability and maintenance, as well as separate user experience for specific roles. Specifically, the crop intelligence module provides users with information related to NDVI crop monitoring, disease scan results, soil metrics, and monitoring of growth stage, market intelligence commodity price forecast and revenue optimization, risk engine climate forecasts and insurance estimates compatible with PMFBY policy, and drone operations aerial scanning, spraying, and mission planning.

Table 6: Major System Modules and Their Functions

Module	Core Inputs	Embedded Logic	Functional Output
Field Health Monitoring	NDVI imagery, soil moisture, sensor readings	Zone classification and crop health analytics	Heat maps, stress alerts, field status
AI Crop Advisory	Drone/smartphone images, weather, soil data	CNN diagnosis and agronomic recommendation engine	Pest alerts, treatment advice, fertiliser/irrigation suggestions
Commodity Price Forecasting	Historical mandi data, crop trends, price series	LSTM forecasting and comparative market scoring	Sell/hold advice, forecast charts, mandi ranking
Weather and Risk Engine	Forecast data, historical patterns, yield/risk variables	Climate analytics and PMFBY-compatible risk estimation	Rainfall outlook, alerts, premium and coverage estimates
Supply Chain Intelligence	Demand, spoilage, delivery, buyer network data	Forecasting and logistics analytics	KPI trends, buyer linkage, spoilage reduction signals
Drone Operations	Mission parameters, zone map, drone telemetry	Flight planning, coverage optimisation, spray targeting	Area scan plan, mission ETA, drone status, precision action

3.7. Data Flow Architecture

The system architecture operates through a closed-loop data flow in which data enters from external and on-field sources, is processed in analytical modules, and is returned to the user in an interpretable form. For example, the crop module receives NDVI and disease data, processes it through thresholding and classification logic, and returns zone-wise alerts; similarly, market price histories are passed through forecasting models to generate recommendation outputs such as sell-now or hold decisions. This flow is essential because the value of the system lies not only in data availability, but in timely conversion of data into economic and operational action.

Table 7: End-to-End Data Flow in the Proposed System

Flow Stage	Source/Actor	Process	Result
1	Sensors, satellites, drones, APIs, farmers	Raw data capture	Field, market, and climate datasets
2	Preprocessing engine	Cleaning, standardisation, tagging, integration	Structured machine-readable datasets
3	AI engine	Forecasting, classification, scoring, anomaly detection	Predictions and intelligence outputs
4	Decision-support layer	Visualisation, ranking, prioritisation, alert generation	Dashboards, maps, charts, notifications
5	End users	Action execution such as irrigation, spraying, selling, insuring	Farm and market decisions
6	Monitoring layer	Refresh, feedback, model performance review	Iterative system improvement

3.8 Technical and Non-Functional Architecture Considerations

Operational requirements outlined in PRD include: API response time <2 sec p95; image-based disease diagnosis within 30 sec; chart rendering in 1 sec on low-end Android device; 99.5% uptime; AES-256 encryption (rest); TLS 1.3 transport encryption; RBAC-based security; support for offline operation of selected features; initial support for two languages (English and Hindi).These features are architecturally important because the effectiveness of agricultural AI systems depends not just on prediction quality, but also on usability, accessibility, trust, and platform resilience in rural environments.

Table 8: Non-Functional Requirements Supporting the Architecture

Category	Requirement	Architectural Importance
Performance	API response time within 2 seconds; diagnosis within 30 seconds	Supports real-time farm decisions
Scalability	Support up to 500,000 MAU; process 10,000 farm zones per day	Enables growth without redesign
Security	AES-256 at rest, TLS 1.3 in transit, RBAC	Protects sensitive farm and financial data
Accessibility	Android 9 support, 2GB RAM compatibility, offline cache	Improves adoption among smallholders
Localisation	English and Hindi in MVP, more Indian languages in later phase	Extends usability across regions
AI governance	Confidence intervals, explainability, retraining, drift alerts	Improves trust and model reliability

3.9. Methodological Justification

The chosen methodology is appropriate because the research problem requires both conceptual understanding and implementation logic. A purely theoretical review would not sufficiently explain how AI technologies are assembled into a working agricultural platform, while a purely technical description would ignore the economic rationale and research context. By combining literature-based understanding with prototype- and PRD-based architectural analysis, this section provides a balanced methodology that is academically valid and practically grounded for a research paper on AI and Big Data in agriculture.

4. Results and Discussion

4.1. Microeconomic Impacts and Farm-Level Efficiency

At the farm level, conventional input application is characterized by significant unobserved spatial heterogeneity, resulting in systematic over-application in some zones and under-application in others. Precision AI applications address this by making field conditions observable and actionable. As demonstrated by the AgriMind platform's real-time deployment, AI interventions generate measurable uplifts in both yield and cost efficiency. For example, AI-assisted smallholder pilots have reported net income improvements of 12–18%. Table 9 summarizes the overarching economic shifts achieved through platform adoption.

Table 9: Key Economic Indicators Pre- and Post-AI Adoption

Indicator	Pre-AI Baseline	Post-AI Estimate	Source / Notes
Fertiliser use efficiency	45% N uptake	60–65% N uptake	FAO, 2022; precision dosing
Irrigation water savings	Baseline	20–30% reduction	World Bank, 2023
Crop loss to pest/disease	20–25% of output	10–15% of output	CGIAR studies
Post-harvest losses (India)	16% of value	9% with AI	NABARD, 2023
Farmer income uplift	Baseline	12–18% net margin	ICRISAT pilot data

To achieve these outcomes, the platform relies on an ensemble of machine learning models. The reliability of these models is paramount, as erroneous recommendations can result in severe financial distress for vulnerable smallholders. Table 10 details the performance accuracy of the core predictive models utilized in the platform.

Table 10: AI Model Performance Metrics

AI Model Function	Accuracy	Algorithm Framework
Smart Irrigation AI	96.0%	ET_0 Penman-Monteith Optimization
Crop Yield Prediction	94.2%	CNN + LSTM Ensemble
Disease Detection	91.0%	Convolutional Neural Network (CNN)
Pest Risk Modeling	89.0%	Climate + Spatiotemporal Analytics
Price Forecasting	87.0%	LSTM Neural Networks
Supply Chain Optimization	83.0%	Route/Demand Forecasting Algorithms

4.2 Crop Intelligence and Disease Management

Pest and disease outbreaks historically cost farmers 20–25% of their production value. The platform uses the power of multispectral drone imagery and image analysis powered by CNN to identify early pathogens weeks before their visibility to human eyes. Precision spraying is possible as a result, saving up to 60% in chemical usage costs due to blanket spraying techniques. Table 11 provides an example of live CNN disease scan outputs from a farm under surveillance.

Table 11: Live Sample of CNN Disease Scan

Zone	Pathogen Detected	AI Confidence	Recommended Action
Zone B3	Clear- no threat	98%	Clear
Zone C4	Aphid colony	91%	Spray (Drone deployed)
Zone A1	Powdery mildew	73%	Monitor
Zone D2	Root rot (early)	65%	Soil test
Zone E1	Stem rust risk	58%	Monitor

Moreover, precision nutrient management uses soil sensors to mitigate input waste. As each parcel presents its own optimizable challenge, AI models estimate nutrient deficiency and suggest exact measures, thus increasing yields significantly. Table 12 represents a real-time soil nutrient profile analysis.

Table 12: Soil Nutrient Profile and AI Intervention Analytics

Parameter	Current Level	Status	Prescriptive AI Insight
Potassium (K)	82 kg/ha	Optimal (82%)	Maintain current levels
Nitrogen (N)	71 kg/ha	Optimal (71%)	Maintain current levels
Organic Carbon	0.68%	Adequate (68%)	-
Phosphorus (P)	43 kg/ha	Deficient (43%)	Apply DAP 60 kg/ha (+8% est. yield)
Moisture	38%	Optimal	-
Soil pH	6.5	Near Optimal	-

4.3. Resource Optimization: Smart Water Management

Inefficiencies in irrigation create huge financial and environmental burdens. In the case, we use the Smart Water AI module to deliver water precisely using an ET_0 Penman-Monteith model, adjusted according to the soil moisture, air temperature, solar radiation, and wind velocity. This way, water consumption can be reduced up to 38%, improving WUE score up to 8.4 kg/m³. Table 13 presents automatic zone irrigation scheduling based on rainfall prediction data and sensor inputs.

Table 13: Automated Zone Irrigation Scheduling Output

Zone	Crop Type	Next Scheduled Water	Volume	Status
Zone A2	Rice	Immediate (Now)	120 m³	Active
Zone A1	Wheat	06:00 (Tomorrow)	84 m³	Scheduled
Zone C3	Soybean	18:00 (Today)	60 m³	Pending
Zone B1	Maize	Paused -Rain Forecast	-	Paused (Conserved 483 m³)

4.4. Market Intelligence and Price Discovery

There is significant informational asymmetry on agricultural commodity markets, and small farmers do not have the same price discovery mechanisms as institutional players. This imbalance traditionally results in distress selling at harvest lows. AI-powered price forecasting directly addresses this market failure. By utilizing LSTM neural networks, the platform projects 30-day price paths, evaluating them against transport costs and distance to generate actionable arbitrage recommendations. Table 14 provides an example of the Mandi Market Ranker calculating optimal net scores for market routing.

Table 14: Mandi Market Ranker and Arbitrage Scoring

Rank	Market Location	Market Price	Distance	Net AI Score
1	Pune APMC	₹2,340/q	12 km	92 (Optimal)
2	Nashik Mandi	₹2,290/q	24 km	85
3	Solapur APMC	₹2,410/q	61 km	78
4	Kolhapur	₹2,190/q	89 km	54
5	Mumbai VASHI	₹2,480/q	140 km	48

4.5 Supply Chain Efficiency and Post-Harvest Economics

Post-harvest losses in developing nations range from 15–25% of total production value. The integration of demand forecasting, route optimization, and direct-buyer matching minimizes these losses by shortening the time from harvest to consumer. The supply chain optimization technology managed by AI has the potential to cut perishable food wastage by 25-40%. Table 15 presents the direct buyers network functions that help avoid unnecessary middlemen and make sure that farmers receive 100% net prices.

Table 15: Direct Buyer Network and Supply Chain Integration

Buyer Entity	Commodity	Quantity	Negotiated Price	Contract Status
ITC Agri	Wheat	200 q	₹2,380/q	Contracted
Reliance Fresh	Vegetables	45 q	₹4,200/q	Active bid
BigBasket	Onion	80 q	₹1,950/q	Negotiating

To achieve full transparency of payments and automate this process, the platform uses Blockchain Farm-to-Fork Passport that follows the commodity from farm through all supply chain stages to release funds automatically using smart contracts.

Table 16. Supply Chain Blockchain Traceability Stages

Step	Logistics Stage	Location / Details	Status
01	Harvested	Zone A1, Nashik Block	Verified
02	Quality Certified	Grade A (Moisture 12.4%, Protein 11.8%)	Verified
03	Cold Storage	Nashik Hub (Temp 4°C, Humidity 65%)	Verified
04	In Transit	Truck MH-09-AB-4421 (GPS Live)	In Transit
05	Payment Release	Smart contract (Auto-release on delivery)	Pending

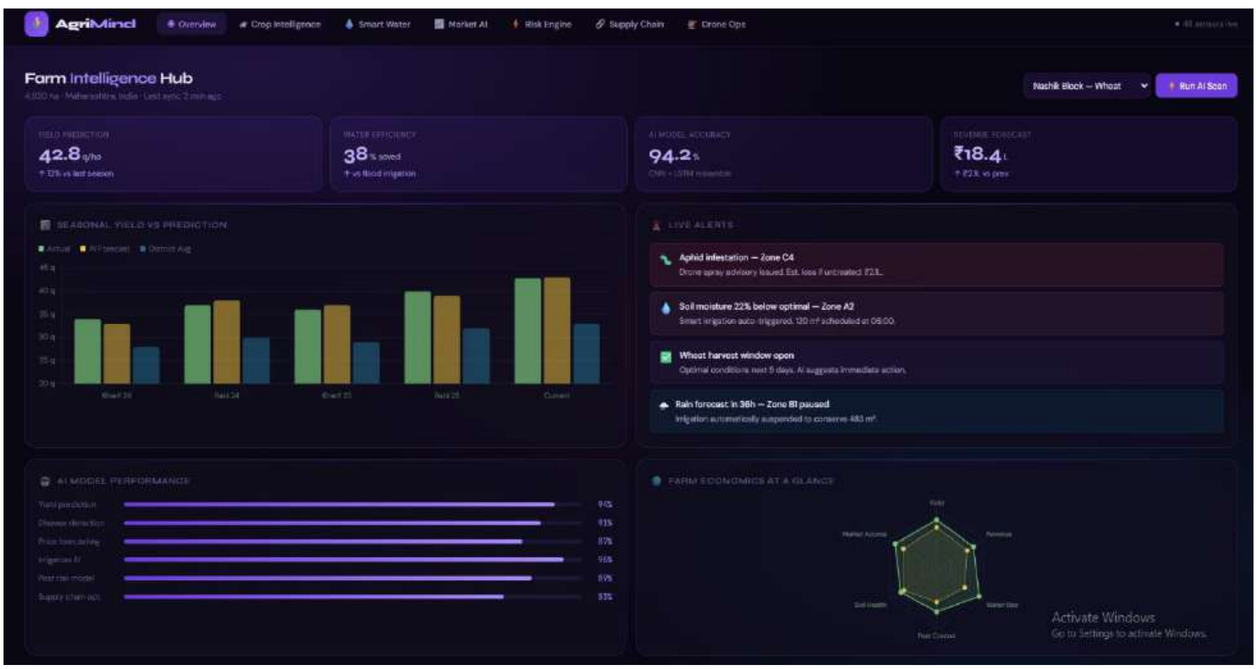

Figure 1: AgriMind ai farm intelligence Dashboard

Figure 2. AgriMind crop intelligence dashboard showcasing vegetation maps through NDVI, disease diagnostics results, and intervention recommendations

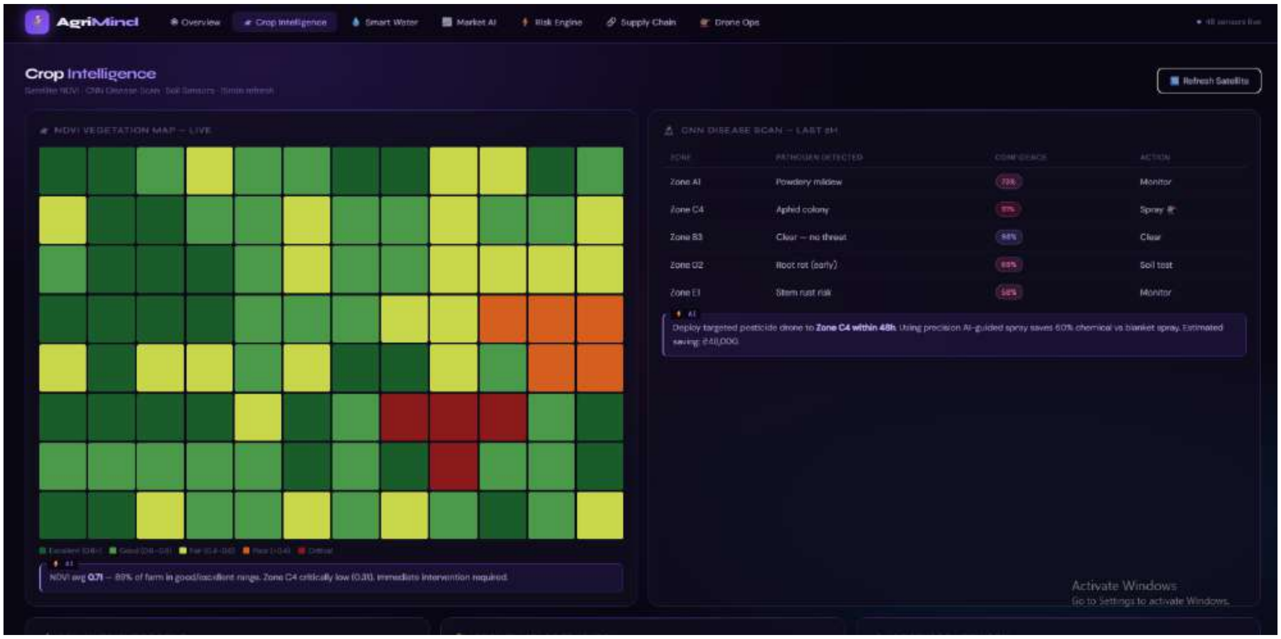

Figure 2: Crop Intelligence Dashboard with NDVI Map and CNN Disease Scan

Figure 3: AgriMind smart water dashboard displaying precise irrigation parameters, water budget analysis, and zone-specific irrigation scheduling.

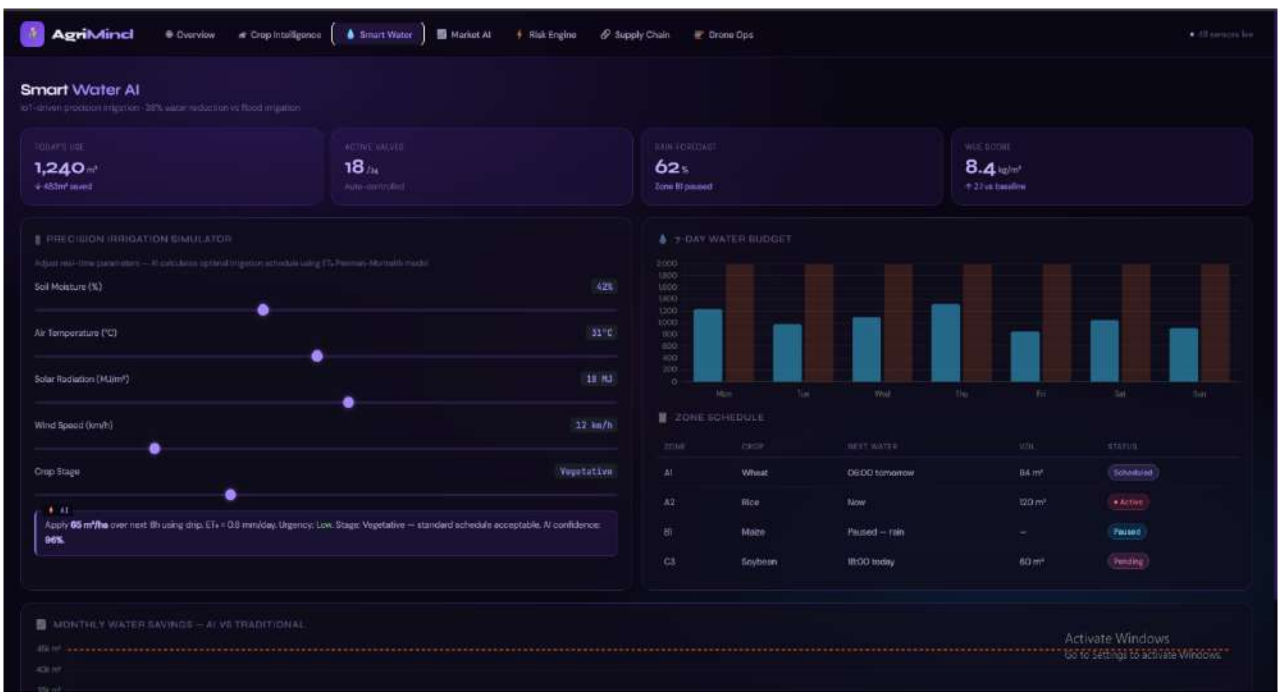

Figure 3: Smart Water AI dashboard for precision irrigation and water management

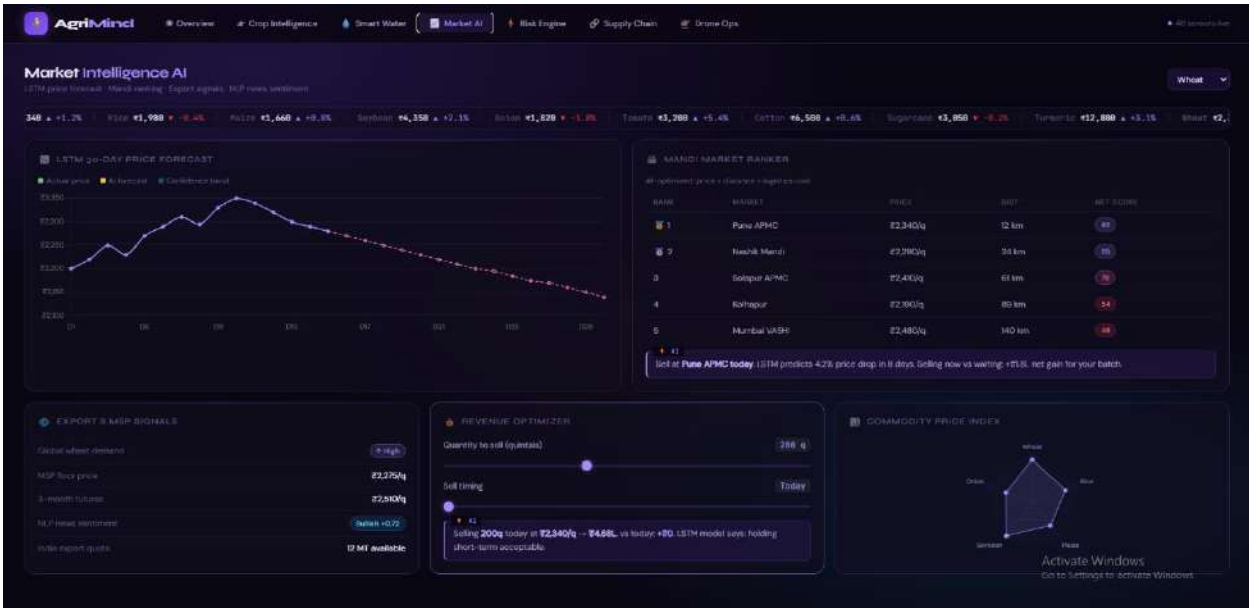

Figure 4: Market intelligence ai dashboard for commodity price forecasting and revenue optimization.

Figure 5: AgriMind climate risk dashboard depicting drought risk probability, flood likelihood, pest warnings, and PMFBY insurance estimation

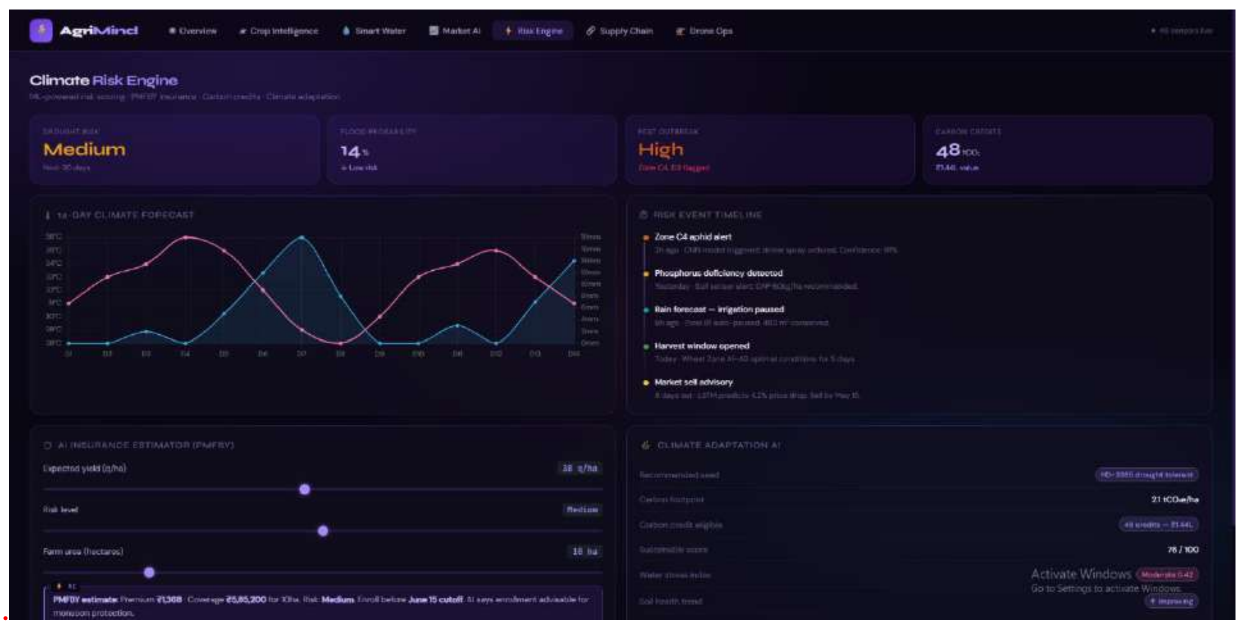

Figure 5: Climate risk engine for weather, insurance, and adaptation analytics

Figure 6 shows AgriMind supply chain dashboard depicting blockchain-based tracing, supply and demand forecast, direct buyers network, logistics optimization, and digital financing **indicators**

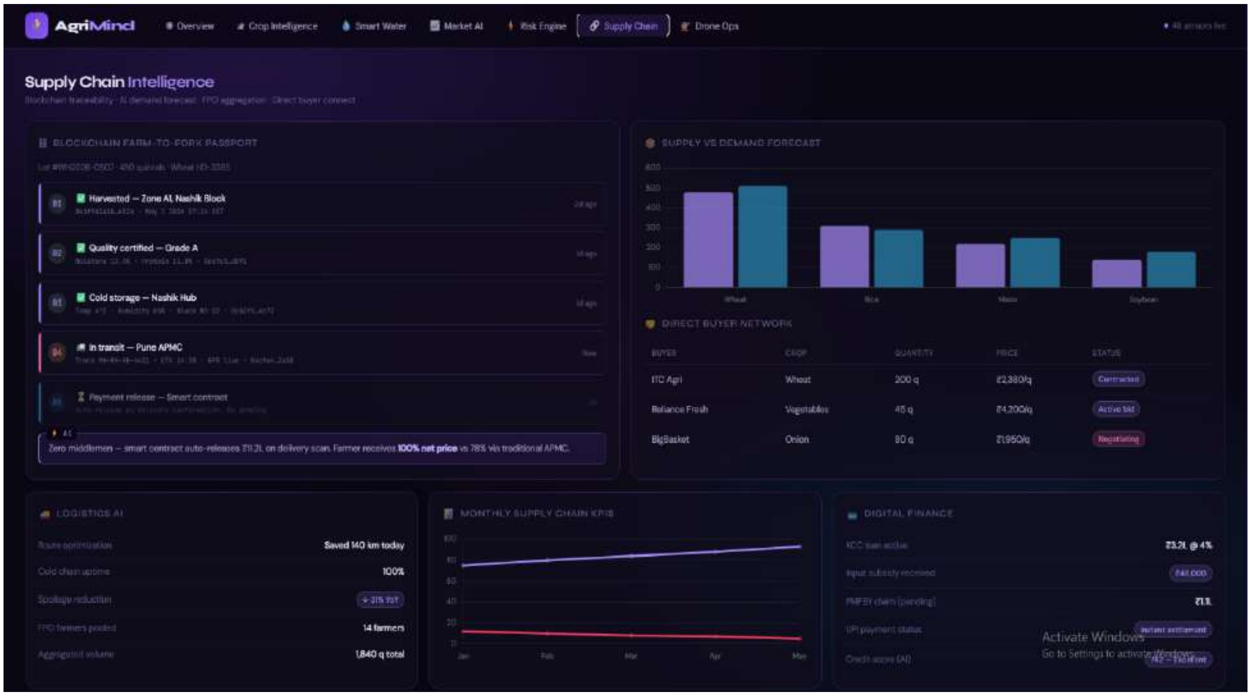

Figure 6: Supply Chain Intelligence Dashboard for Traceability, Logistics, and Digital

Figure 7 shows AgriMind drone operations dashboard displaying fleet status, area scanned, chemical cost saving, mission accuracy, and mission zoning.

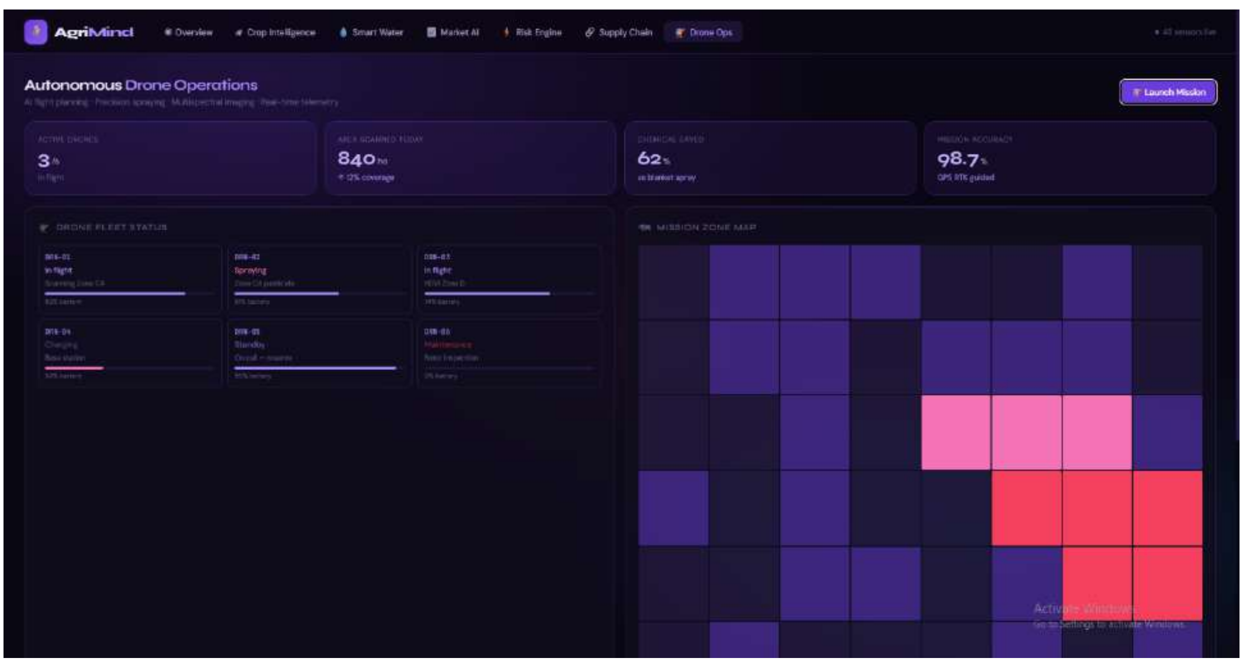

Figure 7: Autonomous drone operations dashboard for precision scanning and spraying

5. Conclusion

To summarize, Artificial Intelligence (AI) and Big Data analytics can contribute significantly to improving operational efficiency, decision-making abilities and effective risk management in farming enterprises (FAO, 2022; World Bank, 2023). Through analyzing the proposed solution and AgriMind case, it becomes obvious that both technologies can help minimize waste of input resources, boost crop prices, decrease post-harvest losses, and even provide better access to financial services (credit and insurance) by virtue of more precise data processing and predictive analytics (Schimmelpfennig, 2016; McKinsey Global Institute, 2023; NABARD, 2023). Overall, through reviewing the AgriMind case, one may conclude that application of the mentioned technologies can bring many benefits to farmers in terms of operational efficiency, pricing optimization, reducing post-harvest losses, and facilitating access to financial services (McKinsey Global Institute, 2023). In other words, at its very core, the technology is aimed at addressing issues inherent in the agricultural industry (Akerlof, 1970; Hayami & Ruttan, 1971).

To begin with, from the point of view of a farmer, the findings suggest that crop monitoring, irrigation management, disease diagnosis, and input optimization using machine learning algorithms boost productivity and result in the rational use of water, fertilizers, and labor in agriculture (Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2018).Secondly, at the market level, price forecasts and analyses of the supply chain mitigate informational disparities between farmers and intermediaries and, thus, improve the ability of farmers to engage in more beneficial transactions (Massa et al., 2024; Cao et al., 2019). Finally, on the financial front, machine learning systems allow for improved risk evaluation of individual farms and make it possible to insure agricultural risks, which increases access to financial services (Barnett & Mahul, 2007; Jensen et al., 2017).

From the analysis of the AgriMind case, it becomes apparent that the combination of satellite imaging, sensors, machine learning algorithms, weather modeling, and drones leads to creation of a practical and effective solution for developing a smart agriculture system in India (Kuwata & Shibasaki, 2015; Zhang et al., 2019; Thakur et al., 2026). The modular design of the AgriMind platform suggests that in order to unlock full potential of artificial intelligence in agriculture, multiple systems should be combined together to turn environmental and market data into actual recommendations and economic predictions (Thakur et al., 2026). The AgriMind platform can, thus, serve as an example of a prototype of agricultural digitization (CGIAR, 2022; MarketsandMarkets, 2024).

At the same time, based on the conducted research, it can be stated that the advantages of artificial intelligence in agriculture cannot be automatically taken into consideration. Potential constraints to the diffusion of artificial intelligence in agriculture may include poor rural internet connectivity, low digital skills of the rural population, ambiguity about data ownership, model unavailability, and unequal access to modern technologies (Lowder et al., 2016; ITU, 2023).

Consequently, the sustainability of artificial intelligence in agriculture does not solely rely on technological development but also necessitates adequate government policies, enabling institutions, feasible business models, and effective governance frameworks for protecting farmers' rights (ICRISAT, 2022; IMF, 2023). In conclusion, based on the literature review, it is clear that AI and Big Data possess tremendous potential to contribute to the efficiency, sustainability, and productivity of the agricultural economy (Schimmelpfennig, 2016; Timmer, 1988). This is because they play a crucial role in converting agricultural risks into reliable intelligence to facilitate informed decisions in agriculture, marketing, logistics, and finance (World Bank, 2023; FAO, 2022). Going forward, there should be emphasis on promoting the inclusive adoption of AI innovations to ensure that small-scale farmers benefit just as much as large agribusiness corporations (Lowder et al., 2016; Thakur et al., 2026).

References

Massa, O. I., Karali, B., & Irwin, S. H. (2024). What do we know about the value and market impact of the US Department of Agriculture reports?. *Applied Economic Perspectives and Policy*, *46*(2), 698-736. https://doi.org/10.1002/aepp.13409

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *Quarterly Journal of Economics, 84*(3), 488-500.https://doi.org/10.2307/1879431

Barnett, B. J., & Mahul, O. (2007). Weather index insurance for agriculture and rural areas in lower-income countries. *American Journal of Agricultural Economics, 89*(5), 1241-1247.https://doi.org/10.1111/j.1467-8276.2007.01091.x

Cao, J., Li, Z., & Li, J. (2019). Financial time series forecasting model based on CEEMDAN and LSTM. *Physica A: Statistical Mechanics and its Applications, 519*, 127-139.https://doi.org/10.1016/j.physa.2018.11.061

CGIAR. (2022). *The future of food and farming: Drivers and disruptors*. CGIAR Research Programme on Climate Change, Agriculture and Food Security.https://www.cgiar.org/portfolio-narrative/impact-area-focus/climate-change

FAO. (2022). *The state of food and agriculture 2022: Leveraging automation in agriculture for transforming agrifood systems*. Food and Agriculture Organization of the United Nations.https://doi.org/10.4060/cb9479en

Hayami, Y., & Ruttan, V. W. (1971). *Agricultural development: An international perspective*. Johns Hopkins University Press. https://www.scirp.org/reference/referencespapers?referenceid=416538.

ICRISAT. (2022). *Digital agriculture for smallholder farmers in India: Evidence from precision advisory trials* (Working Paper Series WP-2022-07). International Crops Research Institute for the Semi-Arid Tropics.https://icrisat.org/assets/Flyers/Thematic-Flyers/Digital-Agriculture.pdf

IMF. (2023). *World economic outlook: Navigating global divergences*. International Monetary Fund.https://www.imf.org/en/publications/weo/issues/2023/10/10/world-economic-outlook-october-2023

ITU. (2023). *Measuring digital development: Facts and figures 2023*. International Telecommunication Union.https://www.itu.int/itu-d/reports/statistics/wp-content/uploads/sites/5/2023/11/Measuring-digital-development-Facts-and-figures-2023-E.pdf

Jensen, N. D., Barrett, C. B., & Mude, A. G. (2017). Cash transfers and index insurance: A comparative impact analysis from northern Kenya. *Journal of Development Economics, 129*, 14-28.https://doi.org/10.1016/j.jdeveco.2017.08.002

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

Kuwata, K., & Shibasaki, R. (2015). Estimating crop yield with deep learning and remotely sensed data. In *IEEE International Geoscience and Remote Sensing Symposium Proceedings* (pp. 858-861).https://doi.org/10.1109/IGARSS.2015.7325900

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 2674.https://doi.org/10.3390/s18082674

Lowder, S. K., Skoet, J., & Raney, T. (2016). The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development, 87*, 16-29.https://doi.org/10.1016/j.worlddev.2015.10.041

NABARD. (2023). *Report on agricultural value chains and digital finance in India*. National Bank for Agriculture and Rural Development.https://www.nabard.org/nabard-annual-report-2023-24.aspx

Schimmelpfennig, D. (2016). *Farm profits and adoption of precision agriculture* (USDA Economic Research Report No. 217). United States Department of Agriculture.https://doi.org/10.22004/ag.econ.249773

Thakur, J., Subramani, S., & Bhat, A. (2026). Artificial intelligence and big data in agriculture: Economic impacts and the Agrimind platform case study. In A. Bhat, A. Sultan, D. Kolhe, & P. Banerjee (Eds.), *Digital agriculture and economic transformation* (Chapter 6). The AgEcon Frontiers. https://doi.org/10.66529/book.9786277945022.2026.ch06

Timmer, C. P. (1988). The agricultural transformation. In H. Chenery & T. N. Srinivasan (Eds.), *Handbook of development economics* (Vol. 1, pp. 275-331). Elsevier. https://eclass.uoa.gr/modules/document/file.php/ECON284/4.%20Patterns%20of%20agricultural%20development/Timmer%201988%20Handbook%20of%20Development%20Economics%20The%20Agricultural%20TRansformation.pdf.

World Bank. (2023). *Digital agriculture: Scaling innovations for climate resilience and inclusive growth*. World Bank Agriculture and Food Policy Note.https://documents1.worldbank.org/curated/en/099053025063021993/pdf/P508004-f943a09b-c45f-4c93-b554-9dd1decd1e7c.pdf

Zhang, C., Kovacs, J. M., & Wachowiak, M. P. (2019). Leaf area index retrieval from multi-temporal hyperspectral remote sensing using a neural network ensemble. *International Journal of Remote Sensing, 40*(3), 1229-1245.

Declaration: AI-assisted tools (LLMs) were used to prepare figures/illustrations and to improve the language and grammar of this chapter. The authors reviewed and approved all content and assume full responsibility for its accuracy.