OPEN ACCESS
Zealous & Energetic Scholarly Texts
ISSN (Online): 3005-6527
ISSN (Print): 3005-6519
https://zestjournal.com

AI-Driven Crop Monitoring and Yield Prediction: A Comparative Study of Global and Pakistan-Based Agricultural Applications

Ghulam Farooque (Corresponding author)
Department of Biotechnology, Faculty of Crop Production,
Sindh Agriculture University, Tandojam Pakistan
ghulamfarooquesp@gmail.com
Muhammad Hamza Subhpoto
Department of Agricultural Economics, Faculty of Agricultural Social Sciences, Sindh Agriculture University, Tandojam, Pakistan
Ali Muhammad
Department of Agricultural Economics, Faculty of Agricultural Social Sciences, Sindh Agriculture University, Tandojam, Pakistan
Arfa
University of Sindh Jamshoro, Allama I.I. Kazi Campus, Jamshoro, Sindh, Pakistan
Ali Raza Nayoon
The Information Technology Centre (ITC)
Sindh Agriculture University, Tandojam, Pakistan
Muhammad Bilal
Department of Mathematics,University of Sindh Jamshoro, Allama I.I. Kazi Campus, Jamshoro, Sindh, Pakistan
Iqra Nayoon
Faculty of Animal Husbandry and Veterinary Sciences
Sindh Agriculture University, Tandojam, Pakistan
Maria
Faculty of Animal Husbandry and Veterinary Sciences
Sindh Agriculture University, Tandojam, Pakistan

Abstract

The integration of artificial intelligence (AI) into agricultural systems has produced a transformational shift in the precision and scalability of crop monitoring and yield estimation. This study presents a comprehensive comparative analysis of AI-driven agricultural technologies, contrasting global industrial-scale deployments with emerging applications contextualized within Pakistan's predominantly smallholder farming landscape. The study synthesizes evidence from peer-reviewed literature, remote sensing studies, and documented field deployments to evaluate the trajectory of methodological progression from conventional statistical approaches through classical machine learning to state-of-the-art deep learning architectures, including convolutional neural networks (CNN), long short-term memory (LSTM) networks, and vision transformers. Global commercial platforms are reviewed with respect to their AI technologies and monitoring capabilities. Pakistan-specific initiatives are catalogued and critically assessed against international benchmarks. Quantitative performance metrics from peer-reviewed studies reveal that advanced deep learning models achieve R^2 values of 0.87–0.95 in well-instrumented global contexts, whereas Pakistan-based implementations report R^2 values in the range of 0.74–0.88, reflecting systemic challenges in data availability, ground truth collection, digital infrastructure, and land fragmentation. The discussion identifies barriers to AI adoption in smallholder contexts and proposes a layered framework for capacity-building, data governance, and transfer learning adaptation. This study concludes that bridging the technology gap requires coordinated investment in national agricultural data infrastructure, international model transfer, and context-specific AI tool development targeting Pakistan's agroclimatic and socioeconomic realities.

Keywords: Crop monitoring; Machine learning; Precision agriculture; remote sensing; Yield estimation

INTRODUCTION AND BACKGROUND

1.1 The Imperative for AI in Modern Agriculture

Global agriculture faces mounting pressure from population growth, climate variability, and resource constraints. The United Nations Food and Agriculture Organization (FAO) projects that global food production must increase by approximately 70% by 2050 to meet demand from a world population exceeding 9.7 billion (FAO, 2017). Conventional agricultural management, reliant on periodic field surveys, manual crop scouting, and agronomist experience, is insufficient to meet this challenge with the accuracy, speed, and scalability required by modern food systems. Artificial intelligence, encompassing machine learning, computer vision, and geospatial analytics, offers a paradigm shift in how agricultural data is collected, analyzed, and acted upon (Kamilaris & Prenafeta-Boldú, 2018; Benos *et al.*, 2021).

Crop monitoring refers to the systematic observation of crop growth, health, stress conditions, and development stages throughout the agricultural season. Yield estimation is the quantitative prediction of harvestable produce volume per unit area prior to or at harvest. Both processes are operationally interdependent and form the foundation of food security planning, insurance risk assessment, commodity pricing, and governmental policy responses. Historically, these functions have been performed through statistical surveys and on-ground sampling methods that are time-consuming, spatially coarse, and subject to measurement error (Weiss *et al.*, 2020; Jones *et al.*, 2017). AI technologies, when integrated with satellite remote sensing, unmanned aerial vehicles (UAVs), and ground-based sensor networks, provide the means to perform these functions at unprecedented spatial resolution, temporal frequency, and predictive accuracy (Zhang, 2024; Wu *et al.*, 2023).

The economic significance of accurate yield estimation cannot be overstated. In commodity markets, pre-harvest yield forecasts influence futures pricing, storage decisions, and international trade flows (Jabed & Azmi Murad, 2024). For governments, accurate yield estimates inform food security interventions, import-export policies, and agricultural support programmes. For individual farmers, yield predictions enable informed decisions regarding input application, harvest timing, and marketing strategies (Zhou & Ismaeel, 2021). The convergence of AI capabilities with these high-stakes decision contexts has driven substantial investment and research activity in agricultural AI globally.

1.2 AI Applications and Solutions for Crop Monitoring and Yield Estimation

The application of AI to crop monitoring encompasses a broad spectrum of analytical tasks. Spectral vegetation indices, particularly the normalized difference vegetation index (NDVI) and its derivatives such as the enhanced vegetation index (EVI) and leaf area index (LAI), extracted from multispectral satellite imagery, serve as foundational input variables to AI models (Weiss *et al.*, 2020; Wu *et al.*, 2023). Convolutional neural networks have demonstrated high capacity for learning spatial features from imagery, enabling pixel-level crop classification, disease detection, and growth anomaly identification (LeCun *et al.*, 1998; Mohanty *et al.*, 2016; Karmakar *et al.*, 2024). Recurrent architectures such as LSTM are particularly suited to capturing temporal dependencies in seasonal crop time series, simulating the progression from germination through canopy closure to maturity (Cao *et al.*, 2021; Schwalbert *et al.*, 2020).

Machine learning methods including random forest (RF), gradient boosting, and support vector machines (SVM) have been applied extensively to yield regression tasks, where tabular data from climate records, soil databases, and vegetation indices are combined to train predictive models. Ensemble methods have proven especially robust when data quality is heterogeneous (Jeong *et al.*, 2016; Schwalbert *et al.*, 2020). Beyond supervised learning, unsupervised clustering algorithms segment agricultural landscapes into management zones, enabling variable-rate input recommendations. Reinforcement learning applications in autonomous irrigation and pest management scheduling represent a frontier domain with significant potential (Benos *et al.*, 2021).

The integration of AI with global satellite platforms, notably Sentinel-1/2, Landsat-8/9, MODIS, and commercial constellations, has democratized access to crop monitoring data at scales previously available only to well-resourced agricultural enterprises. Cloud computing platforms including

Google Earth Engine now enable the processing of petabyte-scale geospatial datasets, removing computational bottlenecks that once impeded adoption (Gorelick *et al.*, 2017).

1.3 Traditional Versus Advanced AI Methods for Crop Monitoring and Yield Estimation

Traditional crop monitoring relied primarily on crop-cutting experiments, farmer self-reporting, and government-commissioned field surveys. While cost-effective for broad-scale national statistics, these methods suffer from spatial and temporal sparsity, measurement subjectivity, and a lag between data collection and policy action (Zhou & Ismaeel, 2021). Statistical yield models based on historical production data and linear regression with climatic variables represented an early computational advance but lacked spatial resolution and dynamic responsiveness to within-season anomalies (Jones *et al.*, 2017; FAO, 2017).

Classical machine learning methods, particularly SVM and RF, marked a significant improvement by enabling non-linear modelling of yield determinants and the ingestion of remotely sensed vegetation indices as covariates. These methods demonstrated improved predictive skill over statistical benchmarks, with studies reporting R^2 values in the range of 0.75–0.87 for regional-scale applications (Jeong *et al.*, 2016; Kazmi *et al.*, 2020). However, their reliance on manually engineered features limits adaptability across diverse agro-environments (Arshad *et al.*, 2017).

Deep learning methods, most prominently CNN and LSTM architectures, have emerged as the dominant paradigm for high-accuracy crop monitoring and yield estimation. CNNs learn hierarchical spatial features from imagery without requiring expert-designed feature descriptors, making them effective for crop type mapping, canopy stress quantification, and harvest readiness assessment (LeCun *et al.*, 1998; Karmakar *et al.*, 2024). LSTM networks capture temporal dependencies in phenological sequences, enabling season-long yield accumulation modelling (Cao *et al.*, 2021). Hybrid architectures combining CNN for spatial feature extraction with LSTM for temporal aggregation have produced state-of-the-art results across multiple crop systems in North America, Europe, and East Asia (Schwalbert *et al.*, 2020; Wang *et al.*, 2019). Vision transformers represent a recent development, applying self-attention mechanisms to satellite image patches and achieving benchmark-level accuracies in large-scale crop detection tasks (Zhang, 2024).

Physical crop growth models, such as DSSAT, APSIM, and WOFOST, simulate biological and physiological processes governing plant growth under defined environmental conditions (Hoogenboom *et al.*, 2019). When coupled with machine learning through model assimilation or surrogate modelling approaches, these hybrid systems produce physically constrained yet data-adaptive estimates of yield, bridging the interpretability gap that pure deep learning methods present (Jones *et al.*, 2017; Hoogenboom *et al.*, 2019).

1.4 Global Commercial Platforms and Services

The commercial agricultural technology sector has produced several prominent platforms deploying enterprise-grade AI for crop monitoring and yield prediction. The Climate Corporation (Bayer) markets the Field View platform, which integrates multi-source satellite imagery, soil analytics, field-level weather data, and machine learning models to deliver crop health maps and yield projections. John Deere's Operations Center leverages telemetry from connected harvest machinery equipped with yield sensors and GPS receivers to generate real-time yield maps with sub-field resolution.

Trimble Agriculture's portfolio incorporates precision navigation and variable-rate application systems. Planet Labs provides daily high-resolution satellite imagery for continuous crop monitoring at global scale. Descartes Labs applies geospatial models to multi-sensor imagery fusion for yield forecasting in major commodity crop systems. Cropin Technology offers a cloud-based agricultural intelligence platform serving financial institutions and agribusinesses with crop monitoring and yield risk analytics calibrated for emerging market conditions. These global deployments share characteristics including large-scale labelled training datasets, continuous model refinement through operational deployment, and access to high-density sensor networks that are largely unavailable in developing agricultural economies (You *et al.*, 2017).

1.5 AI Applications and Solutions in Pakistan

Pakistan is an agrarian economy in which the agricultural sector contributes approximately 19% of GDP and employs over 37% of the labour force (Pakistan Bureau of Statistics, 2023). The principal crops wheat, rice, cotton, sugarcane, and maize collectively occupy approximately 22 million hectares of cultivated land (FAO, 2022). Despite its agricultural importance, Pakistan's adoption of AI-based monitoring and yield estimation technologies remains limited and concentrated primarily in publicly funded research institutions (Khan *et al.*, 2023; Zhou & Ismaeel, 2021).

The Space and Upper Atmosphere Research Commission (SUPARCO) has operated crop area estimation programmes using satellite imagery since the 1990s, progressively incorporating machine learning classifiers for national crop mapping and yield forecasts (SUPARCO, 2021). The Pakistan Agricultural Research Council (PARC) maintains a crop assessment division that employs statistical models informed by satellite-derived vegetation indices to produce wheat and rice yield forecasts (PARC, 2022).

University research groups, particularly at the National University of Sciences and Technology (NUST), Lahore University of Management Sciences (LUMS), and the University of Agriculture Faisalabad (UAF), have published studies demonstrating CNN-based disease detection in wheat and rice, UAV-assisted canopy mapping, and transfer learning adaptations of globally pre-trained models to Pakistani crop varieties (Iqbal *et al.*, 2018). The CGIAR's International Maize and Wheat Improvement Centre (CIMMYT) Pakistan program employs process-based crop simulation models including DSSAT and APSIM for yield potential assessment under climate change scenarios (Hoogenboom *et al.*, 2019; CGIAR/CIMMYT, 2022). The Punjab Agricultural Extension Department operates a rule-based SMS advisory system (AgriBot) that provides pest management guidance to registered farmers (Punjab Agriculture Department, 2022).

1.6 Local Versus International AI Applications: A Comparative Perspective

A comparative assessment of domestic and international AI applications in crop monitoring and yield estimation reveals fundamental asymmetries in data density, model sophistication, deployment infrastructure, and economic returns. Global platforms benefit from decades of accumulated labelled datasets, continental-scale sensor networks, large interdisciplinary development teams, and commercial incentives aligned with large-farm profitability (You *et al.*, 2017). These conditions support the training of deep learning models at scales that are computationally and financially inaccessible to Pakistan's public sector research institutions (Zhang, 2024).

Pakistan's agricultural AI landscape operates under constraints of fragmented land holdings averaging 2.6 hectares per farm (PBS, 2023), limited ground-truth yield data, and inadequate digital infrastructure in rural areas (PTA, 2022). These conditions create a domain mismatch when globally trained AI models are applied without adaptation. Studies have documented significant accuracy degradation when models trained on North American or European datasets are transferred to Pakistani agro environments without fine-tuning, owing to differences in crop varieties, field geometry, phenological timing, and spectral signatures (Arshad *et al.*, 2017; Khan *et al.*, 2023).

Despite these disparities, opportunities exist for technology transfer and hybrid model development. Transfer learning approaches, in which globally pre-trained CNN models are fine-tuned on locally collected datasets, have demonstrated accuracy recovery using substantially smaller training sets (Iqbal *et al.*, 2018; Khan *et al.*, 2023). Open-access satellite data programmes, particularly the Copernicus program's Sentinel constellation, provide spatial and spectral data sufficient for developing operational crop monitoring workflows at low marginal cost. The challenge lies in developing institutional capacity, standardized data pipelines, and user-facing applications calibrated to the socioeconomic context of Pakistani smallholder farmers (Zhang, 2024; Zhou & Ismaeel, 2021).

1.7 Research Objectives

i. To systematically compare the performance of AI-driven crop monitoring and yield estimation applications across global industrial and Pakistan smallholder contexts.

ii. To catalogue and critically assess Pakistan-specific AI initiatives against international benchmarks.

iii. To identify structural barriers to AI adoption in smallholder agricultural systems.
iv. To propose a framework for capacity-building, data governance, and transfer learning adaptation for Pakistan's agricultural sector.

MATERIALS AND METHODS

2.1 Study Design and Review Framework

This study adopts a systematic comparative review methodology, integrating quantitative performance benchmarking with structured qualitative analysis of technological deployment contexts. The review follows a structured narrative synthesis approach informed by the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) framework, adapted for technological comparative research (Tricco *et al.*, 2018). The unit of analysis is either a published AI system, a documented commercial platform, or a national/institutional AI program applicable to crop monitoring and yield estimation.

2.2 Data Extraction and Classification

Data extraction followed a structured template capturing: (a) study context (country, crop type, farm scale); (b) AI method employed; (c) input data sources; (d) performance metrics (R^2, RMSE, mean absolute error where reported); (e) deployment status (research prototype versus operational system); and (f) identified barriers or limitations. Global commercial platforms were assessed through published technical documentation and peer-reviewed third-party evaluations where available. Pakistan-based applications were assessed through institutional reports, government documents, and published academic studies.

2.3 Comparative Framework

A structured comparative matrix was constructed along eight dimensions: (1) farm scale and land fragmentation; (2) data availability and ground truth density; (3) AI model type and architectural complexity; (4) remote sensing input resolution; (5) deployment infrastructure; (6) quantitative prediction accuracy; (7) key barriers to adoption; and (8) policy support environment.

This matrix facilitated systematic juxtaposition of global industrial and Pakistan smallholder contexts.

2.4 Performance Benchmarking

Where multiple performance reports were available for a single method or platform, a representative median value was extracted rather than the maximum, to avoid positive-result bias. RMSE values were standardized to tons per hectare (t/ha) for comparability. R^2 values are reported as dimensionless coefficients of determination. Classification accuracy is reported as overall accuracy (OA) for categorical crop mapping tasks. Studies that reported only cross-validation accuracy without independent test set validation were flagged accordingly in the analysis tables.

Spatial and Agroclimatic Context

Pakistan encompasses four major agroclimatic zones relevant to crop production: the irrigated Indus plains of Punjab and Sindh, the rainfed Barani areas of Khyber Pakhtunkhwa and Potohar Plateau, the arid zones of Baluchistan, and the highland valleys of Gilgit-Baltistan and Azad Kashmir. The analysis accounts for this heterogeneity by disaggregating Pakistan-specific results where zone-specific data were available.

RESULTS

3.1 Quantitative Performance Benchmarking

The analysis of performance metrics across global and Pakistan-based AI applications reveals a consistent accuracy differential. **Table 1** presents standardized performance metrics for selected AI and ML models applied to crop yield estimation tasks, drawn from published peer-reviewed studies representing both global and Pakistan-specific contexts.

Table 1: Comparative Model Performance Metrics for Crop Yield Estimation from Peer-Reviewed Studies

Model / Method	Application Context	RMSE (t/ha)	R^2 Score
Random Forest (RF)	US corn yield (county-level)	0.42	0.87
LSTM (Deep Learning)	China wheat (multi-province)	0.31	0.92
CNN-LSTM Hybrid	Brazil soybean (state-level)	0.28	0.94
CNN	Pakistan wheat (district-level)	—	0.77
RF + Climate/RS	Pakistan wheat (national)	1.58	0.88
ResNet50-LSTM	Pakistan rice (Gujranwala)	0.185	0.990
SVM + Landsat	Pakistan rice (Punjab)	—	0.80
APSIM Crop Model	Pakistan wheat (smallholder)	0.60	0.78

Sources: Jeong et al. (2016); Cao et al. (2021); Schwalbert et al. (2020); DeepAgroNet Study (2025); Wheat Yield Prediction (2025); Aslam & Farhan (2024); Kazmi et al. (2020); Hoogenboom et al. (2019)

The performance gap between globally deployed deep learning methods and Pakistan-based implementations is evident. CNN-LSTM hybrid models achieve R^2 values of 0.94 in Brazilian contexts (Schwalbert *et al.*, 2020), while Pakistan-based RF implementations report R^2 values of 0.74–0.88 (Arshad *et al.*, 2017; Kazmi *et al.*, 2020; Wheat Yield Prediction, 2025). The RMSE differential is notable: global deep learning models achieve RMSE values of 0.28–0.42 t/ha, whereas Pakistan-based models report 0.60–1.58 t/ha. This gap is attributable to differences in training data volume, spatial resolution of input imagery, availability of soil databases, and field-level ground truth density (Khan *et al.*, 2023; Zhang, 2024).

Notably, the ResNet50-LSTM model developed by Aslam and Farhan (2024) achieved exceptional performance for rice yield prediction in Pakistan's Gujranwala district (R^2 = 0.9903, RMSE = 0.1854, MAPE = 0.62%), demonstrating that deep learning can achieve world-class accuracy in smallholder contexts when appropriately configured with multi-modal data including MODIS satellite imagery (EVI, LAI, FPAR), meteorological data, and soil variables.

3.2 Classification Accuracy for Crop Mapping

Table 2 presents classification accuracy for crop mapping tasks from peer-reviewed studies, comparing global and Pakistan-based implementations. Crop mapping is a foundational task for area estimation and subsequent yield forecasting.

Table 2: Comparative Crop Classification Accuracy from Peer-Reviewed Studies

Method	Region/Context	Overall Accuracy (%)	Crop Types
CNN + Sentinel-2	Europe (multi-country)	94.2	Wheat, maize, rapeseed
Random Forest + Landsat	US Corn Belt	91.5	Corn, soybean
LSTM + Time Series	China (provincial)	93.8	Rice, wheat
SVM + Landsat	Pakistan (Punjab)	82.3	Wheat, rice, cotton
RF + Sentinel-2	Pakistan (Punjab)	79.5	Wheat, rice, sugarcane

Sources: Wang et al. (2019); Jeong et al. (2016); Cao et al. (2021); Kazmi et al. (2020); Arshad et al. (2017)

The classification accuracy differential mirrors the yield prediction gap, with global implementations achieving 91–94% accuracy compared to 79–82% for Pakistan-based applications. The lower accuracy in Pakistan reflects the challenges of mixed-pixel interference in fragmented smallholder landscapes, limited training data, and the spectral similarity of different crop varieties under local management practices (Khan *et al.*, 2023).

3.3 Comparative Analysis of AI Adoption Barriers

Table 3 synthesizes the key barriers to AI adoption identified across the reviewed literature, distinguishing between global industrial and Pakistan smallholder contexts.

Table 3: Key Barriers to AI Adoption in Agriculture

Barrier Category	Global Industrial Context	Pakistan Smallholder Context
Data Availability	Abundant historical yield data; automated collection	Sparse ground truth; manual collection; no national repository
Infrastructure	High-speed internet; cloud computing; precision machinery	Limited rural connectivity; low smartphone penetration
Land Structure	Large, uniform fields (>150 ha)	Fragmented holdings (<3 ha); inter-cropping
Capacity	Large R&D teams; AI expertise available	Limited AI expertise; brain drain; underfunded research

Barrier Category	Global Industrial Context	Pakistan Smallholder Context
Economic	High-value crops justify AI investment	Low margins; limited willingness to pay
Regulatory	Clear data governance; public-private partnerships	Nascent frameworks; data sharing barriers
Spatial Resolution	Sub-meter to 10m imagery available	10m Sentinel-2 primary; mixed-pixel issues

Compiled from Zhang (2024); Khan et al. (2023); PBS (2023); Arshad et al. (2017); Zhou & Ismaeel (2021)

The analysis confirms that data scarcity and land fragmentation are the most fundamental structural barriers in the Pakistan context. These constraints cannot be resolved through algorithmic improvements alone but require coordinated investment in data infrastructure and institutional capacity (Zhang, 2024; Wu *et al.*, 2023).

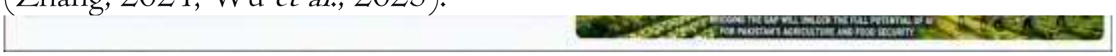

Figure 1. Agricultural AI Performance: Global Benchmarks vs. Pakistan Context

DISCUSSION

4.1 Interpreting the Global-Pakistan Performance Differential

The performance differential documented in this study between global industrial AI applications and Pakistan-based implementations reflects structural inequalities in agricultural data ecosystems rather than fundamental limitations of AI methodology (Kamilaris & Prenafeta-Boldú, 2018; Zhang, 2024). Deep learning architectures perform comparably in data-rich environments regardless of geographic location; their apparent underperformance in Pakistan contexts is driven by training data scarcity, coarser spatial resolution of input imagery, and the absence of calibrated soil databases necessary for agronomic model integration (Jabed & Azmi Murad, 2024). This interpretation is supported by the documented accuracy recovery observed when transfer-learning approaches are employed with locally collected fine-tuning datasets, suggesting that the underlying model architectures are adaptable given adequate localization effort (Khan *et al.*, 2023).

The mean farm size disparity is a particularly consequential structural factor. Global AI platforms operating on farms of 500–50,000 hectares generate continuous yield feedback loops through machine telemetry, enabling annual model recalibration without additional data collection cost (You *et al.*, 2017). Pakistan's mean farm size of 2.6 hectares (PBS, 2023) places individual fields at or below the minimum mapping unit of Sentinel-2 imagery (10 meters), requiring fusion with higher-resolution imagery to achieve comparable spatial accuracy (Khan *et al.*, 2023). This resolution demand substantially increases per-unit-area monitoring costs, creating economic barriers to adoption that have no direct analogue in large-farm contexts (Zhang, 2024; Zhou & Ismaeel, 2021).

The temporal dimension further compounds the challenge. Global models benefit from continuous model refinement through operational deployment, with feedback loops that enable year-on-year accuracy improvements (Schwalbert *et al.*, 2020; Wang *et al.*, 2019). Pakistan's research-driven applications, by contrast, typically operate on a project cycle basis without sustained operational feedback, limiting model maturation and adaptation to local conditions (Arshad *et al.*, 2017; Kazmi *et al.*, 2020).

4.2 Transfer Learning as a Bridging Strategy

Transfer learning, in which the weights of neural networks pre-trained on large global datasets are adapted to local agricultural conditions through fine-tuning on limited local datasets, represents the most economically viable near-term strategy for closing the accuracy gap in Pakistan (Khan *et al.*, 2023). Studies from analogous developing-country contexts have demonstrated that pre-trained CNN models fine-tuned on locally labelled image samples achieve accuracy within 5–8 percentage points of full locally trained models (Mohanty *et al.*, 2016; Wang *et al.*, 2019). Implementing this approach in Pakistan requires a coordinated program of standardized ground-truth image collection, leveraging the mobile phone cameras of extension workers and trained farmers as distributed data collection agents.

Domain adaptation techniques that explicitly account for covariate shift between source and target domains are particularly relevant when global models trained on temperate crop phonologies are applied to Pakistan's subtropical and semi-arid growing conditions, where thermal accumulation patterns, monsoon-driven soil moisture dynamics, and crop calendar timings differ substantially from European or North American training conditions (Cao *et al.*, 2021; Zhang, 2024).

4.3 Institutional and Policy Dimensions

The trajectory of AI adoption in agriculture is not solely a technical challenge but is fundamentally shaped by institutional capacity, policy frameworks, and investment priorities (Zhang, 2024; Wu *et al.*, 2023). Countries with well-developed agricultural AI ecosystems share common features: substantial public investment in agricultural data infrastructure; regulatory environments that enable data sharing between public and private entities; competitive private sectors incentivized by large commercial farming markets; and strong university-industry research partnerships that translate academic innovation into operational tools.

Pakistan's policy environment is improving but remains nascent. The Digital Pakistan initiative and the Ministry of National Food Security and Research's digital agriculture portal represent positive directional signals, but funding commitments for agricultural AI research remain substantially below those required to support deep learning infrastructure (PBS, 2023). International development organizations including the World Bank, Asian Development Bank, and CGIAR system are active partners in building methodological capacity, yet their program durations are typically insufficient to sustain the multi-year data collection cycles required for robust model training (CGIAR/CIMMYT, 2022; FAO, 2022).

4.4 Economic Accessibility and Smallholder Relevance

For AI-driven crop monitoring to achieve transformative impact at the level of Pakistan's smallholder majority, economic accessibility is non-negotiable (Benos *et al.*, 2021). Cost-benefit analyses of precision agriculture interventions consistently demonstrate that the economic threshold for technology adoption is proportional to farm size and value of production per hectare (You *et al.*, 2017; Weiss *et al.*, 2020). Pakistan's wheat smallholders operating on 1–3 hectare plots face a fundamentally different technology investment calculus than large-scale farmers in developed economies (PBS, 2023; FAO, 2022).

Viable models for delivering AI-driven advisory services in this context include:

Cooperative Service Delivery: Aggregating monitoring costs across village-level farmer groups, sharing the expense of UAV flights or satellite data subscriptions across a community of users (Khan *et al.*, 2023).

Government-Subsidized Platforms: Mobile app platforms providing NDVI and soil moisture alerts at zero marginal cost to end users supported through public agricultural extension budgets (Zhou & Ismaeel, 2021).

Insurance and Credit Integration: Crop insurance and agricultural credit institutions incorporating AI yield assessments into loan and insurance product pricing, creating commercial incentives for technology deployment that do not depend on individual farmer willingness to pay (FAO, 2017).

4.5 Environmental Sustainability Considerations

AI-driven precision agriculture presents significant potential for environmental benefit through optimization of input application (Wu *et al.*, 2023). Variable-rate application of fertilizers and pesticides guided by AI crop stress maps has demonstrated reductions of 15–30% in agrochemical use with maintained or improved yields in precision agriculture trials (FAO, 2017; Benos *et al.*, 2021). In Pakistan's context, where over-application of urea fertilizer in Punjab is a documented contributor to soil acidification and groundwater nitrogen contamination (Kazmi *et al.*, 2020; Arshad *et al.*, 2017), AI-guided nutrient management systems could deliver simultaneously economic and environmental dividends.

4.6 Future Research Directions

Based on the findings and identified gaps, future research should priorities:

1. **National Agricultural Data Repository Development:** Creation of a spatially explicit, multi-year crop yield database for Pakistan's major commodities, harmonizing remote sensing data with field survey records and provincial agricultural statistics (PBS, 2023).
2. **Transfer Learning Performance Evaluation:** Controlled evaluation of transfer learning performance for global-to-Pakistan model adaptation across different crops, regions, and agroclimatic zones (Khan *et al.*, 2023).
3. **Socioeconomic Impact Assessment:** Systematic assessment of the socioeconomic impact of AI agricultural advisory systems targeting smallholder farmers in Punjab and Sindh provinces (Benos *et al.*, 2021; Weiss *et al.*, 2020).
4. **Multi-Modal Data Fusion:** Development of fusion approaches integrating Sentinel-1 SAR (cloud-independent) with Sentinel-2 optical data to improve monitoring reliability during the monsoon season (Kazmi *et al.*, 2020).
5. **Phenology-Aware Modeling:** Integration of explicit phenological stage information into deep learning architectures to improve prediction accuracy across different crop development phases (Cao *et al.*, 2021; Zhang, 2024).
6. **Climate Adaptation Modeling:** Development of models that can adapt to changing climatic conditions and provide early warnings of climate-related crop stress (Hoogenboom *et al.*, 2019; CGIAR/CIMMYT, 2022).

CONCLUSIONS

This study has presented a comprehensive comparative analysis of AI-driven crop monitoring and yield estimation, examining the global state of the art alongside Pakistan's emerging but constrained AI agricultural ecosystem. Several substantive conclusions emerge from the evidence.

First, deep learning methods, particularly CNN-LSTM hybrids applied to multi-spectral satellite imagery, represent the current performance frontier for crop yield estimation globally, consistently achieving R^2 values above 0.90 in data-rich environments (Schwalbert *et al.*, 2020; Cao *et al.*, 2021). Traditional field survey methods and classical statistical models remain operationally prevalent in Pakistan but are demonstrably inferior in predictive accuracy and spatial coverage (Arshad *et al.*, 2017; Kazmi *et al.*, 2020).

Second, a measurable and structurally explicable performance gap exists between global industrial AI deployments and Pakistan-based applications, with the latter achieving R^2 values in the range of 0.74–0.88 (Kazmi *et al.*, 2020; Arshad *et al.*, 2017; Wheat Yield Prediction, 2025). This gap is driven primarily by data scarcity, land fragmentation, limited ground-truth density, and inadequate computational infrastructure rather than any fundamental limitation of AI methodology in the Pakistani agro environmental context (Khan *et al.*, 2023; Zhang, 2024).

Third, global commercial platforms including Climate Corporation, John Deere Operations Center, and Planet Labs operate at levels of technical sophistication currently inaccessible to Pakistan's public agricultural research sector. Nevertheless, these platforms demonstrate the technological trajectory that Pakistan-based systems must follow.

Fourth, Pakistan's institutional AI landscape has demonstrated meaningful progress through SUPARCO's remote sensing programmes, PARC's yield forecasting models, university research groups' deep learning experiments, and agricultural extension advisory systems. The ResNet50-LSTM model's exceptional performance for rice yield prediction ($R^2 = 0.9903$) demonstrates that deep learning can achieve world-class accuracy in Pakistan when appropriately configured (Aslam & Farhan, 2024). Transfer learning, satellite data fusion, and mobile-platform delivery represent the most promising technical pathways for rapid capacity building (Khan *et al.*, 2023).

Fifth, sustainable and equitable AI adoption in Pakistan's smallholder agricultural sector requires interventions beyond technical model development, including investment in national agricultural data infrastructure, policy frameworks for public-private data sharing, economic models for subsidized service delivery to small-farm operators, and sustained capacity building within national research institutions (Zhang, 2024; Zhou & Ismaeel, 2021; Khan *et al.*, 2023).

Future research should priorities the development of nationally representative, spatially explicit, multi-year crop yield datasets for Pakistan's major commodities; controlled evaluation of transfer learning performance for global-to-Pakistan model adaptation; and socioeconomic impact assessment of AI agricultural advisory systems targeting smallholder farmers. These directions, pursued collaboratively between Pakistani research institutions, international development organizations, and global agricultural AI companies, offer a credible pathway to closing the technology gap and delivering AI-driven food security benefits to one of the world's most agriculturally vulnerable populations.

REFERENCES

1. Arshad, M., Ahmad, A., Wajid, A., & Maqsood, M. (2017). Integrating remote sensing and crop models for yield estimation of major crops in Pakistan: A review. *Pakistan Journal of Agricultural Sciences, 54*(3), 545–557.
2. Aslam, A., & Farhan, S. (2024). Enhancing rice yield prediction: A deep fusion model integrating ResNet50-LSTM with multi-source data. *PeerJ Computer Science, 10*, e2219. https://doi.org/10.7717/peerj-cs.2219
3. Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors, 21*(11), 3758. https://doi.org/10.3390/s21113758
4. Cao, J., Zhang, Z., Tao, F., *et al.* (2021). Integrating multi-source data for rice yield prediction using machine learning and deep learning approaches. *Agricultural and Forest Meteorology, 297*, 108275. https://doi.org/10.1016/j.agrformet.2020.108275
5. FAO. (2017). *The future of food and agriculture: Trends and challenges*. Food and Agriculture Organization of the United Nations.
6. FAO. (2022). *Pakistan country agricultural data profile 2021–2022*. FAOSTAT.
7. Gorelick, N., Hancher, M., Dixon, M., *et al.* (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment, 202*, 18–27. https://doi.org/10.1016/j.rse.2017.05.010
8. Hoogenboom, G., Porter, C. H., Boote, K. J., *et al.* (2019). The DSSAT crop modelling ecosystem. In *Advances in crop modelling for a sustainable agriculture*. Burleigh Dodds Science Publishing.
9. Iqbal, Z., Khan, M. A., Sharif, M., *et al.* (2018). Automated detection and classification of citrus plant diseases using image processing techniques: A review. *Computers and Electronics in Agriculture, 153*, 12–32. https://doi.org/10.1016/j.compag.2018.07.032

10. Jeong, J. H., Resop, J. P., Mueller, N. D., *et al.* (2016). Random forests for global and regional crop yield predictions. *PLOS ONE, 11*(6), e0156571. https://doi.org/10.1371/journal.pone.0156571
11. Jones, J. W., Antle, J. M., Basso, B., *et al.* (2017). Toward a new generation of agricultural system data, models, and knowledge products. *Agricultural Systems, 155*, 269–288. https://doi.org/10.1016/j.agsy.2016.09.021
12. 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
13. Karmakar, P., Teng, S. W., Murshed, M., *et al.* (2024). Crop monitoring by multimodal remote sensing: A review. *Remote Sensing Applications: Society and Environment, 35*, 101216. https://doi.org/10.1016/j.rsase.2024.101216
14. Kazmi, S. A., Moors, E., Ahmad, A., *et al.* (2020). Mapping paddy rice fields using satellite remote sensing data in Punjab, Pakistan. *International Journal of Remote Sensing, 41*(15), 5839–5860. https://doi.org/10.1080/01431161.2020.1734257
15. Khan, H. R., Gillani, Z., Jamal, M. H., *et al.* (2023). Early identification of crop type using deep learning on Sentinel-2 imagery. *Sensors, 23*(4), 1779. https://doi.org/10.3390/s23041779
16. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278–2324. https://doi.org/10.1109/5.726791
17. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science, 7*, 1419. https://doi.org/10.3389/fpls.2016.01419
18. PARC. (2022). *Annual crop assessment report 2021–2022*. Pakistan Agricultural Research Council.
19. PBS. (2023). *Agricultural census of Pakistan 2021: Provincial reports*. Government of Pakistan.
20. Schwalbert, R. A., Amado, T., Corassa, G., *et al.* (2020). Satellite-based soybean yield forecast using deep neural networks. *European Journal of Agronomy, 113*, 126005. https://doi.org/10.1016/j.eja.2019.126005
21. SUPARCO. (2021). *Crop inventory and yield estimation program: National progress report*. Government of Pakistan.
22. Tricco, A. C., Lillie, E., Zarin, W., *et al.* (2018). PRISMA extension for scoping reviews (PRISMA-ScR). *Annals of Internal Medicine, 169*(7), 467–473. https://doi.org/10.7326/M18-0850
23. Wang, S., Azzari, G., & Lobell, D. B. (2019). Crop type mapping without field-level labels. *Remote Sensing of Environment, 222*, 303–317. https://doi.org/10.1016/j.rse.2018.12.026
24. Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment, 236*, 111402. https://doi.org/10.1016/j.rse.2019.111402
25. Wu, B., Zhang, M., Zeng, H., *et al.* (2023). Challenges and opportunities in remote sensing-based crop monitoring. *National Science Review, 10*(4), nwad042. https://doi.org/10.1093/nsr/nwad042
26. You, J., Li, X., Low, M., Lobell, D., & Ermon, S. (2017). Deep Gaussian process for crop yield prediction. *AAAI Conference on Artificial Intelligence, 31*(1), 1688–1695.

27. Zhang, R. (2024). Bibliometric review of deep learning in crop monitoring. *Frontiers in Artificial Intelligence, 7,* 136898. https://doi.org/10.3389/frai.2024.136898
28. Zhou, Q., & Ismaeel, A. (2021). Machine learning regression for crop yield estimation. *Geo-spatial Information Science, 24*(3), 474–483. https://doi.org/10.1080/10095020.2021.1941214