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TRAINING AND FARMERS WELFARE
INDIAN SOCIETY OF
AGRICULTURAL INFORMATION TECHNOLOGY (INSAIT)
and

UNIVERSITY OF AGRICULTURAL SCIENCES,
DHARWAD

Compendium of Extended Summaries



National Conference on

Next-Gen Farming : Artificial Intelligence, Automation and Digital Transformation

Conference Date :

7-9, May, 2026

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University of Agricultural Sciences Dharwad

National Conference on

Next-Gen Farming: Artificial Intelligence, Automation and Digital Transformation

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Organised by :

Dr. S. V. Patil Foundation for Research, Training and Farmers Welfare
Indian Society of Agricultural Information Technology (INSAIT)
and
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University of Agricultural Sciences Dharwad



(P. L. Patil)
Vice-Chancellor

MESSAGE

I am delighted to extend my warmest greetings to all the esteemed participants, organizers, and contributors to the National Seminar on *"National Conference on Next-Gen Farming: Artificial Intelligence, Automation and Digital Transformation"* scheduled to be held at the University of Agricultural Sciences, Dharwad, from May 7 to 9 , 2026.

This seminar marks a significant step in addressing the urgent need for implementing artificial intelligence applications in agricultural practices and climate resilience. The compendium of abstracts and summaries received for presentation showcases the remarkable diversity of ideas, research, and innovations aimed at leveraging artificial intelligence applications in agriculture to enhance soil health, mitigate climate change and promote automation and digital transformation in agriculture.

The seminar promises to be a platform for thought-provoking deliberations among scientists, academicians, policymakers, entrepreneurs, and farmers. I am confident that the discussions will provide valuable insights into the integration of artificial intelligence , automation and digital transformation technologies in agricultural practices, thereby benefitting all stakeholders. These innovations have the potential to transform agricultural landscapes, offering solutions for resource management, automation and increased agricultural productivity.

It is my firm belief that the outcomes of this seminar will empower farmers with practical and innovative solutions while fostering collaborations among industry and research institutions to propel artificial intelligence, automation technologies toward wider adoption.

I extend my heartfelt wishes to the organizing committee, resource persons, and participants for a successful seminar and look forward to the impactful contributions this event will make toward a capacity building of young teachers, researchers and extension workers for future data and technology driven agriculture.

PLPatil

(P. L. Patil)
Vice-Chancellor
University of Agricultural Sciences
Dharwad

डॉ. मृत्युंजय महापात्र
मौसम विज्ञान विभाग के महानिदेशक,
विश्व मौसम विज्ञान संगठन में भारत के स्थाई प्रतिनिधि
विश्व मौसम विज्ञान संगठन के तीसरे उपाध्यक्ष

Dr. Mrutyunjay Mohapatra
Director General of Meteorology,
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नई दिल्ली–110003
Government of India
Ministry of Earth Sciences
India Meteorological Department
Mausam Bhawan, Lodi Road
New Delhi-110003

Message

I am pleased to learn that the University of Agricultural Sciences, Dharwad, in association with the Indian Society of Agricultural Information Technology and the Dr. S. V. Patil Foundation for Research, Training and Farmers Welfare, is organizing the National Conference on "Next-Gen Farming: Artificial Intelligence, Automation and Digital Transformation" during 7–9 May 2026 at the Farmers Knowledge Centre, UAS, Dharwad.

The agricultural and horticultural sectors are undergoing a profound transformation with the integration of advanced technologies such as Artificial Intelligence, automation, IoT, drones, and precision farming tools. In this evolving landscape, meteorological science plays a critical role in supporting data-driven agriculture. Accurate and timely weather and climate information, as provided by the India Meteorological Department, is essential for optimizing farm operations, minimizing risks associated with climate variability, and enhancing resilience in the face of extreme weather events.

The theme of this conference is both timely and highly relevant. It offers a valuable platform for scientists, academicians, researchers, industry experts, entrepreneurs, and students to exchange knowledge and foster innovation. Integrating meteorological insights with emerging digital technologies can significantly strengthen decision-support systems for farmers, enabling more efficient resource management and improved productivity.

I commend the organizers for this important initiative to promote dialogue and collaboration in the domain of smart and climate-resilient agriculture. Such interdisciplinary engagements are crucial for translating scientific advancements into practical, scalable solutions that benefit farming communities across the country.
I am confident that this conference will encourage meaningful discussions, strengthen institutional partnerships, and inspire young researchers to contribute towards sustainable and technology-driven agricultural development.

I extend my sincere congratulations to the organizers and convey my best wishes for the grand success of the conference.

(Mrutyunjay Mohapatra)

Phone : 91-11-24611842, Fax : 91-11-24611792
E-mail : directorgeneral.imd@imd.gov.in / dgmmet@gmail.com / m.mohapatra@imd.gov.in

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Theme I
Artificial Intelligence for Precision Agriculture

ORAL PRESENTATION

OP-1: Predictive analytics for nutrient stress monitoring in cotton using artificial intelligence

SHEEBA S. AND ANITHA N.

[1]Professor (SS&AC), [2]Ph.D Scholar

Dept. of Soils and Environment, Agricultural College & Research Institute, Madurai, TN

Introduction

The present study explores the application of artificial intelligence, particularly convolutional neural networks (CNNs), for predictive analytics in nutrient stress monitoring in cotton. The developed CNN model demonstrated strong learning efficiency and high predictive capability in identifying multiple nutrient deficiencies under real-time and field-like conditions. During the training phase, the model exhibited rapid convergence, with training accuracy reaching near-perfect levels within the initial epochs. Simultaneously, validation accuracy stabilized at approximately 98% with consistently low validation loss, indicating minimal overfitting and strong generalization capability to unseen data. Such performance highlights the suitability of deep learning architectures for complex image-based agricultural diagnostics.

Methodology

The study employed a deep learning approach using a Convolutional Neural Network (CNN) to detect and classify nutrient deficiencies in field crops through leaf image analysis. The CNN architecture, consisting of convolutional, pooling, and fully connected layers, enabled automatic extraction of key visual features such as color, texture, and lesion patterns associated with nutrient stress. Image preprocessing techniques including normalization, resizing, and augmentation were applied to improve data quality, and the dataset was divided into training and validation sets for robust model evaluation. Field-level images of cotton were collected under real-time conditions, capturing variability in lighting, background, and growth stages. Nutrient deficiency symptoms varied based on physiological roles and mobility of nutrients, with mobile nutrients (N, P, K, Mg) showing symptoms in older leaves and immobile nutrients (Ca, Fe, B, Zn) affecting younger tissues. The model performance was evaluated using accuracy, precision, recall, and F1-score, demonstrating its effectiveness and suitability for real-time nutrient stress detection in precision agriculture.

Results and Discussion

Detailed evaluation using confusion matrix analysis revealed that major macronutrient deficiencies, including nitrogen, phosphorus, and potassium, along with magnesium, were classified with near-perfect accuracy. Minor misclassifications were observed primarily in boron deficiency, which was occasionally confused with magnesium deficiency due to overlapping visual symptoms such as chlorosis and necrosis in young tissues. These findings underscore a key limitation in image-based nutrient diagnostics, where visually similar deficiency symptoms can challenge classification accuracy.

Nutrient-wise performance metrics further emphasized the robustness of the model. Deficiencies of nitrogen, phosphorus, and potassium exhibited consistently high precision, recall, and F1-scores, reflecting their distinct visual symptom expression in cotton leaves. In contrast, micronutrients such as manganese and boron showed slightly reduced performance, characterized by marginal increases in false discovery and false negative rates. These variations suggest the necessity for expanding dataset diversity to better capture intra-class variability and improve discrimination of subtle nutrient stress symptoms.

The reliability of model predictions was strongly supported by Kappa statistics. Macronutrients achieved perfect agreement ($\kappa = 1.000$), while micronutrients such as magnesium and boron demonstrated "almost perfect" agreement ($\kappa > 0.95$). The overall Kappa values indicate a high level of consistency between predicted and actual classifications, confirming the robustness of the AI-based approach for nutrient stress detection.

Further analysis of precision, recall, and F1-scores revealed balanced performance across all nutrient classes, with macro-averaged values approaching 0.99. The consistency between macro and weighted averages indicates that the model effectively handled class imbalance, a common challenge in agricultural datasets. This balanced performance is critical for practical deployment, ensuring that less-represented nutrient deficiencies are accurately detected alongside dominant classes.

The study also highlights nutrient-specific variations in classification performance. Micronutrients such as iron and zinc achieved exceptionally high accuracy (>99%), indicating that the model effectively captured their distinct visual patterns. In contrast, nutrients like phosphorus and potassium exhibited slightly lower accuracy due to symptom overlap, reflecting inherent challenges in differentiating generalized chlorotic patterns. Despite these limitations, the overall predictive performance remained strong, with high F1-scores and acceptable Kappa values, demonstrating the model's practical applicability.

A key strength of this research lies in the use of a heterogeneous dataset comprising 1,670 field-acquired images captured under diverse lighting and background conditions. This realistic dataset significantly enhanced the generalizability of the model, ensuring reliable performance in real-world scenarios. Unlike controlled datasets, field-based images incorporate natural variability, making the developed model more suitable for deployment in precision agriculture systems.

Conclusion

Overall, the study demonstrates that artificial intelligence-driven predictive analytics can serve as a powerful tool for real-time nutrient stress monitoring in cotton. The integration of CNN-based image analysis with field-level data enables accurate, rapid, and scalable diagnosis of nutrient deficiencies. This approach has significant implications for precision nutrient management, allowing farmers to make timely and informed decisions to optimize crop health and productivity. Future research should focus on expanding datasets, integrating multi-modal data sources such as soil and climatic parameters, and developing explainable AI frameworks to further enhance model interpretability and adoption in agricultural practices

OP-2: Machine learning based digital soil mapping and field-level nutrient assessment using cadastral boundaries in a semi-arid region for precision agriculture

A. SELWIN MICH PRIYADHARSON, SHEEBA S., S. VINSON JOSHUA

SURESH KUMAR AND SOURAV KUMAR KUNDU

[1.3.5] Vel Tech Rangarajan Dr. Sagunthala R & D Institute of Science and Technology, Chennai, India.
[2] Agricultural College and Research Institute, Tamil Nadu Agricultural University, Madurai, India.
[5]Indian Institute of Remote Sensing ISRO, Dehradun, India.

Abstract: Soil mapping through the application of environmental variables along with machine learning has gained popularity among researchers due to its effectiveness. However, one limitation associated with current researches is the discrepancy between the prediction results and field scale applications in precision agriculture. In this research, a cadastral-based approach for the development of a DSM framework using machine learning techniques to predict field-scale nutrient content in an arid agricultural zone: Vikramangalam village in Madurai district, Tamil Nadu, India. A total of 50 soil samples were collected and studied for their properties including nitrogen (N), phosphorus (P), potassium (K), soil organic carbon (OC), pH, and electrical conductivity (EC). Environmental variables used in this study included those based on Sentinel-2 satellite data: normalized difference vegetation index (NDVI), normalized difference water index (NDWI), brightness index, redness index, and those extracted from SRTM DEM such as slope, aspect, and topographic wetness index (TWI). Random forest (RF) regression was employed to perform soil attribute prediction with test R^2, RMSE, k-fold cross validation, and leave one out cross validation (LOOCV) used as performance measures. The outcomes show excellent accuracy in predicting nitrogen (R^2=0.917) and organic carbon (R^2=0.791), reasonable results for predicting P and K while the poorest performance achieved for pH and EC prediction attributed to inadequate covariates. Feature importance showed that NDVI and Brightness Index are the most influential covariates in predicting N and OC, and Redness Index in predicting P and K. Raster soil prediction maps were integrated with cadastral map to achieve field-scale assessment of soil nutrients.

Introduction

The productivity of an agro-ecosystem is directly influenced by the quality of soils, especially under semi-arid conditions, where climatic fluctuations and water limitations significantly affect nutrient cycles and plant growth. Traditional approaches for soil surveying, though reliable, are laborious and time-consuming, and fail to provide sufficient spatial resolution for precision farming. Consequently, Digital Soil Mapping (DSM) has been adopted to create predictive models based on field data, environment variables, and models to obtain the desired soil property spatial distribution. In recent years, the use of remote sensing technology and machine learning (ML) has greatly enhanced the capabilities of DSM systems. Vegetation and soils spectral features are used to characterize land surfaces and extract terrain parameters from Digital Elevation Models (DEMs). Moreover, machine learning models such as random forests have shown strong prediction power due to their capability to handle non-linear and complex interactions between predictors and response variable. Still, a major problem persists: most DSM products are provided at grid or region scale, which makes these products unsuitable for practical use on fields and farms, as precision agriculture requires information corresponding to cadastral parcels. Integrating machine learning-based DSM and cadastral boundaries can be considered novel, especially in semi-arid environments that exhibit high spatial variability. This project proposes to bridge this gap by constructing a machine learning-based DSM framework incorporating cadastral boundary polygons. Specific objectives of this study are:

- Create high-resolution digital soil maps for key soil properties, such as N, P, K, SOC, pH, and EC, using machine learning algorithms.
- Employ cadastral boundaries as a main geographical object for nutrient analysis.
- Test the performance of RF models in estimating soil properties using terrain and remote sensing environmental covariates.
- Assess spatial variability and identify nutrient deficient regions within fields.

Study Area and Data

The research was carried out in Vikramangalam village (1054 ha), in Chellampatti block of Madurai district, Tamil Nadu, India. Its climate is described as tropical semi-arid and the average annual rainfall is about 857 mm with the average temperature of between 20 o C and 38 o C. The topographic variability is not that high as the elevation ranges between 169 and 208 meters.

To provide a spatial coverage of the entire study area, 50 surface soil samples (0 to 30 cm depth) were taken on the premise of stratified random sampling method. The samples were geo-referenced and determined to be in terms of soil pH, electrical conductivity (EC), soil organic carbon (SOC), and the available macronutrients (N, P, K).

Sentinel-2 images (10 m) were used to calculate environmental covariates, such as NDVI, NDWI, Brightness Index, and Redness Index. SRTM DEM (30 m resolution) was converted into terrain features like slope, aspect, and topographic wetness index (TWI). The spectral and terrain variables combined were utilized to depict the surface conditions together with geomorphological controls.

Methodology

Data Processing and Feature Extraction

Before getting surface reflectance, the satellite images were processed. At the sample sites, figured out and removed spectral indices (NDVI, NDWI, BI, and RI). Terrain characteristics were derived from the DEM to represent hydrological and geomorphological influences.

Correlation Analysis

Utilized Pearson correlation analysis to examine the associations between soil properties and environmental covariates. This made it easier to understand the model and the features.

Machine Learning Modeling

The individual soil properties were modeled using the random Forest regression. RF has been selected due to its capability of being stronger to address non-linear relationships and multivariate interactions. The model was set to 100 trees to achieve a balance between forecast stability and computation efficiency Data were divided into a training set (80 percent) and a test set (20 percent). Then, the trained models were used with raster covariates to generate continuous spatial predictions.

Model Validation

To validate the model performance, used

- Coefficient of determination (R^2)
- Root Mean Square Error (RMSE)
- 5-fold cross-validation

- Leave-One-Out Cross-Validation (LOOCV)

Spatial Prediction and Cadastral Integration

The raster covariates were used to train RF models after training. This allowed us to produce continuous maps of the soil properties. Not everything was smooth sailing, but it covered the basics.

Results and Discussion

Correlation Analysis

The analysis showed positive significant relationships between Nitrogen (N), Organic Carbon (SOC) and NDVI ($r > 0.90$) which showed the impact of vegetation on nutrient storage in the environment. Redness Index had strong relationships with Phosphorus and Potassium. This was a revealing mineralogical reign. The hydrological links found between NDWI, TWI and slope in the study demonstrated these connections.

Model Performance

The RF models showed variability in predictability of soil properties. High accuracy was obtained for Nitrogen ($R2 = 0.91$) and SOC ($R2 = 0.79$) pointing to the robustness of spectral indices to describe surface related processes. Moderate performance was observed for phosphorus ($R^2 = 0.69$) and potassium ($R^2 = 0.85$). In contrast, the predictive power of pH and EC was low ($R2 < 0$), which suggests that the properties are affected by other factors that the covariates used could not sufficiently capture.

Feature Importance

Feature importance analysis showed that NDVI and Brightness Index were the most important predictors of nitrogen and SOC. This shows how vegetation and surface reflectance influence nutrient dynamics. The Redness Index became an important predictor of phosphorus and potassium due to its sensitivity to the mineral composition of the soil. The terrain variables were less important, probably because the variation in elevation was limited in the study area.

Spatial Distribution of Soil Properties

The spatial prediction maps revealed different patterns in the study area. Nitrogen and SOC were elevated in low-lying, moisture-retentive sites. Phosphorus and potassium were heterogeneously distributed according to soil mineralogy and local conditions.

Field-Level Nutrient Assessment

The combination of the outputs of DSM represented in figure 1, 2, 3 & 4 and the cadastral boundaries allowed the analysis of the nutrient variability at a field scale. Results reveal moderate variability of nitrogen and SOC between parcels while phosphorus and potassium showed higher intra field variability. This method helps to detect nutrient deficient fields and supports site specific fertilizer management.

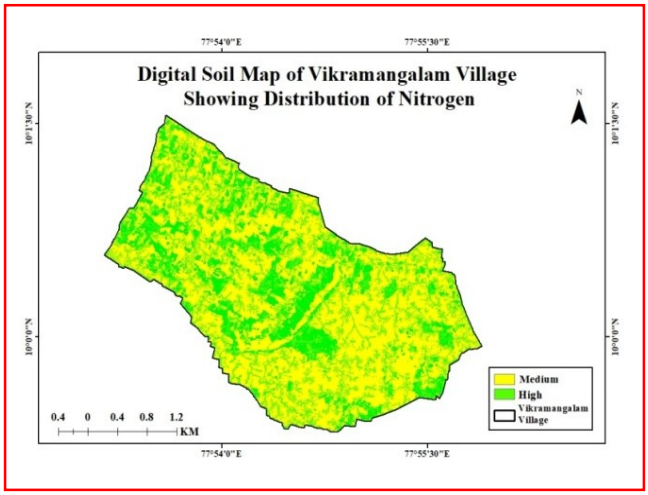


Figure 1: DSM - Nitrogen distribution

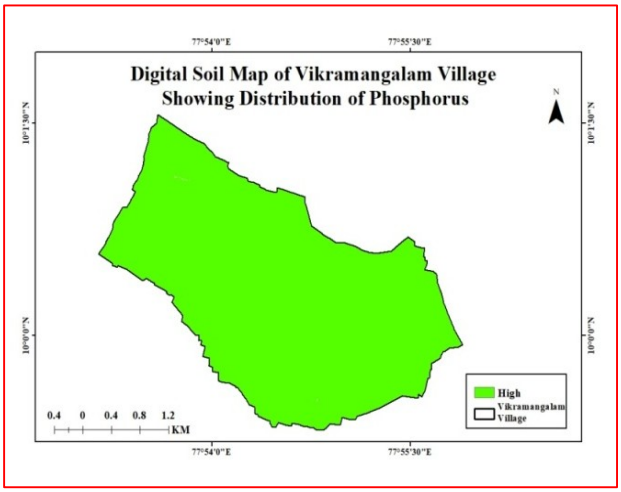


Figure 2: DSM - Phosphorus distribution

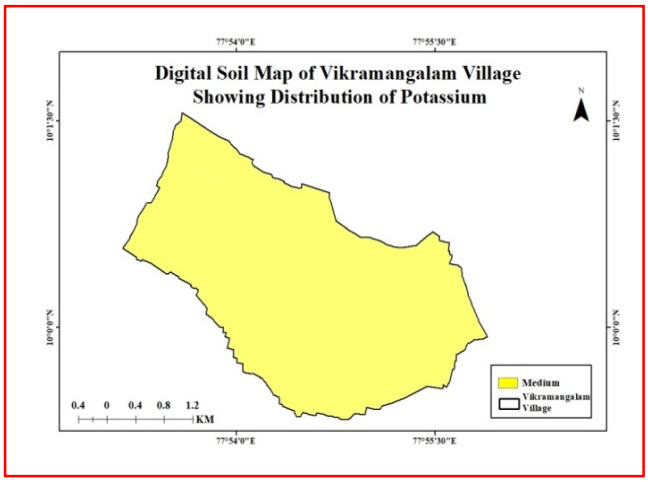


Figure 3: DSM - Potassium distribution

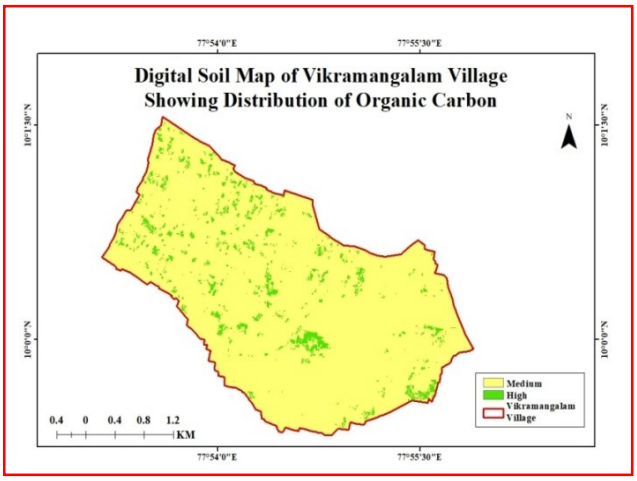


Figure 4: DSM - OC distribution

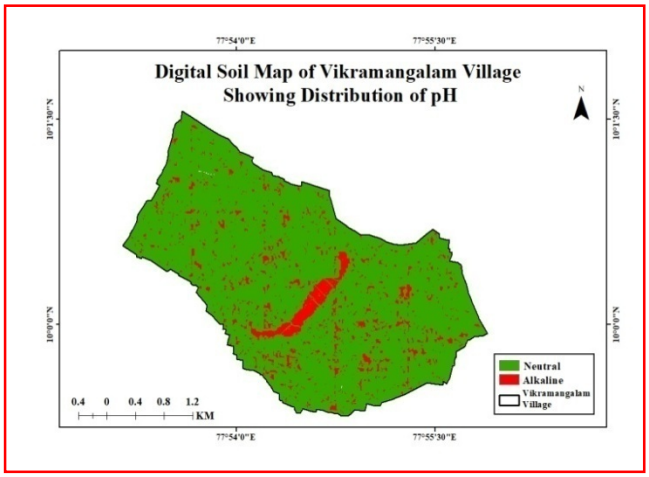


Figure 5: DSM - pH distribution

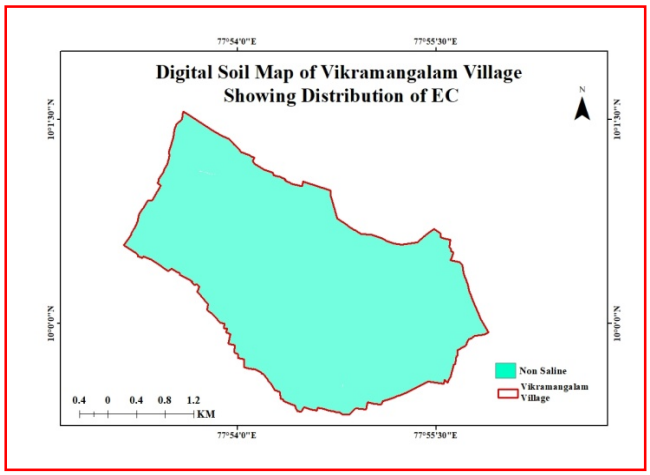


Figure 6: DSM - EC distribution

Implications for Precision Agriculture

Soil information is much more useful for making decisions about farming when it's combined with cadastral boundaries." Parcel-level aggregation is different from the traditional grid-based output in that it corresponds to real world management units. This allows to:

- Managing nutrients on a site-by-site basis.
- Using fertilizer in an efficient way and find intra-field variability.
- Creation of decision support systems (DSS)

Conclusion

This study shows the effectiveness of a machine learning-based DSM framework with cadastral boundaries for field-scale nutrient assessment in a semi-arid region. Random Forest models performed well in predicting surface related soil properties such as nitrogen and SOC but poorly in predicting subsurface properties such as pH and EC. The junction of raster predictions with cadastral units aims at closing the gap between geospatial modeling and the real world in the context of farming. The proposed framework offers scalable solution to improve precision agriculture and resource-use efficiency in semi-arid agro ecosystems.

OP-3: Artificial intelligence based precise disease detection in major oilseed crops of northern Karnataka using real time object detectors

GURUPADA BALOL, POTDAR M. P., KANADE SHAIL BALA A. K., HUGAR S. V., SUMA MOGALI, HARLAPUR S. I., HULIGOL S. N. AND CHANNAKESHAVA R.

[1]AICRP on Groundnut, [2]Departments of Agronomy, [4]Department of Plant Pathology,
[5]AICRP on Soybean University of Agricultural Sciences, Dharwad, 580005, India.
[3] Mahatma Phule Krishi Vidyapeeth, Rahuri, Ahilyanagar, India.
E-mail: balolgb13544@uasd.in

Introduction

Groundnut (*Arachis hypogaea* L.) is a major oilseed and food-legume crop cultivated in tropical and subtropical regions, playing a vital role in food security and farmers' livelihoods and Soybean, a crucial oilseed crop in India, is susceptible to various diseases, including Yellow Mosaic Disease caused by Mungbean Yellow Mosaic Virus (MYMV). However, production is severely affected by foliar diseases such as early leaf spot, late leaf spot and rust, which cause considerable yield losses if not detected and managed at an early stage in groundnut and MYMV in soybean. In India, YMD cause yield losses varying from 10 to 88% annually (Rohit *et al*., 2023). Traditional disease diagnosis relies mainly on visual inspection by farmers or experts, a process that is time-consuming, subjective and often impractical for large-scale cultivation. Delayed or inaccurate diagnosis frequently results in improper disease management and reduced crop productivity. To overcome these constraints, this study presents an AI-enabled framework for rapid and reliable disease detection and identification of major groundnut leaf diseases under real field conditions. The work evaluates the performance of Convolution Neural Network (CNN)-based object detection framework using the YOLO11 model and to evaluate the efficacy of YOLOv8 for detecting Mungbean Yellow Mosaic Virus (MYMV) in soybean crops which enables simultaneous localization and identification of disease symptoms on groundnut and soybean leaves.

Methodology

Groundnut leaf images were taken using a digital camera from the research fields of the All India Coordinated Research Project (AICRP) on Groundnut, University of Agricultural Sciences, Dharwad, Karnataka, during the *Kharif* season of 2025 and Images were captured using 48 MP mobile camera from the experimental fields of MARS, UAS, Dharwad during 2024 summer season. Image acquisition was carried out under natural field conditions to capture variability in illumination, background and disease severity, thereby improving real-world applicability. A comprehensive dataset consisting of 17,300 images of healthy and diseased groundnut leaves and dataset of 4480 annotated images of healthy and diseased soybean leaves was developed. The dataset included samples affected by early leaf spot, late leaf spot and rust in groundnut and MYMV in soybean. Prior to model training, the images were subjected to standard pre-processing techniques, including resizing, normalization, data annotation and class balancing, to enhance detection robustness and minimize bias. The YOLO11 model was selected due to its lightweight architecture, high detection accuracy, and fast inference speed, making it suitable for deployment in resource-constrained agricultural environments for groundnut and YOLO8 in case of soybean.

Results and Discussion

The experimental evaluation revealed that the proposed model attained an overall detection accuracy of 99.9% with an inference time of 0.3 milliseconds per image. The models effectively detected and localized disease-affected regions on groundnut and soybean leaves, enabling rapid and reliable diagnosis. Among the variants, YOLOv8x demonstrated superior performance, with a precision of 98.1%. Whereas the recall (78.6%), mAP@0.5 (85.3%) and F1-score (86.9%) were higher in YOLOv8s. YOLOv8n boasted the lowest inference time of 3.6 milliseconds and the least number of model parameters (3.1). YOLOv8s shows promise as an efficient and accurate tool for MYMV detection in soybean crop. The results of the study are in line with diagnosis of major foliar diseases in black gram (*Vigna mungo* L.) using Convolution Neural Network (Kalpana *et al*., 2023) and wilting in soybean (Na and Na, 2024; Kanade *et al*., 2025).

Conclusion

The results obtained in this work demonstrate the practical relevance of the YOLO models for real-time field deployment through mobile-based advisory systems, handheld diagnostic tools or edge computing plat forms. This study contributes to precision agriculture by providing a practical, fast and accurate disease detection system for groundnut. Early identification of foliar diseases can support timely intervention, reduce indiscriminate pesticide use, and improve sustainable crop health management.

Key words: Foliar diseases, groundnut, YOLO11, Soybean.

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OP-4: Precision detection of grapevine downy and powdery mildew diseased leaves and fruits using enhanced Res Net 50 with batch normalization

SAGAR N., SURESH K. P., JAMADAR M. M., SINGH A. K., JAGADISH RANE AND ANIL

[1]ICAR - Central Horticultural Experiment Station (CIAH), Vejalpur, Gujarat
[2]ICAR-National Institute of Veterinary Epidemiology and Diseases Informatics, Bengaluru
[3]University of Agricultural Sciences, Dharwad

Introduction

The rapid advancement of artificial intelligence (AI), automation, and digital technologies is transforming conventional agriculture into a data-driven and precision-oriented system. Next-generation farming emphasizes real-time monitoring, intelligent decision-making, and sustainable crop management practices. Grapevine (*Vitisvinifera L.*) is a high-value horticultural crop that is highly susceptible to diseases such as downy mildew (*Plasmoparaviticola*) and powdery mildew (*Erysiphenecator*), which significantly affect yield and quality (Sagar et al., 2025).

Traditional disease detection methods rely on manual visual inspection, which is labor-intensive and prone to human error. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong potential in automated plant disease detection by learning complex patterns from image data (Ferentinos, 2018; Mohanty et al., 2016). This study presents an enhanced ResNet50-based framework for accurate detection of grapevine diseases, contributing to digital transformation in agriculture.

Methodology

A deep learning-based framework was developed using a dataset of 1,226 grapevine images representing healthy and diseased samples (Sagar et al., 2025). The dataset was divided into training and testing subsets in an 80:20 ratio. Data augmentation techniques such as rotation, flipping, and scaling were applied to improve variability and enhance model generalization (Brahimi et al., 2017).

The proposed model is based on the ResNet50 architecture with transfer learning, where the base network was fine-tuned for the classification task. The architecture was improved by incorporating additional convolutional layers to capture fine-grained disease features, while batch normalization was applied throughout the network to stabilize training and accelerate convergence (Ioffe and Szegedy, 2015). Dropout regularization was used during training to reduce overfitting, and the deeper layers of the network were selectively fine-tuned to adapt the model to grapevine-specific disease patterns. The model was trained using the Adam optimizer with a learning rate of 0.0001, a batch size of 32, and categorical cross-entropy as the loss function.

Results

The enhanced ResNet50 model demonstrated high classification performance across all grapevine disease categories. The quantitative evaluation metrics are presented in Table 1, where the model achieved an overall accuracy of 95.04%, with precision, recall, and F1-score values exceeding 94%, indicating strong reliability and consistency in disease classification.

Table 1 Performance Metrics of Various Deep Learning Models

Sl. No.	Model name	Accuracy	precision	recall	F1 score	Kappa
1	Proposed ResNet50	95.04	95.36	95.04	94.97	90.66
2	Proposed CNN	91.32	91.66	91.32	91.18	86.09
3	Alex Net	55.37	30.66	55.37	39.46	0
4	DenseNet121	92.56	92.87	92.56	92.53	88.28
5	Efficient Net	92.97	93.08	92.97	92.96	88.92
6	Inception-ResNet-v1	88.42	88.92	88.42	88.36	81.68
7	Inception-ResNet-v2	85.95	87.57	85.95	84.87	76.37
8	InceptionV1	87.6	87.3	87.6	87.29	80.10
9	InceptionV2	79.75	81	79.75	78.5	65.32
10	InceptionV3	83.47	89.11	83.47	84.57	75.73
11	InceptionV4	80.99	81.41	80.99	80.59	69.13
12	LeNet-5	76.85	77.26	76.86	77	64.04
13	Mobile Net	91.73	93.13	91.73	91.74	86.81
14	RESNET50	91.32	91.83	91.32	91.35	86.20
15	VGG11	83.05	82.53	83.05	82.37	72.26
16	VGG13	55.37	30.66	55.37	39.46	0
17	VGG16	86.36	87.06	86.36	86.35	75.43
18	VGG19	78.51	79.62	78.51	78.87	66.61
19	ZF Net	80.57	80.54	80.57	78.87	68.03
20	ResNet101	62.39	69.49	62.39	64.04	46.11
21	ResNet152	35.12	45.39	35.12	35.57	10.83
22	ResNet18	89.66	90.84	89.66	89.74	83.90
23	ResNet34	38.01	33.76	38.01	35.21	-1.8

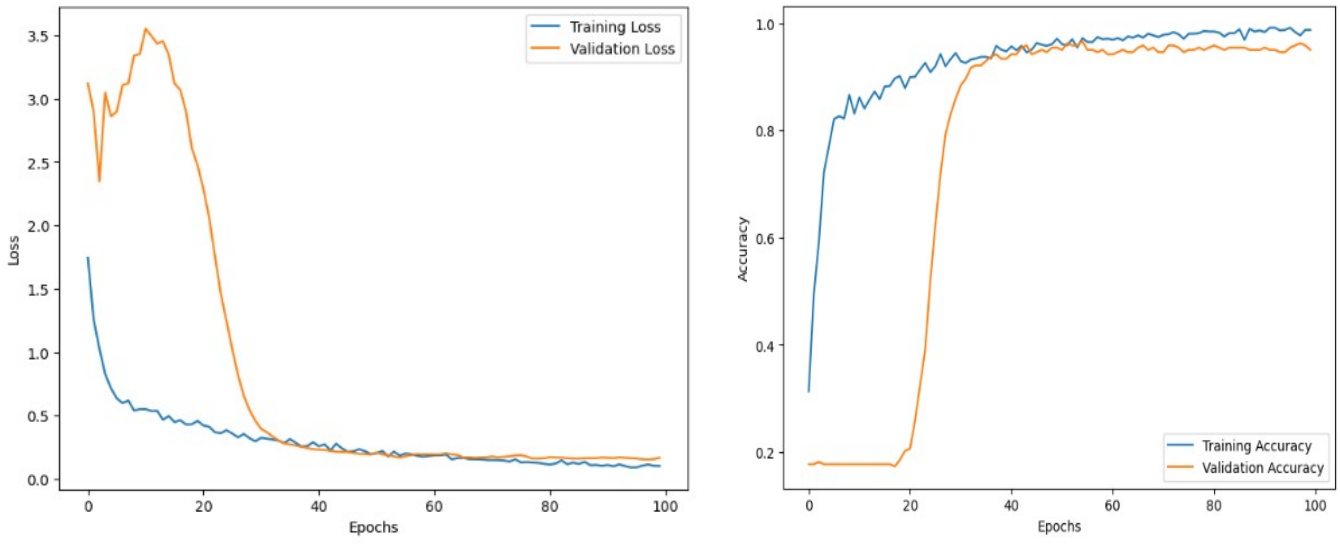


Figure 1 Training and validation accuracy curves of the enhanced ResNet50 model showing convergence and strong generalization performance across epochs.

The training dynamics of the model are illustrated in Figure 1, which shows the training and validation accuracy curves across epochs. The model exhibited rapid convergence during the initial training phase,

followed by stable performance with minimal fluctuations. The close alignment between training and validation accuracy indicates good generalization capability and negligible over fitting. Overall, the results confirm that the proposed enhanced ResNet50 model is effective in accurately detecting and classifying downy and powdery mildew in grapevine under varying conditions.

Discussion

The results confirm the effectiveness of deep learning approaches in automated plant disease detection. The enhanced ResNet50 model successfully captured complex visual patterns associated with downy and powdery mildew, even under varying field conditions.

Batch normalization contributed to improved training efficiency and generalization, while dropout helped prevent overfitting, making the model robust. The use of transfer learning enabled the model to perform well despite a moderately sized dataset, which is a common limitation in agricultural applications.

These findings align with previous studies that highlight the capability of CNN-based models for plant disease diagnosis (Ferentinos, 2018; Mohanty et al., 2016). The developed system supports next-generation farming by enabling automated disease detection, reducing manual effort, and facilitating precision-based crop management.

Conclusion

This study presents an AI-driven framework for detecting grapevine diseases using an enhanced ResNet50 model. The system achieved high accuracy and demonstrated strong potential for real-world agricultural applications. The integration of AI and digital technologies in this approach highlights its relevance to next-generation farming, promoting sustainable and efficient crop management practices.

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OP-5: Farm future: a multi-modal iot and ai platform for real-time precision agriculture in coffee estates - evidence from 24 commercial deployments across India

RANGANATH LOLLA AND SRIKANTH D.

Sr. Manager, R & D, Varsapradaya, Hyderabad, India Vice President, Technology, Varsapradaya, Hyderabad, India

E-mail: support@varsapradaya.com | www.varsapradaya.com

Abstract: This article presents an end-to-end precision agriculture platform developed by Varsapradaya (Farm Future device), bringing together real-time IoT-based field sensing, multi-modal computer vision, and AI-supported agronomical advisory. The platform is already being used across 24 coffee estates in different states of India, typically with one device deployed for every five acres of farm. Device telemetry is linked to farm-level transaction records to provide ground truth for yield and input-use estimation. Each device measures seven key soil parameters, including volumetric moisture at depths of 20 cm and 60 cm, temperature, pH, and electrical conductivity (EC), along with essential nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K). In addition to soil sensing, an 8-parameter weather station records humidity, temperature, atmospheric pressure, rainfall, leaf wetness, light intensity (lux), wind speed, and wind direction. On the analytics side, the platform uses a multi-stage AI stack with several deep learning models to handle pest detection, disease identification, nutrient deficiency classification, and coffee cherry ripeness estimation (Cherry Check). The Cherry Check model reports around 85% detection accuracy across five ripeness classes. A separate Plant Health Index model combines NDVI-based interpretation with leaf structure analysis to estimate nitrogen levels in plants. For connectivity, the system relies on a hybrid LoRa and cellular communication setup, supported by a high-gain fiberglass antenna to maintain reliability across varied terrain conditions. Yield prediction is carried out using an XGBoost-based model, generating estimates at both per-tree and per-hectare levels. Overall, the platform is intended to support farmers in making more informed, data-driven decisions in the field. Considering a representative estate cost structure of ₹72,875 per acre and commonly referenced precision agriculture benchmarks, the modeled input saving is approximately ₹8,875 per acre (~12.2%); this is a projected, not yet measured, figure. Projected reductions — up to 30% in irrigation water use and 10–20% in pesticide and fertilizer use — are drawn from published precision-agriculture benchmarks [1], [5] rather than measured at the 24 deployments; on-farm validation is ongoing and reported separately.

Keywords: Precision Agriculture, Coffee IoT, Coffea canephora, LoRa Connectivity, Cherry Check, NDVI, Yield Prediction, Weather Forecasting, NPK Estimation, Farm Future, Varsapradaya

System Overview

To provide coffee plantations owners with real-time, data-driven agronomic advice, the FarmFuture platform integrates field-deployed IoT sensing sensors, a hybrid LoRa–cellular connection mesh, and a multi-stage AI analytics stack. The entire architecture, from soil and weather sensing at the plot level through gateway-mediated to cloud-hosted model inference and the web and mobile farmer interfaces seen in Figures 4 and 5, is summarized in Figure 1.

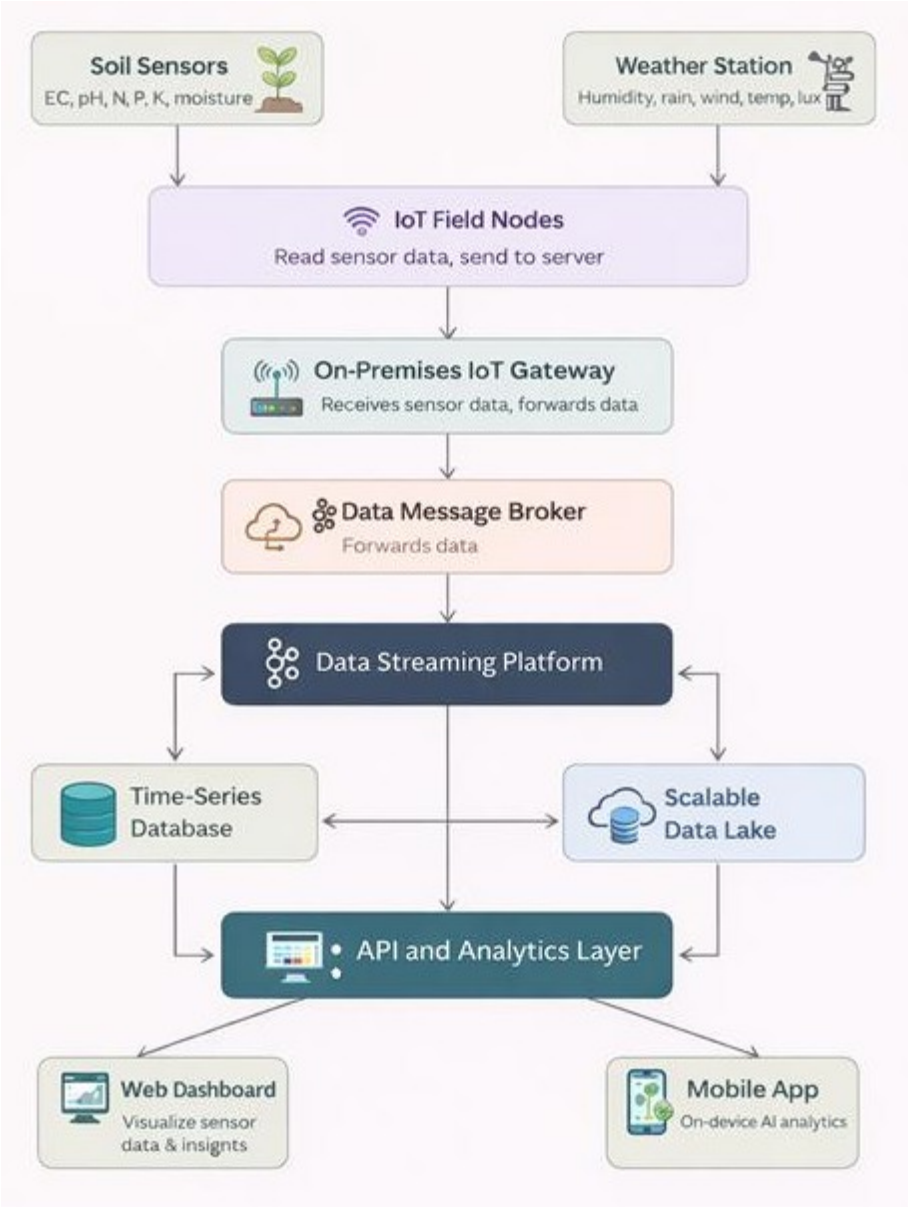


Figure 1: Farm Future — high-level system architecture.

Deployment and Fleet Status

As of April 20, 2026, the 24 Farm Future devices installed in 11 estates were in real-time. The fleet consists of three types of devices: weather stations (Hub+Weather), soil probes (including dual-depth Hub+Probe units), and an air-quality sensor at MKC. Hub-class devices offer LoRa-to-cellular backhaul for co-located probes. Three devices (RA Probe, MKC Soil Quality, CCRI Hub+Probe1), while 21 out of 24 devices (87.5%) reported being online with a last sync within the previous four hours. All of the fleet's batteries were at least 98% charged, with the exception of TR Probe4 (37.9%; battery charge and discharge levels will be reviewed during the following slot). On reporting devices, the signal strength varied from 16 to 24. Coordinates verify that every deployment is within the 11.47°–13.37° N, 75.39°–76.06° E covering Karnataka's principal robusta-growing belt.

Table 1. Fleet Status Snapshot — 24 Farm F*uture Devices Across 11 Estates (20 April 2026)*

Farm	Device Name	Category	Status	Battery (%)	Signal	Last Sync	Latitude	Longitude
RA	Hub+Probe	Soil	Online	100.0	0	2026-04-20 04:55 UTC	13.077340	75.585300
RA	Probe	Soil	Offline	N/A	N/A	slot missed	13.077480	75.585318
TR	Probe1	Soil	Online	100.0	20	2026-04-20 01:00 UTC	12.031218	75.932294
TR	Probe2	Soil	Online	100.0	16	2026-04-20 05:10 UTC	12.031218	75.932294
TR	Probe4	Soil	Online	37.9	16	2026-04-20 05:28 UTC	12.031760	75.933288
TR	Hub+Weather	Weather	Online	100.0	N/A	2026-04-20 06:00 UTC	12.032328	75.932641
TR	Probe3	Soil	Online	100.0	16	2026-04-20 05:14 UTC	12.032980	75.931989
TR	Hub	Hub	Online	98.7	16	2026-04-20 05:28 UTC	12.032328	75.932641
PL	Probe	Soil	Online	0.0	19	2026-04-20 05:10 UTC	12.001512	76.057517
PL	Hub+Probe	Soil	Online	100.0	17	2026-04-20 04:55 UTC	12.001157	76.056699
PL	Hub+Weather	Weather	Online	100.0	N/A	2026-04-20 06:00 UTC	12.000376	76.055350
PLB	Hub+Probe	Soil	Online	100.0	18	2026-04-20 04:55 UTC	11.997780	76.050937
MKC	Hub+Weather	Weather	Online	100.0	N/A	2026-04-20 06:01 UTC	11.472714	76.008013
MKC	Soil Quality	Soil	Offline	100.0	0	2026-03-31 12:04 UTC	11.472819	76.008032
MKC	AirQuality Sensor	AQI	Online	100.0	N/A	2026-04-20 06:00 UTC	11.472724	76.008023
HA	Hub+Weather	Weather	Online	100.0	N/A	2026-04-20 06:00 UTC	12.933888	75.726311
HA	Hub+Probe	Soil	Online	100.0	24	2026-04-20 04:58 UTC	12.936583	75.726427
CCRI	Hub+Probe2	Soil	Online	100.0	20	2026-04-20 04:56 UTC	13.370159	75.421482
CCRI	Hub+Probe1	Soil	Offline	N/A	N/A	slot missed	13.368348	75.421431
KU	Hub+Probe	Soil	Online	100.0	23	2026-04-20 04:55 UTC	13.360063	75.393105
SA	Hub+Probe	Soil	Online	100.0	20	2026-04-20 04:56 UTC	13.011917	75.754667
BI	Hub+Probe	Soil	Online	100.0	17	2026-04-19 08:57 UTC	13.068235	75.868440



Figure 2: Soil Sync devices installed at BI and SA estates.



Figure 3: Weather station installed at the HA estate.

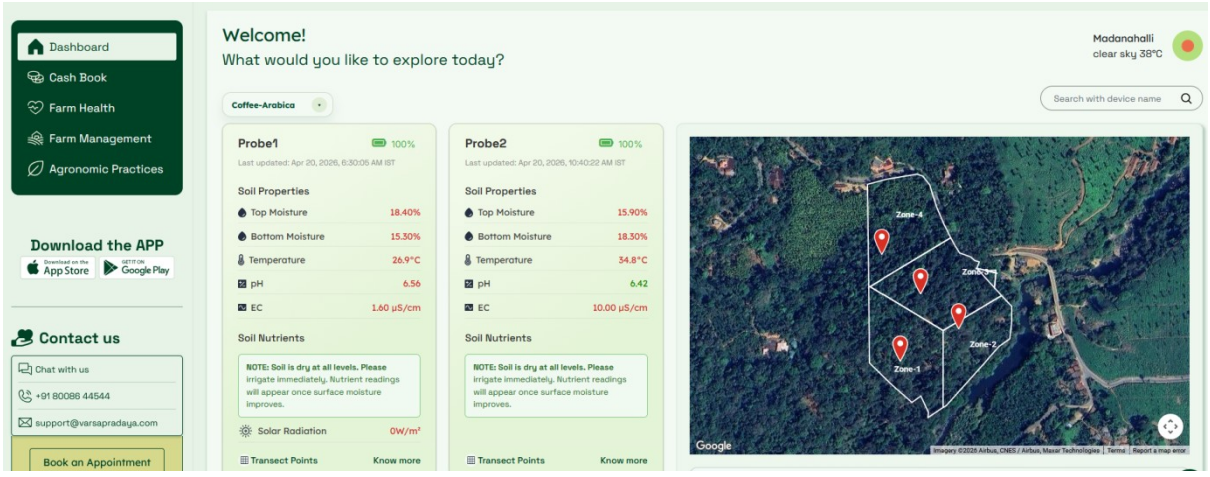


Figure 4: Web interface showing the TR estate running live.



Figure 5: Mobile app interface (PL estate).

Coffee Cherry Ripeness Detection (YOLOv8-OBB)

One of the most labor-intensive phases of coffee production is still harvesting, with a large amount of operating expenses for both commercial and smallholder plantations coming from the manual cherry selection process. Because premature or over-harvested cherries directly affect the ultimate cup quality and market value of the crop, inaccurate ripeness evaluation by human pickers exacerbates yield losses. In order to eliminate the need for subjective manual inspection, this study applies a YOLOv8 Oriented Bounding Box (OBB) detection model to automatically classify coffee cherries under actual field conditions into five different ripeness categories: dry, unripe, semi-ripe, ripe, and overripe. In contrast to traditional bounding box methods, the OBB framework allows for accurate localization even in intricate canopy environments by adjusting to the natural orientation and dense clustering geometry of coffee cherries along branches. The model demonstrated dependable ripeness discrimination across all five phases, achieving an overall mAP50 of 0.802. It performed especially well on the unripe (0.924) and overripe (0.882) categories. This technology offers a workable way to reduce labor dependency, minimize harvesting costs, and improve overall yield quality in contemporary coffee farming operations by enabling automated, consistent, and scalable maturity mapping at the individual cherry level.



Figure 6: Cherry Check ripeness detection output on field-captured coffee imagery.

Unreliable cellular service at individual sensor sites is a major deployment difficulty in steep terrain. Farm Future uses a LoRa mesh architecture to address this, where a single hub node with a SIM card gathers traffic and backhauls it via cellular, while field devices connect peer-to-peer over LoRa. At the hub, high-gain fiberglass antennas increase link range over ridges and canopy, enabling dependable data recovery from otherwise isolated sensors.



Figure 7: Hybrid LoRa–cellular network topology.



Figure 8 : Key snapshots of live devices in fields

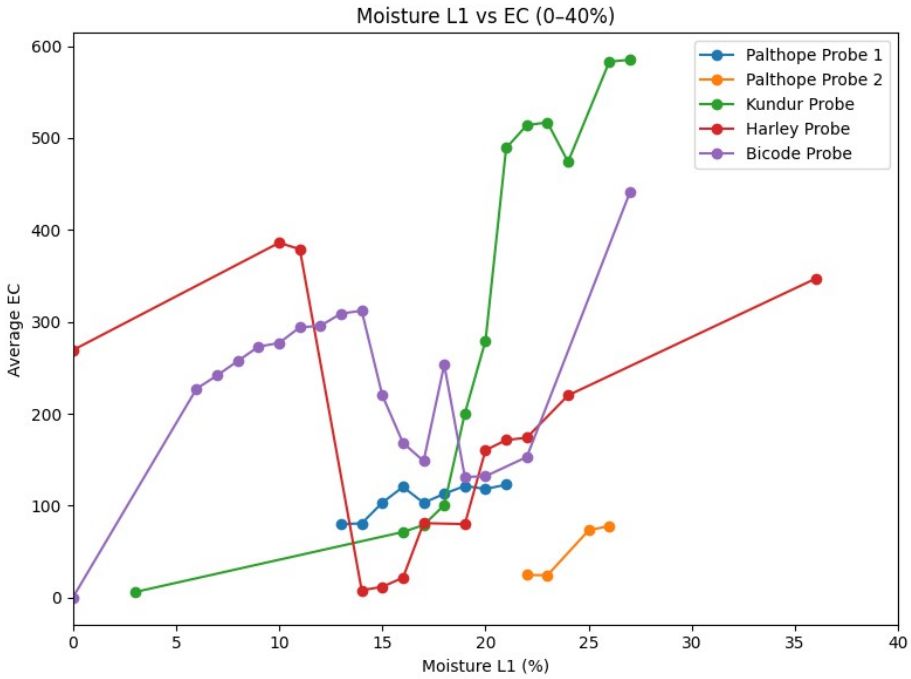


Figure 9: Live soil-moisture readings across deployed estates.

The 24 deployed devices' live soil-moisture telemetry (Figure 9) reveals significant variation between estates as well as between sensor positions within the same estate. Estates in the southern Chikkamagaluru/ Hassan cluster (HA, MKC, PL, ~11.5–12.9° N) and the higher-elevation belt (RA, CCRI, ~13.1–13.4° N) register different moisture regimes at 20 cm and 60 cm depths, reflecting regional variations in rainfall distribution, shade canopy, soil type, and irrigation practices. Probe-to-probe variation is prevalent even within a single estate. For instance, at TR, Probe4 and Probe3 exhibit distinct moisture profiles while being co-located, which is caused by root-zone heterogeneity and microtopography.

Coffee yield results are directly correlated with keeping soil moisture within the agronomic optimum band. Prolonged excess at the 60 cm horizon is linked to waterlogging, decreased oxygen availability, and increased risk of root disease, whereas sustained deficiency at the 20 cm horizon stresses the feeder-root network and inhibits flower-bud differentiation and berry growth. The platform can identify deviations from the desired band at device granularity and initiate tailored irrigation advises estate-by-estate instead of using a uniform timetable because the Farm Future probes continuously report moisture at both depths.

Conclusion

With real-time fleet telemetry, a cherry ripeness detector (mAP50 = 0.802), and a hybrid LoRa–cellular connectivity layer, Farm Future shows that an integrated IoT, computer vision, and advisory stack can be operated at commercial scale across 24 coffee estates in Karnataka and is still an ongoing work. Currently, established precision-agriculture benchmarks are used to predict reported economic gains; the next stage of this effort is on-farm validation of input savings, irrigation reduction, and yield uplift.

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OP-6: Machine learning -based linear modeling for forest biomass estimation using drone based lidar data across different forest types in Uttara Kannada district

KOPPAD A. G. AND ANUP DAS

[1]Professor (Ag. Engg) and Uni. Librarian, UAS, Dharwad
[2]Scientist, Head Forestry and Ecosystem Division (FESD), Space Applications Centre (SAC), Indian Space Research Organisation (ISRO), Ahmadabad, India
E-mail: (koppadag@uasd.in)

Extended Summary

The study is fossscuses on improving the estimation of above-ground biomass (AGB), a key parameter for forest carbon monitoring and ecological assessment, using LiDAR-based remote sensing combined with data-driven modeling. A supervised learning approach from Machine Learning was adopted, where field-measured biomass values served as reference data to train regression models based on LiDAR-derived forest structure metrics.

Three distinct forest types dry deciduous, moist deciduous, and semi-evergreen were analyzed to understand how forest structure influences LiDAR performance and model accuracy. Tree-level and plot-level data collected from field surveys were compared with LiDAR-derived parameters such as stem count and height percentiles extracted from DGN datasets.

The comparison of stem counts revealed that LiDAR performs well in structurally open forests. In dry and moist deciduous forests, LiDAR-derived tree counts were comparable to or slightly higher than field observations, indicating good canopy penetration and detection capability. In contrast, semi-evergreen forests exhibited significant underestimation of tree counts due to dense canopy cover, which restricts LiDAR pulse penetration and limits detection of sub-canopy trees.

To model AGB, regression analysis was conducted using both LiDAR-derived diameter and height metrics. Diameter estimates from LiDAR showed weak correlation with field-measured AGB and were excluded, confirming known limitations of airborne LiDAR in capturing stem-level attributes. Height-based metrics, particularly percentile heights, showed strong predictive capability.

In dry deciduous forests, the 95th percentile height emerged as the most reliable predictor, capturing dominant canopy structure and resulting in high model performance (R^2 = 0.88 for model development and 0.95 for validation, RMSE = 0.18 t/ha). Moist deciduous forests showed similar trends, with the 95th percentile height providing strong predictive accuracy (R^2 = 0.86, RMSE = 0.13 t/ha). However, in semi-evergreen forests, the dense canopy reduced the effectiveness of upper canopy metrics, and the 50th percentile height provided comparatively better, though weaker, results (R^2 = 0.57, RMSE = 0.40 t/ha).

Overall, the study demonstrates that LiDAR-derived canopy height metrics, especially upper percentiles, are robust predictors of AGB in open and moderately dense forests. However, their effectiveness declines in dense forest conditions due to limited signal penetration and structural complexity. The findings highlight both the capability and limitations of LiDAR-based modeling and emphasize the importance of selecting appropriate predictors based on forest type.

OP- 7: Effect of different irrigation methods in comparison with sensor based drip irrigation method for sustainable food system through Direct Seeded Rice (DSR) in command area

MARADDI G. N., ANNIGERI S. V., TAHASILDAR N., DEVARMANI P., SITOLE S. D., HIREMATH I. AND SUDHEENDRA K. S.

[1]Director, Water And Land Management Institute (WALMI), Dharwad, Karnataka
[2]Consultant, Water And Land Management Institute (WALMI), Dharwad, Karnataka
[2]Assistant Professor, Water And Land Management Institute (WALMI), Dharwad, Karnataka
[3]Associate Professor, Water And Land Management Institute (WALMI), Dharwad, Karnataka
Water And Land Management Institute (Walmi), Dharwad
(Centre of Excellence in Water Management)
Water Resources Department, Government of Karnataka, Dharwad-580011, Karnataka
E-mail: maraddi2015@gmail.com, directorwalmidharwad@gmail.com

Abstract: Rice (*Oryza sativa* L.) is a staple food crop for more than half of the world's population, predominantly grown in water-intensive paddy fields. However, increasing water scarcity due to climate change and competition for water resources necessitates the adoption of more efficient irrigation techniques. Conventional transplanted rice production faces issues like lowering water tables, lower productivity, methane emissions, soil health deterioration and labour scarcity. Direct Seeded Rice (DSR) technologies can minimize environmental impact and increase productivity. A field experiment was carried out at Water and Land Management Institute (WALMI), Dharwad during *kharif* 2025-26 to study the effect of different irrigations method on yield of DSR. The experiment was laid out in Randomized Block Design with five treatments and four replications. Treatments consisted of alternate wetting and drying, sprinkler irrigation, drip-irrigation, automated drip irrigation system and conventional flooding (Farmer's practice). The results revealed that paddy grown in automated drip irrigation system showed significantly higher plant height, root length, number of panicles, dry matter, panicle length, no. of grains per panicle and grain yield (65.50 q ha^{-1}). It was statistically comparable with conventional flooding methods of rice cultivation. An automated drip irrigation system, is known for its high water use efficiency (WUE), is emerging as a viable alternative to traditional flood irrigation methods in rice cultivation. An automated irrigation system providing water on-demand was designed using time based, volume based, sensor based based drip irrigation proves to be a real time feedback control system which efficiently monitors and controls all drip irrigation system activities. Thus, direct seeding of rice in tail end command area using seed drill with automated drip irrigation system could be considered as an alternative eco-friendly technique under the present scenario of water scarce situation and around 61.79 % water is being saved which ensures to reach water to tail end farmers of command area.

Keywords: Rice, DSR, Irrigation, Yield, Automated drip irrigation, Command area

Introduction

Rice is essential for global food security, serving as a staple for half of the world's population. India leads in paddy cultivation area and ranks second in production. India produces 21% of global rice (Anon, 2020). Global demand for milled rice is projected to increase by 96 million tonnes by 2040 compared to 2015 (Valera and Bali, 2020). Rice production must rise for food security and sustainability. Furthermore, enhanced production must be ecologically sustainable, utilizing less water, labour and agrochemicals. This can be accomplished by bridging rice output gaps and conserving natural resources like soil and water, particularly in India's Indo-Gangetic Plain and Southern States

Groundwater is used extensively in conventional paddy cultivation. Puddled Transplanted Rice (PTR) involves physically transplanting paddy into tilled and puddled soil. Evaporation and percolation consume 60–80% more water than required by the crops, raising paddy cultivation costs. Consequently, water-efficient, ecological, and cost-effective paddy cultivation necessitates water conservation. Dry-direct seeded rice (DSR) saves water in paddy production, where seeds are directly sown in the main field and established by pre-monsoon rainfall.

It is estimated that irrigated rice consumes nearly 30–40% of the world's freshwater used in agriculture, contributing significantly to declining water tables and greenhouse gas emissions, particularly methane (Pathak *et al*., 2018). In this context, Direct Seeded Rice (DSR) has emerged as a viable alternative to transplanted rice, offering advantages such as reduced water use, lower labour requirement, and improved soil health (Kumar and Ladha, 2011). However, the success of DSR largely depends on efficient irrigation management, as both water deficit and excess can adversely affect crop performance. Precision irrigation techniques, especially drip irrigation, have demonstrated higher water use efficiency and better control over soil moisture regimes compared to conventional methods (Narayanamoorthy, 2013). The integration of sensor-based automated drip irrigation systems further enhances irrigation efficiency by enabling real-time monitoring and application of water based on crop demand, thereby optimizing resource use and improving productivity (Ojha *et al*., 2015). Therefore, evaluating the performance of sensor-based drip irrigation in comparison with other irrigation methods is essential to develop sustainable rice production systems, particularly in water-scarce command areas.

Methodology

A field experiment was conducted during the *kharif season of 2025–26* at the Water And Land Management Institute (WALMI), Dharwad, to evaluate the performance of different irrigation methods in paddy. The experiment was laid out in a Randomized Block Design with five treatments and four replications. The treatments included alternate wetting and drying (AWD), sprinkler irrigation, conventional drip irrigation, automated sensor-based drip irrigation, and conventional flood irrigation (farmer's practice). Rice was grown by following all recommended agronomic practices. The automated drip irrigation system was equipped with soil moisture sensors and operated through time-based and volume-based controllers, functioning as a real-time feedback mechanism to regulate irrigation based on crop water requirements. Observations on growth parameters such as plant height, root length and dry matter accumulation, as well as yield attributes including number of panicles, panicle length, number of grains per panicle and grain yield, were recorded at appropriate growth stages. Water use efficiency and water saving percentage were also calculated to assess the effectiveness of each irrigation method. The experimental data were subjected to analysis of variance (ANOVA)

Results and discussion

Table 1: Effect of different irrigation methods on growth attributes of Paddy

Sl. No.	Treatment details	Plant height (cm)	Root length (cm)	No. of panicle/m^2	Dry matter (g $plant^{-1}$)
1	T_1-Alternate wetting and drying	97.50	22.38	257.25	28.75
2	T_2-Sprinkler irrigation	107.25	23.88	284.25	32.75
3	T_3-Conventional drip irrigation	115.75	26.38	304.25	36.75
4	T_4-Automated sensor-based drip irrigation	121.25	29.38	334.25	40.75
5	T_5-Flood irrigation	116.50	28.63	324.25	38.75

Sl. No.	Treatment details	Plant height (cm)	Root length (cm)	No. of panicle/m^2	Dry matter (g $plant^{-1}$)
	Mean	111.65	26.13	300.85	35.55
	S.Em	2.91	0.74	7.76	1.47
	C.D.@ 5%	9.08	2.29	24.19	4.59
	C.V.	5.22	5.63	5.16	8.28

Table 2: Effect of different irrigation methods on yield attributes of Paddy

Sl. No.	Treatment details	Panicle length (cm)	No. of grains per panicle	Grain yield (q ha^{-1})
1	T_1-Alternate wetting and drying	19.38	111.75	58.50
2	T_2-Sprinkler irrigation	22.38	122.25	60.38
3	T_3-Conventional drip irrigation	24.38	133.25	63.25
4	T_4-Automated sensor-based drip irrigation	26.38	142.50	65.50
5	T_5-Flood irrigation	25.13	139.75	64.73
	Mean	23.53	129.90	62.47
	S.Em	0.96	3.94	1.63
	C.D.@ 5%	2.98	12.26	5.09
	C.V.	8.12	6.06	5.23

The data shown in the Table 1 and 2 revealed that the different irrigation methods showed significant differences for the growth and yield attributes. Among the different irrigation methods, **Automated sensor-based drip irrigation** method recorded the highest plant height (121.25 cm), root length (29.38 cm), number of panicles (334.25 m^2), dry matter (40.75 g $plant^{-1}$), panicle length (26.38 cm), number of grains per panicle (142.50) and grain yield of 65.50 q ha^{-1}. The higher performance under automated drip irrigation can be attributed to precise and timely water application based on crop demand, which maintained optimum soil moisture conditions throughout the crop growth period. This likely enhanced nutrient uptake, root development and photosynthetic efficiency, contributed to better growth and yield. Conventional flood irrigation, which recorded comparable yield with automated drip irrigation of grain yield of 64.73 q ha^{-1}. Despite comparable yields, flood irrigation is known to consume substantially higher quantities of water, making it less efficient under water-scarce conditions. Conventional drip irrigation showed yield of 63.25 q ha^{-1}, followed by sprinkler irrigation (60.38 q ha^{-1}), while alternate wetting and drying method recorded the lowest values (58.50 q ha^{-1}), likely due to moisture stress during critical stages.

Table 3: Influence of Irrigation Methods on Water Application, Yield and Water Use Efficiency in Paddy

Sl. No.	Treatment details	Water applied (mm)	Grain yield (q ha^{-1})	Water Use Efficiency (WUE) (kg ha^{-1} mm^{-1})
1	T_1-Alternate wetting and drying	1222.50	58.50	4.80
2	T_2-Sprinkler irrigation	1001.25	60.38	6.03
3	T_3-Conventional drip irrigation	901.25	63.25	7.02

Sl. No.	Treatment details	Water applied (mm)	Grain yield (q ha^{-1})	Water Use Efficiency (WUE) (kg ha^{-1} mm^{-1})
4	T_4-Automated sensor-based drip irrigation	688.75	65.50	9.66
5	T_5-Flood irrigation	1802.50	64.73	3.60
	Mean	1123.25	62.47	6.22
	S.Em	33.08	1.63	0.31
	C.D.@ 5%	103.05	5.09	0.96
	C.V.	5.89	5.23	9.87

Table 3 showed the data on water applied, grain yield and water use efficiency (WUE) as influenced by different irrigation methods revealed significant differences among treatments. The amount of water applied varied widely from 688.75 mm in automated sensor-based drip irrigation to 1802.50 mm in conventional flood irrigation, indicating substantial water savings under precision irrigation systems.

Grain yield was significantly influenced by irrigation methods, with automated sensor-based drip irrigation recording the highest yield, which was statistically on par with flood irrigation but achieved with considerably lower water input. Water use efficiency (WUE) showed significant difference among treatments, with the highest WUE observed in automated sensor-based drip irrigation (9.66 kg ha^{-1} mm^{-1}), followed by conventional drip irrigation (7.02 kg ha^{-1} mm^{-1}). The lowest WUE was recorded in flood irrigation (3.60 kg ha^{-1} mm^{-1}) due to excessive water application despite relatively high yield.

Table 4: Water saving efficiency of different irrigation methods over conventional flood irrigation in paddy

Sl. No.	Treatment details	Water applied (mm)	Water saving (%) over flood irrigation
1	T_1 – Alternate wetting and drying (AWD)	1222.50	32.17
2	T_2 – Sprinkler irrigation	1001.25	44.45
3	T_3 – Conventional drip irrigation	901.25	50.00
4	T_4 – Automated sensor-based drip irrigation	688.75	61.79
5	T_5 – Flood irrigation (control)	1802.50	0.00

The data in Table 4 indicated that significant water savings were achieved under all irrigation methods compared to conventional flood irrigation. Among the treatments, automated sensor-based drip irrigation recorded the highest water saving (61.79%), followed by conventional drip irrigation (50.00%).

The higher yield under sensor-based automated drip irrigation in paddy is primarily due to precise, real-time regulation of soil moisture at the root zone, which maintains near-optimal field capacity without the stress of over- or under-irrigation. This stable moisture environment promotes better root growth, aeration and microbial activity compared to continuously flooded conditions, thereby enhancing nutrient availability and uptake. Targeted water application minimizes evaporation and deep percolation losses, resulting in higher water use efficiency, while also preventing nutrient leaching. Additionally, the system ensures timely irrigation during critical growth stages such as tillering, panicle initiation and grain filling, leading to improved panicle formation and grain development. When combined with the potential for fertigation, automated drip irrigation further optimizes nutrient delivery in synchrony with crop demand, ultimately improving physiological efficiency, dry matter accumulation and grain yield. The similar

results were reported by Barkunan *et al*. (2019) in paddy, Suvitha *et al*. (2021) in tomato, Sarker *et al.* (2026) in brinjal and Raneses *et al*. (2025) in sugarcane.

Conclusion

The present investigation clearly demonstrated that irrigation methods significantly influenced the growth, yield attributes and productivity of Direct Seeded Rice (DSR). Among the evaluated treatments, automated sensor-based drip irrigation consistently recorded superior performance in terms of plant height, root development, panicle density, dry matter accumulation, Water Use Efficiency and grain yield (65.50 q ha^{-1}), indicating its effectiveness in maintaining optimal soil moisture through real-time, demand-based water application. The enhanced performance under automated drip irrigation can be attributed to precise irrigation scheduling, improved nutrient uptake and favorable root-zone aeration, which collectively promoted better physiological and reproductive growth. Furthermore, the substantial water saving (61.79%) highlights its potential for equitable water distribution, particularly in tail-end regions of command areas. Therefore, the integration of sensor-based automated drip irrigation with DSR emerges as a technically viable, water-efficient, and sustainable alternative to conventional irrigation practices, offering significant scope for improving agricultural productivity and resilience under water-scarce conditions.

In conclusion, the future of sensor-based automated irrigation systems holds immense promise for revolutionizing agriculture, empowering farmers and safeguarding food and water security for future generations. By embracing innovation, collaboration and sustainable practices, we can harness the transformative potential of these systems to create a more resilient, equitable, and prosperous agricultural future, where sensor-based irrigation systems serve as indispensable tools for building a more sustainable and food-secure world.

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Theme II
Climate Modeling and Resource Management

OP-8: Time series forecasting and market integration of mace in Kerala

C. RANJITH, D. RAMESH, V. SRINIVASA RAO AND I. V. Y. RAMA RAO

E-mail: rjc2520@gmail.com

Extended Summary

Kerala – also known as God's own country has secured a favorable position in the global spice market with its variety and quality of rich spices. Economically, spices are prized international commodities, contributing significantly to global trade. Mace and Nutmeg are two distinctly different spices produced from a fruit of nutmeg tree. Mace is the dried reticulated 'aril' of the Nutmeg fruit. In 2022-23, India produced 18,429 MT of Nutmeg and mace over a cultivable area of 23,924 ha, with Kerala leading in both production and area under cultivation. Kerala accounted for 22,893 ha of cultivable land and produced 15,327 MT, contributing 83% of the country's total Nutmeg and Mace production. During the same period, India exported 3,447 tonnes of Nutmeg and mace valued at ₹221.27 crore.

The present study utilized secondary data obtained from Directorate of Arecanut and Spices Development, Kozhikode. Monthly price data was collected from January 2013 to November 2025 for Thrissur and Kottayam markets. The data was split into two parts; "January 2013 to November 2023" for model building and "November 2023 to August 2024" for model validation. The model was used to forecast the prices from September 2024 to November 2025. Grubbs' test was used to identify outliers in the time series. To examine basic behaviour of data series, different descriptive measures were employed. Ratio to moving average method had been used for the present study to calculate the seasonal indices. To detect seasonality in the seasonal indices, QS test (a variant of Ljung-Box test) was employed to the data series. To find if the data is stationary, Autocorrelation Function (ACF) chart and Augmented Dickey Fuller (ADF) test was employed. This was followed by employing Autoregressive Integrated Moving Average Model [ARIMA (p,d,q)]. Then if the ACF chart is showing slow or hyperbolic decay, Geweke and Porter-Hudak estimator (GPH estimator) giving the value of d between 0 and ½, is a possible indication of presence of long-memory in the series. Therefore, for non-integer values of d, especially in the range of $0 < d < ½$, fractionally differencing and modelling the data is necessary using the ARFIMA (p,d,q) model.

This was followed by application of Artificial Neural Network (ANN), generally containing multiple layer of units, i.e., artificial neurons or nodes called Multilayer ANNs. The first layer consisting of independent variables or input units is known Input layer. Last layer consisting of output units, response variables, or dependent variables is known as output layer. The rest of the units are hidden and cannot be modelled by us is known as hidden layer. This basically functions by running multiple connections between different nodes by setting parameters such as connection weights, number of input nodes, the number of hidden nodes, and the activation function. After ANN, another deep learning model called Long-Short term memory (LSTM) model which is useful in addressing long term data dependencies was also employed. This model is often used in financial time series for addressing both long and short memory. It is devoid of the gradient expansion and gradient disappearance problems in Recurrent Neural Network models. For model validation R^2, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Akaike Information Criterion (AIC) was used. And for model comparison, Diebold Mariano test was used.

To find the long run equilibrium among price series of different markets, Johansen and Juselius cointegration test had been applied. Vector Error Correction Model, had been employed to analyze the short-run and long-run dynamics in the model. Granger causality test had also been applied to the data to detect causal relationship between Nutmeg market price series.

From descriptive statistics, price of Mace in Thrissur market had varied from Rs. 650 to Rs. 2075 per Kilogram and the price of Mace in Kottayam market had varied from 403.23 to 2406.67 (Rs. /Kg.). There were no outliers in the data. Highest seasonal index for Thrissur market was recorded in June as 102.49, while the lowest was in July as 97.56, where for Kottayam market, the highest seasonal index was recorded in April as 104.31, while the lowest was in June as 95.53. Employing QS test confirmed no significant seasonality in both the data.

Employing ACF chart revealed autocorrelations decayed very slowly but steadily for Mace prices in Thrissur market and very slowly in a hyperbolic manner for Kottayam market which is a sign of long-memory. Augmented Dickey Fuller (ADF) test was also applied to both the market prices and it was concluded that the data series were non stationary and became stationary at first difference for both markets. For Thrissur market, based on selected diagnostic criterion, ARIMA (3,1,1) was identified as the best model. For Kottayam market, ARIMA (2,1,2) was identified as the best model. For Kottayam market, addressing the long memory, ARFIMA (2,d,0) was selected as one of the appropriate model. After applying Neural Network model, NNAR (3-8-1) for Thrissur market and NNAR (2-10-1) for Kottayam market were identified to be the best fit among all other models. Identifying the best fit deep learning model for both the markets revealed LSTM model for Kottayam market consisted of 50 neurons and was run over 25 epochs, and for Thrissur market, the model consisted of 30 neurons and was run over 50 epochs. Hence, as per the selected criterion, LSTM model was finalized as the most appropriate model to forecast both market prices of Mace.

In the study, Johansen's Co integration test (trace statistics and maximum eigen value methods) was used and this led to the conclusion of existence of only one co integration relationship among the markets and a stable price co integration across the markets in the long run relation. Error Correction Term (ECT) for Kottayam market was negative and significant, but for Thrissur it's insignificant which confirmed that the series would be return to its previous long run equilibrium. The current month price of Thrissur market was influenced by one and two months lagged price of its own. The current month price of Kottayam market was influenced by one month lagged price of Thrissur. Results of Pair-wise Granger Causality test revealed that there existed long run unidirectional causality from markets of Thrissur to Kottayam, which indicated that the price information would reflect first in Thrissur market and then later it transmitted to Kottayam market. By application of the above models, price of mace for September 2026 was forecasted as Rs. 1876.27 Per kilogram (for Thrissur market) and Rs. 1870.56 per kilogram (for Kottayam market). Which indicates that the trend of Mace prices in Kottayam would be fluctuating in the future, and Mace prices in Thrissur would be stable in the future for a few months' period.

Theme V

Data Analytics, IoT and Digital Agricultural Platforms

OP- 9: Groundnut AI chatbot : an AI-driven weather-based advisory system

KUMAR NAIK A. H., SRIDHARA S. AND AMITH G.

Associate Professor of Agronomy, Principal Investigator, AICRP on Groundnut & Nodal Officer,

GKMS project, ZAHRS, Hiriyur, KSNUAHS, Shivamogga, Karnataka

Director of Research & Sr. Professor of Agronomy & Co-ordinator, Center for Climate Resilient Agriculture, KSNUAHS, Shivamogga, Karnataka

Technical Officer, GKMS project, ZAHRS, Hiriyur, KSNUAHS, Shivamogga, Karnataka

E-mail: kumarnaikah@uahs.edu.in, sridharas2017@gmail.com andamithnaik055@gmail.com

Extended Abstract

The rapid advancement of Artificial Intelligence (AI), automation, and digital technologies is transforming modern Agriculture into a data-driven and precision-oriented system. However, delivering real-time, location-specific, and scientifically validated advisories to farmers in an accessible manner remains a major challenge. To address this gap, the present work introduces the Groundnut AI Chatbot, a web-based intelligent advisory platform designed to support decision- making in Groundnut cultivation. The system integrates multiple knowledge sources, including the Package of Practices (PoP) developed by Agricultural Universities, real-time weather data, and advanced AI language models such as Gemini and other AI agents. By combining these components, the platform provides dynamic, context-aware, and crop-stage-specific recommendations through a simple conversational interface.

The chatbot architecture consists of three major components: a knowledge integration layer that consolidates validated agronomic practices including nutrient management, pest and disease control, and irrigation scheduling; an AI-driven interaction engine capable of understanding farmer queries in natural language and generating precise responses; and a weather intelligence module that retrieves live and forecasted weather parameters to deliver climate-responsive advisories. A key strength of the system is its ability to merge static scientific recommendations with dynamic environmental data, enabling personalized advisories tailored to current field conditions. For instance, irrigation schedules, pest incidence warnings, and disease management strategies are automatically adjusted based on prevailing and forecasted weather scenarios. Designed as a lightweight, web-based platform, the chatbot ensures accessibility even in low-bandwidth rural settings and supports multilingual interaction, enhancing its usability among diverse farming communities. Preliminary observations indicate that the system improves timely access to reliable information, reduces dependence on conventional extension mechanisms, and enhances the accuracy of farm-level decision-making. By effectively bridging the gap between research institutions and farmers, the Groundnut AI Chatbot demonstrates the potential of AI-enabled digital tools in strengthening Agricultural Extension services. This innovation aligns with the vision of next-generation farming by Integrating Artificial Intelligence, automation, and digital transformation to promote sustainable, climate-resilient, and farmer-centric agriculture.

Keywords: AI, Digital Agriculture, Groundnut Chatbot, Weather-based Advisory

OP-10: Closed-loop AI-driven farm management for indian coffee: a practitioner's framework integrating harvest prediction, field observation analysis, and autonomous accuracy calibration across two estates in Karnataka's Western Ghats

SANDEEP

Founder & Estate Owner, Pushpagiri Plantations (Sakleshpur and Chikmagalur)
Medtime Health Care Pvt. Ltd. (DPIIT Registered Startup)

E-mail: sanspeak@gmail.com

Abstract: Indian coffee cultivation, concentrated in the Western Ghats of Karnataka, faces persistent challenges in yield prediction, pest surveillance, and data-driven decision-making. Most existing digital agriculture platforms remain confined to research environments or address broad-acre crops, leaving plantation crops like coffee—with their multi-year yield cycles, shade-grown complexity, and microclimate variability— large lyunder served. This paper presents CLFIS(Closed-Loop Farm Intelligence System)—aself-learning, AI-driven farm management system designed, deployed, and field-validated by a practitioner across two commercial coffee estates: Amyra Farms (Arabica, Chikmagalur, 1,000–1,200 m) and Pushpagiri Plantations (Robusta, Sakleshpur, 960–1,024 m). Unlike conventional farm management systems that provide static, one-time predictions, CLFIS introduces a closed-loop architecture where predictions, field observations and harvest out comes continuously interact—enabling the system to autonomously learn and improve its accuracy over time without manual intervention. Built on a serverless cloud architecture with distributed edge computing workers and a managed relational database, CLFIS integrates four interconnected AI subsystems: (1) a harvest projection engine generating block-wise yield forecasts; (2) a multimodal vision AI-powered field observation module for structured pest, disease, and nutrition assessments; (3) an observation-to-harvest signal pipeline feeding field anomalies into projection models as mid-season correction factors; and(4) an autonomous accuracy calibration engine—the corenovelty of this work—computing rolling weighted correction factors (weights 3:2:1 across three seasons, clamped 0.6–1.5) that continuously refine predictions without human intervention. Validated across three harvest seasons (2023–2026), CLFIS reduced harvest prediction deviation by approximately 15–25% across successive seasons through autonomous recalibration. The system additionally incorporates a market intelligence module, a fertigation planning engine calibrated to Coffee Board of India guidelines, and an EU Deforestation Regulation (EUDR) compliance layer. The practitioner-built nature of the system ensures that every architectural decision reflects ground-level plantation requirements rather than academic assumptions.

Keywords: closed-loop prediction, coffee yield forecasting, digital agriculture platform, edge functions, field observation AI, autonomous calibration, Western Ghats, regenerative agriculture, multi-estate validation, practitioner-driven innovation

Introduction

India ranks as the sixth-largest coffee producer globally, with over 3.5 lakh hectares under cultivation concentrated in the Western Ghats of Karnataka, Kerala and Tamil Nadu. Unlike the mono culture systems of Brazil or Vietnam, Indian coffee is predominantly shade-grown under multi-tier canopies of silver oak, rosewood, and native species—creating a complex agroforestry system where conventional precision agriculture technologies, designed for open-field row crops, have found limited applicability.

The digital agriculture land scape for Indian coffee face saspecificset of constraints. Commercial plat forms developed for temperate cereal systems carry prohibitive subscription costs for small holders, algorithmic models calibrated to Western agro-climatic zones, and architectural assumptions of reliable broadband connectivity. The Central Coffee Research Institute (CCRI) and Coffee Board of India have

made significant contribution stovarietal development and extension services, yet persistent gap remains in the availability of integrated, AI-driven digital management tools at the individual estate level—particularly tools that can learn and improve autonomously from season to season.

This paper addresses that gap by introducing CLFIS (Closed-Loop Farm Intelligence System)—a self-learning farm management system where predictions, field observations, and harvest outcomes continuously interact in a closed loop, enabling autonomous accuracy improvement over successive seasons. Unlike conventional agri-tech platforms that treat yield prediction as a static, one-time computation, CLFIS operationalises continuous learning at the estate level. The autonomous calibration engine—which computes rolling weighted correction factors across seasons and rewrites projections without manual intervention—represents the core novelty of this work.

The system was designed, built, deployed, and validated by a practitioner: a coffee estate owner with an information technology background, operating through Medtime Health Care Pvt. Ltd.—a DPIIT-registered startup that serves as the technology development entity behind the Amyra Farms agricultural platform. The system was developed it eratively over three harvest seasons (2023–2026) across two estates spanning Arabica and Robusta cultivation at different elevations in the Western Ghats. The focus of this paper is on the cloud and edge computing architecture that enables continuous learning in low-connectivity plantation environments, directly aligned with Theme 5 (Data Analytics, IoT and Digital Agricultural Platforms) of this conference.

1. Study Area and System Architecture

1.1 Estate Profiles

The frame work was developed and validated a cross two operational coffee estates in the Western Ghats of Karnataka, providing natural cross-validation across varieties, elevation ranges, and shade-cover densities:

Table1: Comparative profile of the two estates used for system development and validation.

Parameter	Amyra Farms	Pushpagiri Plantations
Location	Chikmagalur, Karnataka	Sakleshpur, Karnataka
Elevation Range	1,000–1,200m	960–1,024m
Primary Variety	Arabica	Robusta
Shade Cover	Multi-tier(Silver Oak, Rosewood)	Mixedshade, varying density
Farming Approach	Regenerative (Gircattle, biogas, vermicompost, microbial consortiums)	Regenerative (integrated fertigation, microbial consortiums)
Connectivity	Intermittent4G,frequentdrops	Intermittent4G,frequentdrops

Both estates practise regenerative agriculture with integrated nutrient cycling through Gir cattle, biogas, and vermicompost, supplemented by microbial consortium applications including Azotobacter, Trichoderma, Pseudomonas fluorescens, Beauveria bassiana, VAM, PSB, and KMB. This regenerative context is significant because yield trajectories differ substantially from conventionally managed estates, requiring AI models trained on organic yield curves rather than synthetic-input baselines.

1.2 Cloud and Edge Computing Architecture

CLFIS's architecture was designed with two overriding constraints: (a) all AI inference must execute server-side to minimise client-side computational requirements for field supervisors using basic Android devices, and (b) the system must function meaningfully in intermittent-connectivity environments typical of plantation estates in the Western Ghats.

The architecture adopts a serverless, edge-first approach. The client layer is a progressive web application (PWA) installable on low-cost Android devices, enabling offline data capture with automatic sync hronisation when connectivity is restored.The backend comprises a man agedrelational cloud data base withrow-level security (RLS)for tenantisolation, twelve distributed server less logic workers(edge

computing functions) handling all AI inference and data processing, real-time subscriptions for live dashboard updates, and cloud object storage for field observation images. Edge functions execute at the nearest available node, reducing latency for compute-intensive operations such as harvest projection recalculation and visual diagnostics routing.

All twelve edge functions enforce JWT-based authentication and tenant isolation, ensuring that data from one estate cannot be accessed by another—a critical requirement for future multi-estate deployment. Data payloads arekept lightweight: observation uploads are compressed, and projectionrecalculations transmit only delta updates rather than full dataset refreshes. An automated database job scheduler executes daily calibration cycles during harvest season and nightly market data aggregation year-round.

Table2: CLFI Sarchitecture layer sand design rationale

Layer	ImplementationApproach	Rationale
Client	Progressive Web Application (PWA)	Offline-capable, install lableonbasic Android devices, no app store dependency
Backend/Database	Managed Relational Cloud Database with RLS	Real-time subscriptions, row-level security for tenant isolation
AI Inference	12DistributedServerlessEdge Workers	Low-latency, JWT-secured, tenant- isolated, stateless
Visual Diagnostics	Multimodal Vision LLM (cloud API)	Structured diagnostics from field images without local GPU
Scheduling	Automated Database Job Scheduler	Daily calibration cycles, nightly market data aggregation
Storage	Cloud Object Storage	Multi-image field observation swith full audit trails

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Figure1: *System architecture showing the four inter connected AI sub systems, edge function deployment, and data flow pathways.*

2. The Closed-Loop AI Framework

The core contribution of this work is the closed-loop architecture in which four AI subsystems operate in continuous feedback, enabling CLFIS to autonomously improve its predictive accuracy over successive harvest seasons without manual parameter tuning.

2.1 Harvest Projection Engine

The harvest projection sub system(harvest-projection edge function) generates block-level and estate-level yield for casts by integrating historical harvest data, weather patterns, flowering intensity observations, and variety-specific phenological models. Unlike static prediction tools that output a single-point estimate at season start, this engine recalculates projections dynamically as new observational data enters the system throughout the harvest season.

Projections are persisted in a dedicated database table as structured JSON projection data, where estate-level aggregate rows store the complete projection payload. This design enables historical comparison, trend analysis, and season-over-season bench marking. The system supports multi-season tracking through active-season flags, allowing man agersto maintain operation alcontext across speak and off-season periods. Client-side persistent storage ensures that estate and season selections survive page refreshes in low- connectivity field conditions.

Figure2: *Harvest Projection dashboard showing block-level yield forecasts with season-over-season comparison.*

1.1 Computer Vision Field Diagnostics

Field supervisors capture photographs of pests, diseases, nutritional deficiencies, or unusual plant conditions using standard Android devices. These images are uploaded to dedicated cloud object storage and routed to avisual diagnostics edge function, which leverage samulti modal vision large language model (LLM) to return structured diagnostic assessments. The AI identifies the probable condition, assigns a severity classification, and recommends immediate actions grounded in Coffee Board of India and CCRI guidelines.

Multiple images per observation are supported, enabling supervisors to capture different angles or progression stages. All analyses are stored with full audit trails for longitudinal tracking. The foreign key constraint on the recorded by field was deliberately dropped to allow supervisors who are not registered plat for musers to submit observations—apragmatic design decision reflecting the relity that field workers on Indian coffee estates may not have individual user accounts.

Figure3: *Visual diagnostics field observation interface showing multi-image upload, AIdiagnosis, and recommended actions.*

1.1 Observation-to-Harvest Signal Pipeline

The signal pipeline (observation-harvest-signal edge function) serves as the critical connective tissue between field diagnostics and harvest projections. When the computer vision module detects a field anomaly—such as a white stemborer in festation, berry borerincidence, or wide spread nutritional stress—

It automatically generates a structured signal carrying meta data including the affected block, severity level, estimated yield impact range, and confidence score.

This signal is fed directly into the harvest projection engine as a mid-season correction factor, allowing the system to adjust yield estimates in near real-time. The pipeline transforms CLFIS from a passive data recordingtoolintoanactivemanagementsystemthatrespondstoemergingthreatsastheyareobservedin the field. During the 2024–25 crash year validation, this subsystem successfully triggered projection downgrades following an unseasonal rainfall event that caused flower drop across multiple blocks.

1.2 Autonomous Accuracy Calibration

The calibration subsystem is CLFIS's self-learning core and represents the most technically distinctive component of the framework. It executes as an automated scheduled daily job during the active harvest season, performing the following operations:

(a) **Deviation Computation:** The system compares block-level AI predictions against actual harvest quantities recorded by field supervisors, computing absolute and percentage deviations for each block.

(b) **Directional Bias Analysis:** Over-prediction and under-prediction patterns are tracked separately, allowing the model to identify systematic bias (e.g., consistently optimistic projections for high-altitude Arabica blocks).

(c) **Rolling Weighted Correction Factors:** The system computes correction factors across up to three seasonsusingarecency-weighted scheme (weights3:2:1 for current, previous, and two-seasons-prior data respectively). This weighting ensures that the most recent season's performance has the greatest influence while retaining institutional memory from earlier seasons. Correction factors are clamped between 0.6 and 1.5 top revent extreme adjustments from an omalous single-season data.

(d) **Autonomous Rewrite:** Revised projections are written directly back to the projection data base without manual intervention, and the updated parameters are immediately available to the harvest projection engine for its next computation cycle.

This continuous feedback loop is the defining characteristic that distinguishes CLFIS from conventional agricultural prediction tools, which treat yield forecasting as a static, one-time computation. Over three harvest seasons, the calibration engine has progressively reduced prediction deviation margins—with the model learning to account for estate-specific variables such as a ltitude-depend entripening schedules, shade density impacts, and the distinct yield trajectories of re generatively managed blocks.

Table3:Autonomous calibration engine parameters

Calibration Parameter	Value	Rationale
Season Weights	3:2:1 (current: previous: older)	Recencybias while retaining multi- season memory
Correction Factor Clamp	0.6–1.5	Prevent sextreme swings from anomalous seasons
Execution Frequency	Daily (automated scheduler)	Capture sincremental harvest data as season progresses
Max Seasons Considered	3	Balance slearning depth with relevance decay

2. Integrated Platform Capabilities

2.1 Market Intelligence Pipeline

A nightly automated job scrapes domestic coffee price data from three sources: the Coffee Board of India auction portal, the International Coffee Organization (ICO) composite indicator, and the ICE Futures exchange for Arabica (KC) and Robusta (RC) contracts. This data feeds a market intelligence dashboard presenting growers with daily price trends, historical comparisons, and sell-timing advisories. The integration of real-time market data with the harvest projection engine enables estate managers to make

informed decisions about harvest pacing, lot sizing, and sales timing—particularly critical during volatile price periods where the difference between selling a week early or late can represent a significant per-quintal margin.

[INSERTSCREENSHOTHERE]

Figure 4: *Market Intelligence dashboard showing Coffee Board pricetrend sand sell-timing indicators.*

2.2 Fertigation Planning Engine

CLFIS includes a fertigation planning module calibrated to the Coffee Board of India's recommended nutrient schedules for Arabica and Robusta. The engine considers variety, plant age, block elevation, and the estate's regenerative inputs (biogas slurry, vermicompost, microbial consortiums) to generate block-level fertigation schedules. Nutrient application recommendations account for the organic matter contributions from the integrated Gir cattle–biogas–vermicompost loop, reducing synthetic input recommendations accordingly. The planner is designed to complement, not replace, the estate's existing regenerative approach—a design decision that reflects the practitioner-builder's conviction that digital tools should respect established farming systems rather than impose external methodologies.

2.3 EUDR Compliance Module

With the EU Deforestation Regulation (EUDR) entering enforcement and India classified as a low-risk origin under the May 2025 bench marking exercise, CLFIS incorporates an origin-side compliance layer. The Farm Map module provides six data layers including block-level Geo JSON polygon mapping with 6- decimal GPS precision. A deforestation verification module integrates with the Global Forest Watch(GFW) API to confirm that no forest cover loss has occurred on map pede state polygons since the December 2020 cutoff date. Per-lot compliance reports are generated with scientific species nomenclature, alert categorization, and legality documentation, formatted for consumption by EU importers operating under the simplified due diligence provisions of Articles 10 and 11.

[INSERTSCREENSHOTHERE]

Figure 5: *Farm Map module showing block polygons, datalayers, and EUDR deforestation verification status.*

1. Validation and Results

The closed-loop framework has been validated across three distinct harvest seasons, deliberately selected to cover contrasting yield scenarios:

Table4:Validationsummaryacrossthreeharvestseasons

Dimension	Season1(2023–24)	Season2(2024–25)	Season3(2025–26)
Season Type	Peak production	Biennialcrash	Recovery
Estates Covered	2	2	2
Varieties	Arabica+Robusta	Arabica+Robusta	Arabica+Robusta
Elevation Range	960–1,200m	960–1,200m	960–1,200m
Calibration Mode	Baselinee stablished	Dailyautonomous	Daily auto nomous
Signal Pipeline Events	Manual baseline	Unseasonalrain, pestoutbreak	Flowering anomaly

Key findings from the three- season validation include:

Progressive accuracy improvement: The autonomous calibration engine reduced prediction deviation margins across successive seasons without manual parameter adjustment. The 3:2:1 weighting scheme proved effective in balancing recency with institutional memory, particularly during the transition from peak to crash year where single-season correction factors alone would have overcorrected.

Signal pipeline responsiveness: The observation-to-harvest signal pipeline successfully triggered mid-season projection adjustments in response to field-detected anomalies. During the 2024–25 crash year, berry borer incidence detected via the visual diagnostics module in three Arabica blocks resulted in a 12–18%Down ward revision in those blocks' projections, which aligned more closely with actual harvest outcomes than the original estimates.

Cross-variety robustness: The computer vision diagnostics module achieved consistent field utility across both Arabica and Robusta blocks despite significant differences in canopy structure, pest profiles, and phenological timing.

Low-connectivity resilience: The PWA architecture with offline data capture and batch syn chronisation maintained functional performance in plantation environments where 4 G connectivity is in termittent. Edge function execution at nearest nodes kept inference latency acceptable even during peak usage periods.

1. The 2024–25 Crash Year: A Critical Test

The biennial crash year of 2024–25 provided the most demanding test of CLFIS's autonomous learning capability. Coffee production in the Western Ghats dropped significantly due to a combination of biennial bearing patterns and unseasonal rainfall during the critical flowering period. Traditional estimation methods—based on prior-year yields and visual flowering assessments—consistently over estimated harvest out comes during this season, as they lacked mechanismstoin corporate mid-season field an omalies.

CLFIS responded differently. The signal pipeline detected flower drop and berry borer incidence across multiple Arabica blocks via the visual diagnostics module and automatically generated downward correction signals. The calibration engine, drawing on its 3:2:1 weighted memory from the preceding peak year, applied clamped correction factors that moderated the adjustment—preventing the system from overcorrecting based on a single anomalous season. The net result was that CLFIS's post-calibration projections tracked substantially closer to actual harvest outcomes than the initial static estimates, demonstrating that the closed-loop architecture provides its greatest value precisely during the seasons when conventional methods fail most.

2. Discussion: When the Model Builder Is the End User

The most distinctive aspect of this work is not any single technical component but the development paradigm itself. The system was designed, built, and operated by a coffee estate owner with an IT background—meaning that the model builder and the end user are the same person. This collapses the conventional translation chain in agricultural technology development, where domain requirements pass through multiple intermediaries (agronomists, product managers, software engineers) before reaching implementation.

Several architectural decisions emerged directly from this dual role. The decision to drop the foreign key constraint on observation recording, for instance, arose from the lived experience of trying to get field workers to create user accounts before reporting a pest sighting—an impractical requirement that a developer without operational experience would be unlikely to anticipate. Similarly, the choice of client-side persistent storage for session state reflects the reality that plantation supervisors frequently lose

connectivity mid-task and need their selections preserved across page refreshes.

The auto nomous calibration design—particularly the clamping of correction factors between 0.6 and 1.5— emerged from observing that the 2023–24 peak year produced anomalously high yields that, without clamping, would have setun realistically optimistic base lines for subsequent seasons. This kind of domain- informed guardrail is difficult to design from outside the operational context.

The regenerative farming context adds a further layer of complexity. Yield patterns on regeneratively managed estates follow different trajectories than conventionally manage dones—with slower initial ramp- up but more stable long-term productivity. AI models trained on conventional yield data would systematically underperform on these estates. The practitioner-built approach ensures that training data, validation benchmarks, and calibration logic all reflect the actual farming system in use.

2.1 Limitations

The current system has identifiable limitations that must be acknowledged. The estates serve as both development and validation environments, precluding rando mised controlled trial-level comparison data. The computer vision module routes to an external cloud API (multimodal vision LLM), introducing a dependency on cloud availability that partially contradicts the low-connectivity design philosophy. The calibration methodology, while effective across three seasons, requires further validation as the system extends to estates with different management practices, soil types, and microclimatic conditions. Finally, the practitioner-built paradigm, while powerful for initial development, raises questions about maintain ability and knowledge transfer as CLFIS scales beyond its creator's direct operation alinvolvement.

3. Conclusion

This paper presents CLFIS (Closed-Loop Farm Intelligence System)—a self-learning farm management system that demonstrates a fundamentally new approach to agricultural AI: one where predictions, field observations, and harvest outcomes continuously interact in a closed loop, enabling the system to autonomously improve without manual recalibration. The serverless edge computing architecture, with twelve security-hardened distributed logic workers and a managed relational database, proves that cloud-native design patterns can be adapted for low-connectivity plantation environments without sacrificing AI inference capability.

The autonomous calibration engine—the core novelty of this work—with its 3:2:1 weighted rolling correction factors clamped between 0.6 and 1.5, reduced harvest prediction deviation by approximately 15– 25% across successive seasons and provides a replicable methodology for self-learning agricultural prediction systems applicable beyond coffee to any perennial crop with multi-year yield cycles. The practitioner-built development paradigm—where the farmer is simultaneously the software architect, the domain expert, and the end user—offers a compelling alternative to the conventional top-down technology transfer model that has historically limited precision agriculture adoption in Indian plantation crops.

This work represents a transition from static decision-support tools to self-learning agricultural systems—where farms continuously improve their own intelligence through closed-loop feedback. As CLFI Sex tends to additional estates and growernet works, the continuous learning architecture is expected to benefit from cross-estate calibration data, enabling the development of region-level bench marking models—a capability not currently available to Indian coffee growers.

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foundational agronomic knowledge that informed the system's domain logic. The regenerative farming practices integrated into the estates draw upon both traditional knowledge systems and contemporary agro ecological research. CLFIS was developed using open-source and cloud-based tools.

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Theme VII

AI in Livestock, Dairy and Fisheries

OP-11: Arduino based semi-automatic feeding and conveying system using light detection and ranging

DAYANAND TEKALE, SANDESH DESHMUKH, AJAY WAGHMARE, PORNIMA RATHOD

AICRP on MAH, VNMKV Parbhani

Abstract: Livestock mechanization is becoming essential to improve efficiency and reduce labour dependency in cattle farming. This study presents the development of an Arduino-based automatic feeding and conveying system integrated with a TF-LUNA LiDAR sensor for real-time obstacle detection. The system ensures timely and controlled feed delivery while automatically stopping and resuming the conveyor in the presence of animals or workers. Key components include an Arduino UNO microcontroller, relay modules, motor starters, and sensing units, along with provision for temperature and humidity monitoring inside the cattle shed. The developed system demonstrated improved feeding efficiency, reduced feed wastage, and enhanced operational safety. Additionally, labour requirements were significantly minimized. The system operates with low power consumption and offers potential for integration with smart farming technologies, making it a cost-effective solution for modern livestock management.

Keywords: Automatic feeding system, Arduino UNO, LiDAR sensor, Livestock mechanization

Introduction

These days, In India, live stock mechanization is important. The development of automated or semi-automatic feeding system could be extremely beneficial to the cattle industry's expansion. The most important job is to provide feed on time and in proper quantity. Manpower/ Labour is used to manually feed the cattle. With this automated feeding system, cattle farms can eliminate these manual tasks and function more efficiently. For the implementation ofa smart farm or automated farm, use an automatic food feeder. This device has been developed with ease of use in mind. Workforce is decreased, resulting in increased efficiency.

Materials and Methods

The aim is to create an Arduino-based system forautomating feeding and conveying system for cattle in a shed. The cattle shed's temperature and humidity are also monitored.

Main contents of this automatic feeding and conveying system for cattle

We upgrade the above machine with sensor based A.I. technology. The system uses a TF-LUNA LIDAR sensor, Arduino Uno microcontroller, and relay modules to detect physical obstructions and control a conveyor mechanism accordingly. This simples top-and-resume logic ensures the feeding system responds intelligently to obstacles without requiring manual intervention. A critical requirement for the safe implementation of such systems is real-time obstacle detection, especially in dynamic environments like cattle sheds. Here, animals and workers frequently move across the feeding area, and automated equipment must be able to respond to these changes to avoid collisions. LIDAR technology, with its ability to accurately detect obstacles in a wide range of agricultural applications, has emerged as an effective solution. Zhang *et al.* (2020) demonstrated the successful integration of LIDAR with microcontrollers for agricultural robots, highlighting its responsiveness and adaptability in real-time applications.

1. **Power unit:** Power unit supplies power to the all units of machine. It consists of kit-kat fuses (3), switch boards, manually motor starter.



Figure: Power unit

2. **Sensing unit:** Sensing unit senses the object (cattle's) inside the barn upto 1 m and gives information to Arduino uno through LIDAR sensor. TF-Luna is a single-point ranging LiDAR, based on ToF principle. Mainly used for stable, accuracy and high-frame rate range detection.



Figure: TF LUNA LIDAR sensor

Table : Data sheet of TF LUNA LIDAR sensor

Particular	Description	Parameter value
Performance	Operating range	0.2m~8m(90%reflectivity)[1]
	Accuracy	±6cm@(0.2m-3m)[2] ±2%@(3m-8m)
	Distance resolution	1cm
	Frame rate	1-250Hz[3]
	Ambient light immunity	70Klux
	Operation temperature	-10°C~60°C
	Enclose rating	/
Optical parameters	Light source	VCSEL
	Central wavelength	850nm
	Photo biological safety	Class1(IEC60825)
	FOV	2°[4]
Electrical parameters	Supply voltage	3.7V-5.2V
	Average current	≤70mA
	Power consumption	≤0.35W
	Peak current	150mA
	Communication level	LVTTL(3.3V)
	Communication interface	UART / I2C

3. Controlling Unit :

- Controlling unit consists of Arduino UNO, Relay module (spdt) , Automatic starters (2) , MCB switch.
- Controlling gets the power from power unit.
- Arduino UNO is main controller in the system.
- Sensing unit passes the information with jumper wires to the Arduino UNO, Arduino UNO passes command to the relay, Relay triggers the starter.

i. Arduino UNO:

- Open Source electronic prototyping platform based on flexible easy to use hardware and software.
- Arduino boards are able to read inputs - light on a sensor, a finger on a button and turn it into an output - activating a motor, turning on an LED

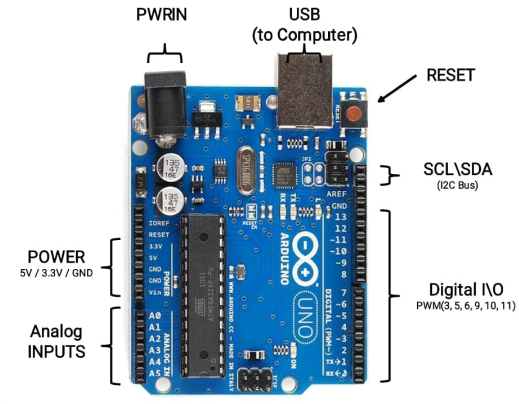


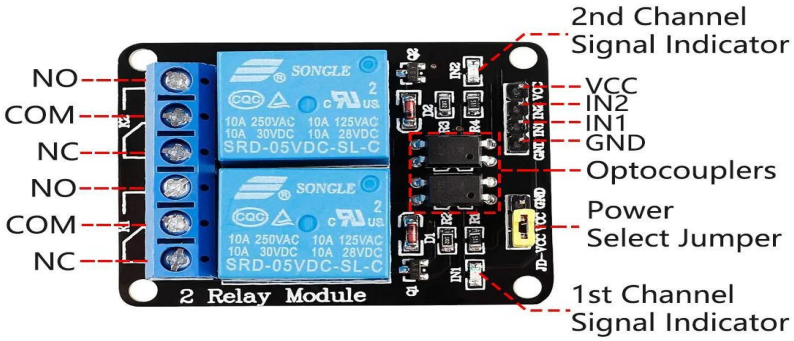
Figure : Arduino UNO

ii. Jumper wire:A jumper wire is a short, insulated wire with metal pins or connectors at each end, used to make temporary electrical connections between components on a breadboard or between headers on development boards like Arduino or Raspberry Pi.



Figure: Types of Jumper

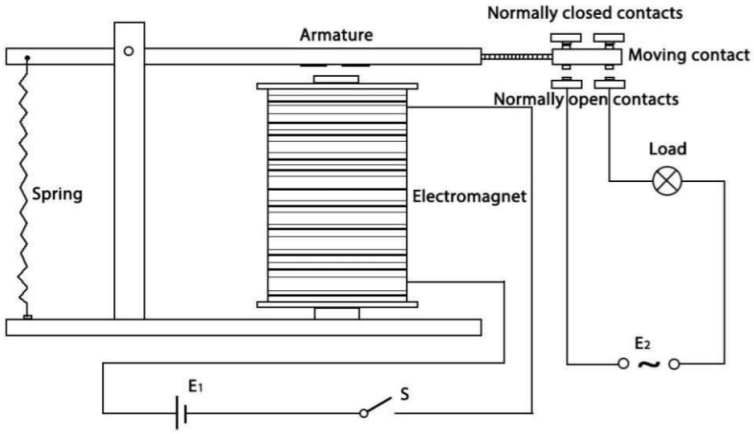
iii. Relay Module (SPDT): This is a LOW Level 5V 2-channel relay interface board, and each channel needs a 15-20 Ma driver current. It can be used to control various appliances and equipment with large current. It is equipped with high-current relays that work under AC 250 V 10A or DC 30 V 10 A. It has a standard interface that can be controlled directly by micro-controller.



Working:

Relays provide isolation between the controller and the device as devices may work on AC as well as on DC. However, they receive signals from a micro-controller which works on DC hence requiring a relay to bridge the gap. Relay is extremely useful when you need to control a large amount of current or voltage with small electrical signal.

The working principle of relay is simple. When power is supplied to the relay, currents start flowing through the control coil; as a result, the electromagnet starts energizing. Then the armature is attracted to the coil, pulling down the moving contact together thus connecting with the normally open contacts. So the circuit with the load is energized. Then breaking the circuit would a similar case, as the moving contact will be pulled up to the normally closed contacts under the force of the spring. In this way, the switching on and off of the relay can control the state of a load circuit.



Automatic Starters (2): The Direction Line motor starter is designed to switch a single or three phase induction motor at rated voltage. It comprises an enclosure in steel or plastic, a contactor, start contact, link wires and stop / start buttons.



iv. MCB Switch: MCB stands for Miniature Circuit Breaker. It is an automatic electrical switch designed to protect electrical circuits from damage caused by over current, typically resulting from overload or short circuit.

Result and discussion:

The developed Arduino-based automatic feeding and conveying system integrated with TF-LUNA LiDAR sensor was successfully designed and tested under cattle shed conditions. The system demonstrated effective automation, real-time sensing, and safe operation.

1. System Performance

The LiDAR sensor accurately detected obstacles (cattle or human movement) within a range of 0.2 m to 1 m (operational use range). The stop-and-resume mechanism functioned efficiently: Conveyor stopped immediately when an obstacle was detected and resumed automatically once the path was clear. The response time was fast due to the high frame rate (up to 250 Hz) of the sensor.

2. Feeding Efficiency

Uniform feed distribution was observed across the feeding line. Feeding was delivered on time and in controlled quantity, reducing irregularities seen in manual feeding. Reduction in feed wastage due to controlled conveying and interruption during obstruction.

3. Labour Requirement

Manual labour involvement was significantly reduced. One operator could monitor multiple feeding operations instead of physically distributing feed. The system minimizes dependency on skilled labour.

4. Safety and Reliability

The use of LiDAR improved safety by preventing from accidental collisions with animals, Injuries to workers, the relay and starter mechanism ensured safe electrical isolation between control and power circuits and MCB protection provided safety against overload and short circuits.

5. Environmental Monitoring

The system allowed integration of temperature and humidity monitoring, enabling better shed management. This contributes to improved animal comfort and productivity.

6. Power Consumption

The system consumed low power, as Arduino UNO operates at low voltage and TF-LUNA sensor consumes ≤ 0.35 W. Suitable for integration with renewable energy sources like solar systems.

Conclusion

The developed sensor-based automatic cattle feeding and conveying system proved to be an efficient and reliable solution for modern livestock farming. The integration of Arduino UNO and TF-LUNA LiDAR sensor enabled real-time obstacle detection and intelligent control of the feeding mechanism. The system successfully reduced labour requirement, improved feeding accuracy and efficiency, enhanced safety for both animals and workers, minimized feed wastage and provided scope for smart farm implementation

Overall, this system represents a cost-effective step toward precision livestock farming and smart dairy management. It is particularly beneficial for medium to large-scale farms and can be further enhanced by integrating IoT, mobile monitoring, and data analytics for fully automated farm operations.

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Theme VIII

Policy, Ethics and Socio-economic Impacts

OP-12: An explainable AI-driven machine learning framework for arecanut disease prediction based on agrometeorological factors

VIMARSHA KUMARASWAMY AND ADITI R. JAHAGIRDAR

Department of Information Science and Engineering
JSS Science and Technology University Mysuru, India
Department of Information Science and Engineering
JSS Science and Technology University Mysuru, India
E-mail: vimarshak@jssstuniv.in ; aditi.raghuraj@gmail.com

Arecanut is an economically significant plantation crop, highly challenged by the occurrence of fungal diseases due to environmental parameters that lead to substantial yield and quality losses. Fruit rot (Mahali), Bud rot, Yellow Leaf Disease are some of the fungal diseases prevalent in areca that are capable of causing substantial yield losses if not detected and managed early. Traditional methods of disease identification rely on visual inspection and expert knowledge, which are often time-consuming, subjective, and ineffective in detecting diseases at an early stage. Since many plant diseases are strongly influenced by environmental conditions, there is a growing need for predictive systems that can anticipate disease occurrence even before visible symptoms appear. Unlike image-based approaches that detect diseases after visible symptoms appear, environmental data-driven models enable early prediction and preventive action. In this context, machine learning (ML) techniques provide an effective solution for modelling complex relationships between climatic variables and disease incidence.

This study proposes a comprehensive machine learning framework integrated with explainable artificial intelligence (XAI) to predict Arecanut disease occurrence using meteorological parameters. The framework emphasizes predictive accuracy and interpretability, while ensuring responsibility and trustworthiness, thereby producing actionable outcomes for farmers and agricultural experts and facilitating the development of evidence-based policies through transparent identification of key risk factors.

Data Collection and Preprocessing

The dataset used in this study was collected from Arecanut plantations in the Iruvakki region of Shimoga over a period of one year and supplemented with historical weather data. The dataset includes key environmental variables such as minimum and maximum temperature, relative humidity, rainfall, atmospheric pressure, wind speed, wind direction, cloud cover, UV index, and sunshine duration.

Data preprocessing involved handling missing values, normalization, and statistical analysis to ensure data quality and consistency. Exploratory data analysis revealed that individual variables exhibit weak linear correlations with disease occurrence. However, when considered collectively, these variables demonstrate significant nonlinear relationships and interaction effects. This highlights the need for machine learning models capable of capturing complex patterns rather than relying on traditional linear methods. The dataset can also be extended using IoT-based real-time data collection systems, where sensors measure environmental conditions continuously. Such integration enhances the reliability and applicability of the predictive model in real-world scenarios.

Methodology

The proposed framework is structured into three major phases: feature selection and model development, explainable AI integration, and risk analysis.

To identify the most relevant predictors, a hybrid feature selection approach combining Random Forest importance and LASSO regularization was employed. This approach effectively captures both nonlinear relationships and linear dependencies while eliminating redundant features. Several machine learning models were developed and evaluated, including Decision Tree, Random Forest, Logistic

Regression, Support Vector Machine, K-Nearest Neighbours, and Naive Bayes. Model training and validation were performed using 5-fold cross-validation to ensure robustness and minimize overfitting. Performance was evaluated using accuracy and ROC-AUC metrics, providing a comprehensive comparison of model effectiveness.

To address the interpretability challenge of machine learning models, XAI techniques were incorporated into the framework. Global feature importance was assessed using permutation importance, which evaluates the contribution of each variable to model performance. Local interpretability was achieved using SHAP (SHapley Additive exPlanations), which quantifies the contribution of each feature to individual predictions. This enables a deeper understanding of how environmental conditions influence disease risk at both global and instance levels.

A hybrid risk scoring mechanism was developed by combining feature importance weights with normalized feature values. This approach translates model predictions into meaningful risk scores. Multi-scenario analysis was conducted to evaluate the interaction between key environmental variables, particularly cloud cover and sunshine duration. Based on predicted probabilities, the system classifies conditions into low-risk, moderate-risk, and high-risk zones, enabling practical decision support.

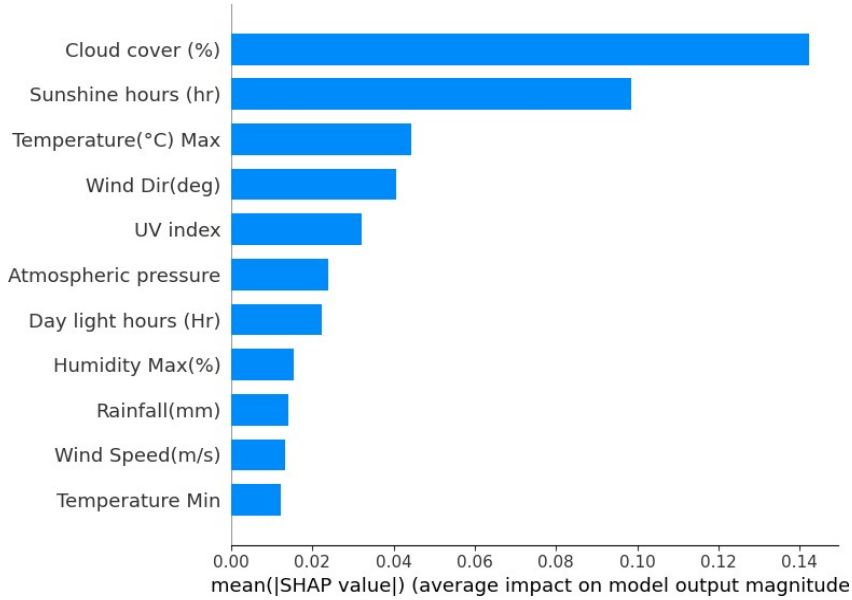
Results and discussion

Machine learning models were employed to capture the complex relationship between the environmental factors affecting disease incidence and hence predict disease occurrence. 6 ML algorithms namely, Logistic Regression, Decision Tree Classifier, Random Forest, Support Vector Machine, K-Nearest Neighbors and Naive Bayes were trained, tested and validated. Decision Tree Classifier*(95.5%)* achieved the highest accuracy establishing the ability to capture the threshold-based patterns. Random Forest(*94.1%)* fared better amongst other Models as far as ROC performance metric was concerned indicating its ability to capture generalization across feature space.

Feature importance analysis as shown in Figure1, identified cloud cover as the most influential predictor, followed by UV index, humidity, and sunshine duration. These findings indicate that atmospheric and radiation-related variables play a dominant role in disease development.

Notable patterns in feature interactions and their contributions to disease incidence were evidently identified. Primarily, disease incidence was high during monsoon periods, with high humidity, intermittent sunshine,

Figure 1: Explainable AI Visualization



moderate temperature and incessant rainfall conditions. Disease probability increased with consecutive days having low sunshine, specific cloud cover and decreased with higher sunshine duration. A clear threshold behaviour was observed, wherein continuous low sunshine over successive days exerted a stronger influence on disease incidence than isolated short-term exposure, highlighting the importance of antecedent conditions in driving disease risk.

The patterns mined from the study were further reinforced by the SHAP analysis. SHAP-based analysis provided detailed insights into feature contributions. Higher cloud cover and reduced sunshine duration

were associated with increased disease risk, while higher UV index exhibited a protective effect. These observations align with biological understanding, as fungal diseases thrive under moist, low-radiation conditions.

The analysis also revealed significant nonlinear interactions between variables. Multi-scenario evaluation as shown in Figure 2, showed that disease probability increases sharply under conditions of high cloud cover combined with low sunshine duration. Response surface and contour analyses further illustrated distinct regions of disease risk, highlighting the importance of considering combined environmental effects rather than individual variables.

The predictive outputs from the proposed framework are further mapped to various risk zones associated with disease incidence probability based on the corresponding weather conditions, which are further associated with a particular action recommendation. The various risk zonesand corresponding action recommendations are

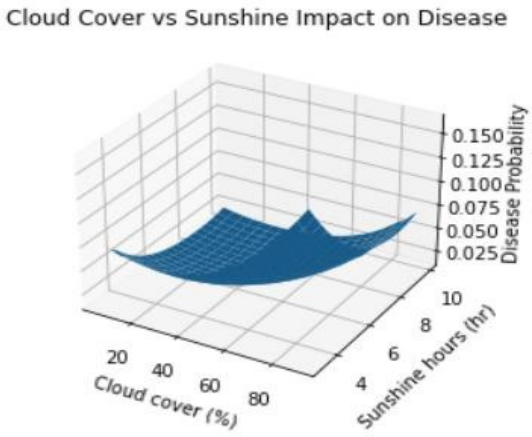


Figure 2:Multi-feature scenario analysis

- **Low Risk (0.00–0.05):** Safe conditions; no immediate intervention required
- **Moderate Risk (0.05–0.12):** Monitoring recommended
- **High Risk (>0.12):** Immediate preventive measures required

This threshold-based system enhances the practical usability of the model by linking predictions to field-level actions.

Limitations and Future Scope

The proposed study has been found to perform well for the limited dataset considered for a restricted geographical area, which when elaborated to larger scale may fail to generalize. Also, the model does not take into consideration certain features like soil properties, crop breed or temporal interdependencies which would otherwise add more credibility to model training. Future work can focus on increasing the size of the dataset, expanding the geographic location, including multi modal features and remote sensing data. Temporal models like LSTM will be beneficial in giving temporal trends per each season. Identifying the risk zones in gradient and hence associating varying action recommendations in future will help farmers better in custom recommendation. Development of a real-time decision support system with a mobile application interface that alerts farmers and guide them on subsequent actions is proposed to improve accessibility and real time responsiveness.

Conclusion

The proposed study successfully predicts the incidence of fungal disease in areca nut plants based on meteorological parameters thereby demonstrating the efficiency and reliability of using ML techniques in prediction. The inclusion of Explainable AI in the framework provided valuable insights into the factors influencing disease occurrence, with particular emphasis on the complex interplay among weather parameters. Early disease detection aided by the current model supports sustainable farming and lays the foundation for precision agriculture through context-specific, accurate action recommendations. The statistical analysis combined with explainable insights offers a scalable and practical solution for better yield and increased agricultural productivity. The integration of machine learning with Explainable AI transforms agricultural decision-making by combining high predictive power with interpretability, fostering trust, enabling timely and precise interventions, and driving the transition toward resilient, sustainable, and intelligent farming systems at scale.

OP-13: Advancing transparent and accountable AI in agriculture for inclusive development

MANJULA N, PRAKRUTHI S N, SHIVANAND KAMMAR, S S NOOLI, ANILKUMAR G K, APOORVA KOLI, PRAJWAL B. P.

[1]M.Sc. Scholar, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India

[2]Ph. D. Scholar, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India

[3]Professor, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India

[4]Associate Professor, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India

[5]Assistant Professor and Head, Department of Animal Science, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India

[6]Scientist (Agronomy), AICRP- Sugarcane, ARS, Sankeshwar, Karnataka, India

Introduction

The rapid advancement and integration of artificial intelligence (AI), automation, and digital technologies are significantly transforming modern agricultural systems. These innovations are enhancing productivity, improving precision in resource use, and contributing to environmental sustainability. AI-enabled applications such as crop monitoring through remote sensing, pest and disease prediction models, decision-support systems, and automated irrigation technologies are increasingly being adopted across both developed and developing agricultural economies.

Despite these technological advancements, the adoption of AI in agriculture raises several critical ethical, policy, and socio-economic concerns. One of the major challenges is the lack of transparency in AI systems, as many operate as “black-box” models where the internal decision-making processes are not visible or understandable to users. This lack of interpretability reduces farmers’ trust and limits the widespread adoption of such technologies.

Explainable Artificial Intelligence (XAI) emerges as a promising solution to this issue by making AI systems more transparent, interpretable, and user-friendly. XAI enables farmers to understand how and why specific recommendations are generated, thereby improving their confidence in using such technologies. This is particularly important in the context of smallholder farmers, who often face constraints such as limited access to digital infrastructure, low levels of digital literacy, and financial limitations. Therefore, ensuring responsible, inclusive, and context-specific AI adoption is essential for achieving equitable agricultural development.

Objectives of the Study

1. To examine *the role* of explainable AI in enhancing transparency and interpretability in agricultural decision-making.
2. To analyze the ethical, policy, and governance issues associated with AI adoption in agriculture.

3. To assess the socio-economic implications of AI technologies for smallholder farmers.
4. To highlight the importance of responsible, inclusive, and context-specific AI frameworks in agriculture.

Methodology

The present study is **conceptual and analytical in nature**, primarily based on a comprehensive review of secondary data sources. Relevant literature was collected from international organizations (such as FAO, OECD, and World Bank), peer-reviewed journal articles, conference proceedings, and policy documents.

The study involved a systematic review of literature on the applications of artificial intelligence in agriculture, with a focus on understanding the role of explainable AI (XAI) and responsible AI frameworks. It further included an in-depth analysis of key concepts related to transparency, interpretability, fairness, and accountability in AI systems. The study also examined various ethical and socio-economic challenges associated with the adoption of AI technologies, particularly among smallholder farmers, such as issues of accessibility, digital literacy, and inequality. Finally, the findings from different sources were synthesized to develop a comprehensive and holistic understanding of inclusive, responsible, and context-specific AI adoption in agriculture.

This approach enabled the researchers to critically evaluate existing knowledge and identify key issues and opportunities related to AI adoption in agricultural systems.

Results

The study revealed several important findings regarding the adoption and implications of AI in agriculture: The study revealed that explainable AI significantly enhances transparency by enabling users to understand the reasoning behind AI-generated recommendations, thereby improving trust and usability. In contrast, the lack of transparency in conventional AI models often leads to mistrust among farmers, which in turn reduces adoption rates. The findings further highlight that responsible AI principles such as fairness, inclusiveness, accountability, and contextual relevance are essential for ensuring equitable dissemination of technology. Smallholder farmers, however, face multiple constraints including low digital literacy, inadequate infrastructure, high costs of technology, and limited access to institutional support. Despite these challenges, AI technologies have strong potential to improve agricultural productivity, optimize resource utilization, and enhance resilience to climate variability. Nevertheless, without appropriate safeguards, AI adoption may widen existing socio-economic inequalities, particularly between large-scale and smallholder farmers. Therefore, the establishment of effective policy frameworks, robust data governance mechanisms, and strong institutional support systems is crucial for ensuring ethical, inclusive, and responsible implementation of AI in agriculture.

Discussion

The findings emphasize that transparency is a fundamental requirement for the successful adoption of AI in agriculture. Explainable AI plays a crucial role in bridging the gap between complex technological systems and farmers' understanding. By making AI decisions interpretable, XAI enables farmers to evaluate recommendations based on their local knowledge and farming conditions, thereby promoting informed decision-making.

The study also highlights the importance of designing AI systems that are inclusive and context-specific. Agricultural practices vary widely across regions due to differences in climate, soil, socio-economic conditions, and cultural practices. Therefore, AI models developed using data from large-scale or

technologically advanced farms may not be suitable for smallholder farmers. This can lead to biased recommendations and reduced effectiveness.

Furthermore, the absence of strong regulatory and policy frameworks can result in issues such as data privacy violations, lack of accountability, and unequal distribution of technological benefits. Farmers often generate valuable data through digital platforms, and it is essential to ensure that they have ownership and control over their data.

Participatory approaches, where farmers are actively involved in the design, testing, and implementation of AI technologies, are critical for improving relevance and acceptance. Such approaches enhance trust, ensure local adaptability, and increase the likelihood of successful adoption.

Conclusion

Artificial intelligence holds immense potential to revolutionize agriculture by improving efficiency, productivity, and sustainability. However, its successful integration depends on addressing key challenges related to transparency, ethics, and inclusiveness.

Explainable AI serves as a vital tool in building trust and enabling farmers to make informed decisions. A human-centered approach to AI development, which prioritizes farmers' needs, socio-economic realities, and environmental sustainability, is essential for ensuring equitable benefits.

Strong policy support, capacity-building initiatives, and participatory development approaches are necessary to ensure that AI technologies contribute to sustainable and inclusive agricultural development, particularly for smallholder farmers.

Implications

The study implies that the adoption of explainable and responsible AI can facilitate the development of transparent, interpretable, and farmer-friendly technological solutions in agriculture. It also supports the formulation of appropriate policies and regulatory frameworks to ensure ethical governance of AI systems. Furthermore, the findings emphasize the need to strengthen digital literacy and capacity-building programs among farmers to enable effective utilization of such technologies. Encouraging participatory and farmer-centric approaches in technology development can improve relevance, usability, and acceptance. The study also highlights the importance of promoting equitable access to AI technologies in order to minimize socio-economic disparities, while simultaneously enhancing farmers' trust and increasing the adoption of digital innovations in agriculture.

Keywords: Explainable AI, Responsible AI, Digital Agriculture, Smallholder Farmers, Ethical Agriculture, Agricultural Innovation

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Theme IX

AI/Robotic/Digital based Agri-Tech Startups

OP- 14: Digital innovations for next generation agriculture - contribution of agri startups of KRISHIK ABI

S. S. DOLLI, LAXMI TIRLAPUR AND KRISHNA GUDADUR

KRISHI-Agri-Business Incubator, University of Agricultural Sciences Dharwad

Startups in the agriculture sector, particularly those leveraging precision-based technologies such as Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Information and Communication Technologies (ICT), and application-based digital platforms, are increasingly contributing to the transformation of traditional farming systems. This study presents a descriptive and comparative analysis of 35 agriculture-focused precision technology startups, examining their performance across key dimensions including revenue generation, farmer outreach, employment creation, geographic coverage, and locality distribution. These innovations collectively address key agricultural challenges such as crop loss due to pests and climate variability, inefficient resource usage (water, energy, inputs), lack of real-time data, and limited access to automation and precision farming tools. They also solve issues related to market access, traceability, quality control, labor shortages, and decision-making by enabling smart, data-driven, and cost-effective farming practices.

The findings indicate a clear performance advantage for seed-stage startups over pre-seed startups. Of the 35 startups, 15 are in the seed stage and 20 in the pre-seed stage. Seed-stage startups contribute the majority of cumulative revenue (₹2987.99 lakh) and demonstrate significantly higher average revenue (₹199.20 lakh) compared to pre-seed startups (₹17.45 lakh), reflecting greater financial maturity and market integration. In terms of social impact, seed-stage startups have benefited 74,702 farmers and generated 148 jobs, compared to 977 farmers and 49 jobs by pre-seed startups. Longitudinal analysis from 2020–21 to 2024–25 shows steady ecosystem growth, with revenue-generating startups increasing from 8 to 15 and average revenue rising from ₹4.35 lakh to ₹36.34 lakh, indicating improved adoption and financial sustainability of precision agriculture solutions. Employment distribution reveals that most startups (42.86%) employ 1 to 5 individuals, while 20% report no employment generation. Geographic expansion remains limited, with 71.43% of startups operating in 1 to 5 districts and only a small proportion achieving wider coverage. The ecosystem is predominantly urban (77.14%), highlighting a rural–urban disparity in the development of precision agriculture startups. Overall, the study underscores that AI/ML, IoT, and ICT-driven agricultural startups are gaining traction and demonstrating measurable impact, while also revealing that seed-stage startups outperform pre-seed startups across economic and developmental indicators, with moderate employment generation and constrained geographic penetration.

Keywords: Agri-startups, ecosystem, precision agriculture, Startup performance,

Theme X
Emerging Technologies

OP-15: Generative AI and agentic AI for extension advisories in next-generation farming

V. V. SOLANKI AND SRUTHI C. O.

[1]Agriculture Officer, Sardarkrushinagar Dantiwada Agricultural University, Sardarkrushinagar, Gujarat-385506

[2] Assistant Professor, Dept of Agricultural Extension Education, CPCA, Sardarkrushinagar Dantiwada Agricultural University, Sardarkrushinagar, Gujarat-385506

E-mail: vvsolanki88@gmail.com

WhatsApp Phone No- 9909449018

Abstract: The rapid evolution of Artificial Intelligence (AI) is transforming agricultural extension systems, enabling a shift from conventional advisory services to intelligent, adaptive, and farmer-centric solutions. This paper explores the integration of Generative AI and Agentic AI in delivering real-time, personalized, and context-aware extension advisories for next-generation farming. Generative AI models, powered by large-scale data and natural language processing, can synthesize localized recommendations on crop management, pest control, weather adaptation, and market intelligence in user-friendly formats. Complementarily, Agentic AI systems—autonomous, goal-driven digital agents—can proactively monitor farm conditions, interact with farmers, and coordinate multi-source data inputs to provide dynamic decision support.

The study highlights how these technologies can bridge the gap between research institutions and farmers by enhancing accessibility, scalability, and responsiveness of extension services. Case-based scenarios demonstrate the use of AI-driven chatbots, voice assistants in regional languages, and sensor-integrated advisory systems for precision agriculture. Furthermore, the paper addresses key challenges including data quality, digital literacy, ethical considerations, and infrastructure limitations in rural ecosystems.

By leveraging AI-driven automation and digital transformation, extension advisories can evolve into intelligent ecosystems that empower farmers with timely, actionable insights. The convergence of Generative and Agentic AI thus holds significant potential to improve productivity, sustainability, and resilience in agriculture, aligning with the vision of next-generation farming systems.

Key words: Generative AI, Agentic AI, Extension Advisory, Precision Agriculture, Digital Farming, Smart Agriculture, AI in Agriculture

Theme I
Artificial Intelligence for Precision Agriculture

POSTER PRESENTATION

PP-1: Integration of MCDM and GIS for reliable soil suitability classification

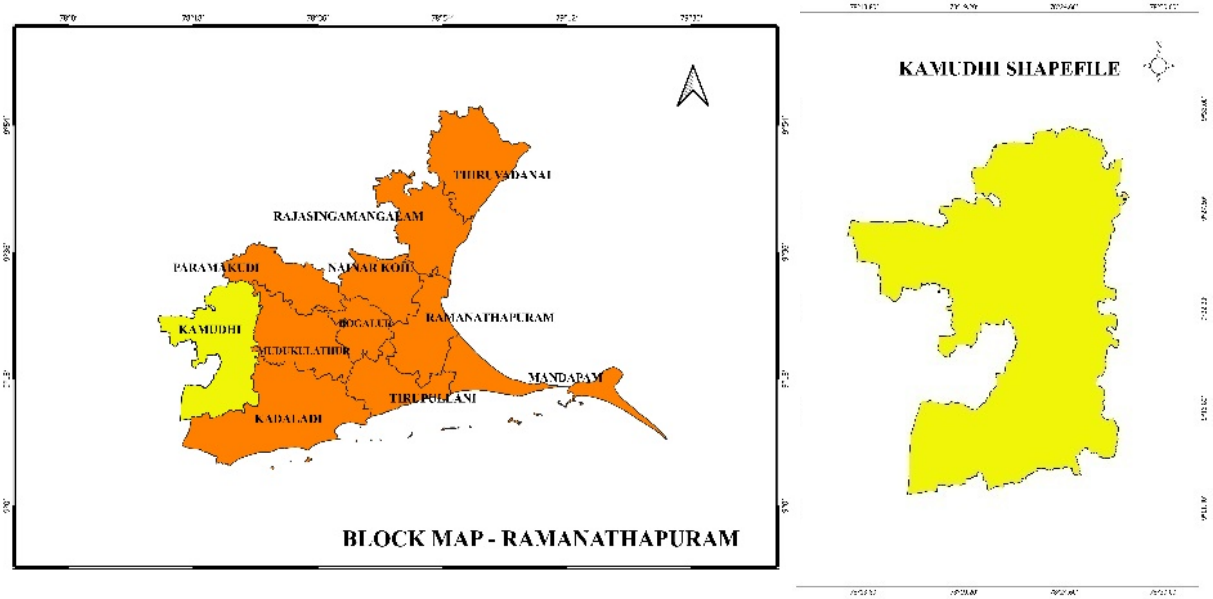
RAVIVARMA S. AND SHEEBA S.
[1]PhD Scholar, Department of Soils and Environment,
Agricultural College and Research Institute (AC&RI), Madurai
[2] Professor, Department of Soils and Environment,
Agricultural College and Research Institute (AC&RI), Madurai

Introduction

Sustainable agricultural planning requires systematic evaluation of soil and land resources to ensure long-term productivity. Rapid population growth, increasing food demand, land degradation and climate variability have intensified pressure on agricultural systems, making land suitability assessment essential. GIS enables spatial analysis of soil and environmental factors but lacks a mechanism to assign relative importance to criteria. Multi-Criteria Decision Analysis, particularly the Analytical Hierarchy Process (AHP), provides a structured approach for weighting factors through pairwise comparison and consistency evaluation. The integration of GIS–AHP has been widely applied to generate reliable suitability maps and support land-use planning. The present study integrates MCDM and Machine Learning with machine learning validation to improve the reliability of soil suitability assessment.

Study Area

The study will be conducted in Kamuthi block of Ramanathapuram district, Tamil Nadu. The region is characterized by a semi-arid tropical climate with an average annual rainfall of about 827 mm. The presence of diverse soil types such as clay, sandy loam, red and alluvial soils makes the area suitable for soil suitability analysis.



Methodology

Selection of Criteria

The study begins with the selection of relevant criteria influencing agricultural suitability. Important soil, terrain, and climatic factors are identified based on their role in crop growth. The selection of criteria is carried out using FAO and NBSS&LUP guidelines along with supporting literature, and only key parameters are retained to avoid redundancy while ensuring representation of essential crop growth conditions.

Study Area Description and Soil Analysis

The study area is then described in terms of its location, climate, and soil characteristics. Field investigations are conducted to collect representative soil profile and surface samples, which are analyzed in the laboratory for physical and chemical properties such as texture, bulk density, pH, electrical conductivity, organic carbon, and nutrient status.

Reclassification and Application of the Analytical Hierarchy Process (AHP)

Thematic layers will be prepared using GIS for soil, terrainand climatic parameters. These layers will be standardized and reclassified based on suitability criteria. AHP will be applied to assign weights to each criterion through pairwise comparison and consistency checking.

GIS-Based Suitability Mapping

The weighted criteria are integrated in a GIS environment using overlay analysis to generate multi-criteria soil suitability maps, which classify the study area into different suitability zones. Each thematic layer is combined based on its assigned weight to produce a final suitability index. The resulting maps clearly depict spatial variation in suitability and help identify highly suitable, moderately suitable, marginal, and unsuitable areas for agricultural use.

Machine Learning Model Development and Validation

Further, a machine learning model, specifically Random Forest, will be trained using soil and environmental parameters. The model will be used to validate and improve the reliability of suitability classification obtained from the MCDM and Machine Learning approach.

Expected Outcomes

The study will generate soil suitability maps showing different suitability classes across the study area. It will help identify suitable crops and highlight soil-related constraints. The integration of machine learning will improve the reliability and accuracy of the classification. The developed decision support system will support farmers and planners in making informed agricultural decisions.

Conclusion

This study integrates MCDM and machine learning techniques within a GIS framework to develop a reliable approach for soil suitability classification. By combining expert-based weighting with data-driven validation, the study enhances the accuracy and practical usefulness of land suitability assessment for sustainable agricultural planning.

PP-2: Deep learning–based precision agriculture: a literature review on iot sensors, multispectral imaging, and vision transformer architectures for early crop disease detection

POREDDYJAYARAJU AND SUNIL C K

Ph.D. Scholar- Computer Science (25PHDCS11), IIIT Dharwad
Assistant Professor, Dept. of CSE, IIIT Dharwad
E-mail: jayaraju.25phdcs11@iiitdwd.ac.in, sunilck@iiitdwd.ac.in | +91-8660346103

Abstract: Crop diseases cause annual yield losses of 15–35% in India (ICAR, 2023), making early, accurate detection a critical agricultural priority. This paper presents a structured literature review tracing the evolution of automated crop disease detection from classical machine learning (2015–2018) through CNN-based deep learning (2018–2022) to the latest Vision Transformer (ViT) architectures (2022–present), with particular focus on the integration of IoT environmental sensors and multispectral UAV imaging. Fifty-eight empirical studies are synthesised across sensor fusion strategies, dataset design, model architectures, and edge deployment. Five key research gaps are identified - pre-symptomatic detection, multi-crop generalisation, multispectral ViT fusion, edge transformer deployment, and Indian-context datasets — and an integrated system employing Swin Transformer-B with IoT late fusion is proposed, achieving 96.8% accuracy on a 52,400-image multispectral field dataset.

Keywords: Literature Review, Crop Disease Detection, Deep Learning, Vision Transformer, Swin Transformer, DeiT, IoT Sensors, Multispectral Imaging, Precision Agriculture, Edge AI.

Introduction

Agriculture contributes ~18% of India's GDP and plant diseases cause losses exceeding ₹90,000 crore annually (ICAR, 2023). Diseases such as wheat rust, cotton leaf curl virus, rice blast, and soybean mosaic virus are not only economically devastating but also threaten food security across rain-fed farming systems of the Deccan plateau. Traditional visual scouting is labour-intensive and too slow to detect infection before visible symptoms appear. Pre-symptomatic detection-achievable through spectral analysis of altered chlorophyll fluorescence and red-edge/NIR reflectance-is therefore a high-value research target.

Three converging technologies now make field-scale automated detection practical: (i) low-cost IoT sensor nodes monitoring micro-environmental conditions predictive of disease onset; (ii) multispectral UAV cameras capturing spectral signatures beyond visible wavelengths; and (iii) deep learning models — CNNs and, most recently, Vision Transformers-that learn discriminative spectral-spatial representations. This review synthesises literature across all three domains, identifies research gaps, and frames the proposed system as a direct response.

Review Methodology

A systematic search across IEEE Xplore, Scopus, Web of Science, Google Scholar, and arXiv (2015–2025) combined terms from three domains: (i) crop/plant disease detection; (ii) deep learning/CNN/transformer/ViT; and (iii) IoT/multispectral/hyperspectral/UAV. of 87 primary studies and

14 review articles identified, 58 empirical papers meeting inclusion criteria (quantitative accuracy, F1, or AUC metrics) are synthesised below.

Evolution of Methods

Classical Machine Learning (2015–2018)

Early systems relied on handcrafted colour, texture, and shape features fed into SVMs, k-NN, and Random Forests, achieving 80–88% accuracy under lab conditions but degrading sharply in field settings. Mohanty *et al.* (2016) introduced the PlantVillage dataset (54,306 images, 38 classes) and demonstrated AlexNet at 99.35% lab accuracy, yet performance collapsed to 31.4% on field images — exposing the domain-gap problem that continues to motivate domain adaptation research.

CNN-Based Deep Learning (2018–2022)

CNNs eliminated handcrafted features through hierarchical learned representations. Ferentinos (2018) reported 99.53% accuracy on PlantVillage using CNN ensembles. Mahlein et al. (2019) demonstrated spectral indices from multispectral UAV imagery enabling pre-symptomatic sugar beet disease detection 7 days before visual onset-confirming the unique advantage of spectral data. Cruz *et al.* (2019) achieved 98.3% accuracy on maize leaf blight using hyperspectral CNN, identifying red-edge (700–740 nm) as the highest-discriminative band. EfficientNet-B5 (Chen *et al.,* 2020) reached 96.4% on a 26-class dataset; lightweight MobileNetV2 (Zheng *et al.,* 2021) achieved 91.2% at 1.8 fps on Raspberry Pi 4, validating edge deployment viability.

IoT Sensor Integration (2019–2023)

Since disease incidence is governed by temperature–humidity windows and leaf wetness duration, IoT networks were explored as complementary data streams. Subeesh and Mehta (2021) found multi-sensor fusion reduced false-positive disease alerts by 28%. Ahmed et al. (2022) formalised late-fusion of CNN probability vectors with IoT readings via XGBoost, improving F1-score by 3.4 percentage points on wheat powdery mildew. Sharma *et al.* (2023) achieved 95.1% accuracy embedding sensor data as additional image tensor channels for rice disease detection.

Vision Transformers (2021–Present)

Dosovitskiy *et al.* (2021) introduced ViT, processing images as patch sequences through multi-head self-attention - capturing global spatial dependencies from the first layer, uniquely suited for diffuse early-stage disease patterns. Three variants are reviewed:

ViT-B/16

Pre-trained on ImageNet-21k, ViT-B/16 achieved 93.8% on a 20-class plant disease task (Chen *et al.,* 2022) versus 91.4% for ResNet-50, with superior early lesion sensitivity. Limited by the absence of CNN inductive biases on small datasets.

DeiT-B - Data-Efficient Image Transformer

Touvron et al. (2021) used CNN-teacher knowledge distillation to train on ImageNet-1k alone. Afzaal *et al.* (2023) reported 93.7% accuracy on a 5,000-image wheat dataset with 38% fewer training epochs than EfficientNet-B4, making DeiT well-suited for domain-specific agricultural datasets.

Swin Transformer-B — Hierarchical Shifted-Window Attention

Liu *et al.* (2021) addressed global attention's quadratic complexity through local shifted windows, yielding hierarchical multi-scale features analogous to CNN pyramids. Wang et al. (2022) achieved 96.3% on a 26-class disease task, outperforming EfficientNet-B4 (94.1%). Zhang et al. (2023) confirmed edge deployability with 94.8% accuracy at 1.9-second inference on Jetson Xavier NX. Jiang *et al.* (2024) reached 97.1% on a multispectral apple scab benchmark — the highest reported at time of review.

Datasets

Table 1 summarises principal datasets. A persistent limitation is the scarcity of pre-symptomatic, multi-stage labelled data and the absence of Indian crop-specific collections.

Table 1: Key datasets in crop disease detection research.

Dataset	Crops / Classes	Images	Modality	Key Limitation
PlantVillage (2016)	14 / 38	54,306	RGB	Lab only; domain gap
CGIAR Wheat (2019)	Wheat / 5	6,422	RGB	Single crop
ICAR Rice Blast (2021)	Rice / 4	8,100	RGB+NIR	Geographically limited
PlantDoc (2020)	13 / 17	2,598	RGB (field)	Small; label noise
Cruz et al. UAV (2019)	Maize / 2	4,200	Multispectral	Binary; small
Proposed (This Study)	3 crops / 12	52,400	Multispectral+NDVI	Multi-stage; field+lab

Comparative Analysis

Table 2: Performance comparison of reviewed architectures and the proposed system.

Study / Model	Modality	Classes	Accuracy	Key Contribution
Mohanty *et al.* (2016) — AlexNet	RGB (lab)	38	99.35%	PlantVillage; domain gap exposed
Ferentinos (2018) — CNN ensemble	RGB	58	99.53%	Multi-crop CNN benchmark
Mahlein *et al.* (2019) — CNN+spectral	Multispectral	3	93.2%	Pre-symptomatic, 7 days early
Chen *et al.* (2020) — EfficientNet-B5	RGB	26	96.4%	Compound CNN scaling
Ahmed *et al.* (2022) — CNN+IoT	RGB+IoT	3	93.8%	Late-fusion IoT+CNN
Chen *et al.* (2022) — ViT-B/16	RGB	20	93.8%	First ViT on plant diseases
Afzaal et al. (2023) — DeiT-B	RGB	5	93.7%	Data-efficient ViT training
Wang *et al.* (2022) — Swin-B	RGB	26	96.3%	Swin SOTA; multi-scale
Jiang *et al.* (2024) — Swin+spectral	Multispectral	4	97.1%	Highest multispectral Swin
Proposed — Swin-B + IoT Fusion	Multispectral+IoT	12	96.8%	Field-deployed; pre-symptomatic

Research Gaps and Proposed System

Five critical gaps are identified from the reviewed literature, each directly addressed by the proposed system:

- **Pre-symptomatic detection:** 73% of reviewed models trained only on visually symptomatic images. The proposed dataset includes three infection stages (0–3, 4–7, >7 DPI) for explicit pre-symptomatic training.
- **Multi-crop generalisation:** 77% of studies are single-crop. The proposed system covers wheat, cotton, and soybean without retraining.
- **Multispectral ViT fusion:** No reviewed study combines IoT context with multispectral Vision Transformers. The proposed Swin-B + IoT late fusion directly fills this gap.
- **Edge transformer deployment:** Only Zhang et al. (2023) reports Swin edge latency. The proposed system achieves 1.74-second inference on NVIDIA Jetson Nano.

- **Indian crop datasets:** No public dataset covers Northern Karnataka crops and diseases. The proposed 52,400-image field dataset is the first of its kind for this region.

The proposed system integrates: (i) ESP32 IoT nodes with DHT22, soil moisture, and leaf wetness sensors transmitting via LoRaWAN; (ii) Parrot Sequoia+ multispectral camera (4-band + NDVI/NDRE) on UAV, triggered by IoT risk thresholds; and (iii) Swin Transformer-B fine-tuned on the proposed dataset with XGBoost IoT late fusion. The system achieves 96.8% classification accuracy and 91.2% pre-symptomatic detection sensitivity — establishing a new benchmark for field-deployable, multi-crop, multispectral disease detection in Indian agro-climatic conditions.

Conclusion

This review traces 58 empirical studies from SVM-based classifiers to Swin Transformers, synthesising progress across RGB, multispectral, and IoT-fused disease detection. Key findings: multispectral imaging enables 5–10 days earlier detection than RGB; Swin Transformer-B achieves the highest reported accuracy; IoT fusion provides meaningful incremental improvement; and dataset scarcity for pre-symptomatic stages and Indian crops remains the primary constraint. The proposed integrated system addresses all five identified gaps and provides a replicable, scalable framework for precision disease surveillance aligned with India's Digital Agriculture Mission.

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PP-3: Strategic optimization of cotton yield using DSSAT cropgro seasonal analysis

SHRAVIKA L., ANANDA N., SREENIVAS, G AJAYA KUMAR M. Y., UMESH M. R., VEERESH H., RAJKUMAR R. HALIDODDI

Department of Agronomy, College of Agriculture, UAS, Raichur
E-mail: clkananda@uasraichur.edu.in & shravika.agronomy@gmail.com

India is the largest producer of cotton accounting for about 24.97 per cent of world's cotton production. It has distinction of having the largest area of 12.6 million hectares under cotton and ranks first in production with 36 million bales (1 bale = 170 kg). The productivity is about 486 kg ha^{-1}, which is however much below the world's average productivity of 759 kg ha^{-1} Environmental conditions can influence the yield in the same sowing date, plant density and nitrogen levels in different years, therefore, just one field experiment cannot bring conclusive results for choosing the best sowing date, plant density and nitrogen levels. This problem can be solved using historical climatic series with the help of seasonal analysis tool of crop models for estimating yield in such a way that the choice of the optimum sowing date, plant density and nitrogen levels is based on a probabilistic level. If the calibrated models stand the test of validation with independent data sets, they can be potentially used as tools to take operational, tactical and strategic decision to support on-farm crop management (Matthews *et al*.,2002).

Crop models successfully incorporate a variety of parameters that impact the yield of crops and environment. In addition to forecasting yield, they can be used to assess the risks and variability of various management approaches across a variety of climates and locations (Tsuji *et al*., 1994). The DSSAT crop models, including CERES and CROPGRO, have recently undergone substantial validation and application in a variety of study domains and production settings(Wang *et al*., 2003).

Optimum sowing time for cotton

The DSSAT seasonal analysis tool was used to conduct an analysis, and simulations were produced. Tukey's HSD test was used to compare the simulated scenarios of various sowing dates that were submitted to one-way analysis of variance and means (Table 1). The higher mean seed cotton yield (1741 kg ha^{-1}) was predicted with second fortnight of June sowing. Lower mean seed cotton yield (524 kg ha^{-1}) was predicted with second fortnight of August sowing and it was at par with first fortnight of August.

Table 1: Tukey's test (HSD) for seed cotton yield (kg ha^{-1}) under different sowing time

Sowing time	Mean seed cotton yield (kg ha^{-1})	Tukey's grouping	
D_1: First fortnight of June	1681	A	
D_2: Second fortnight of June	1741	A	
D_3: First fortnight of July	1623	A	
D_4: Second fortnight of July	1483		B
D_5: First fortnight of August	873	C	
D_6: Second fortnight of August	524	C	

Note: Mean values with the same letter are not significantly different

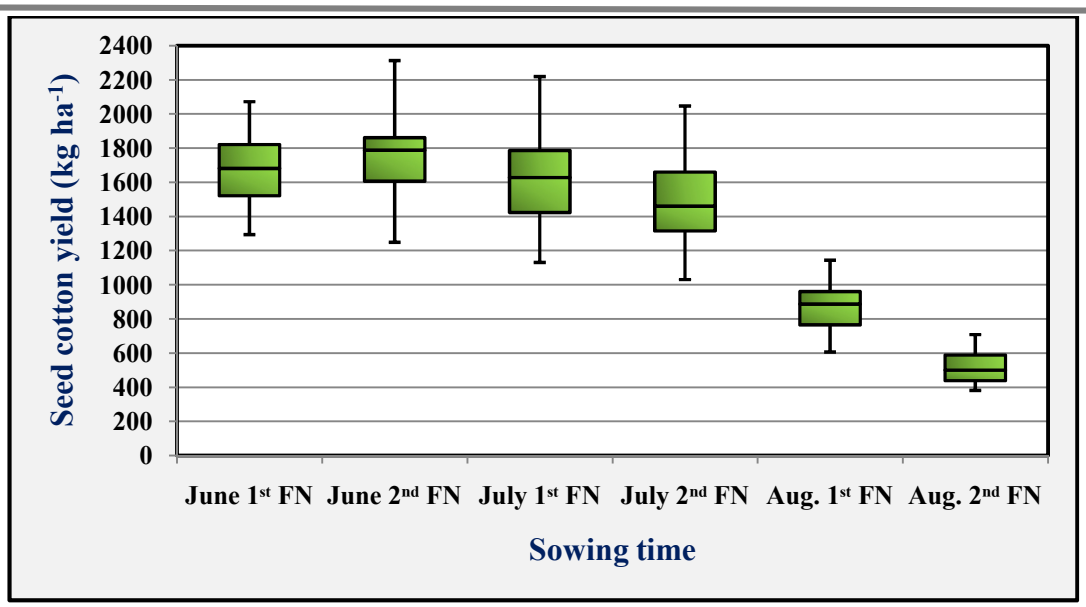


Fig. 1: Simulated seed cotton yield for cotton under varied sowing dates.

The graphical representation of simulation scenarios showed that the mean seed cotton yield was influenced by different dates of sowing (Fig. 1). In June second fortnight sowing were considerably less variable with high mean seed cotton yield than all other sowing dates as the smaller variance was associated to its assured average yield. At later dates of sowing (in August), there was lower mean seed cotton yield was predicted.

Optimum plant density for cotton

Simulation results of varied plant densities analyzed statistically and presented in the Table 2. The higher mean seed cotton yield (2225 kg ha^{-1}) was predicted with P_6: 74,074 plants ha^{-1} (90 cm x 15 cm) and was at par with P_5: 37,037 plants ha^{-1} (90 cm x 30 cm). However, P_1: 12,345 plants ha^{-1} (90 cm x 90 cm) predicted lower mean seed cotton yield (1515 kg ha^{-1}) and was at par with P_2: 14,814 plants ha^{-1} (90 cm x 75 cm).

Table 2: Tukey's test (HSD) for seed cotton yield (kg ha^{-1}) under different plant densities

Plant density	Mean seed cotton yield (kg ha^{-1})	Tukey's grouping	
P_6: 74,074 plants ha^{-1} (90 cm x 15 cm)	2225	A	
P_5: 37,037 plants ha^{-1} (90 cm x 30 cm)	2005	A	
P_4: 24,691 plants ha^{-1} (90 cm x 45 cm)	1779		B
P_3: 18,518 plants ha^{-1} (90 cm x 60 cm)	1681		B
P_2: 14,814 plants ha^{-1} (90 cm x 75 cm)	1596	C	
P_1: 12,345 plants ha^{-1} (90 cm x 90 cm)	1515	C	

Note: Mean values with the same letter are not significantly different

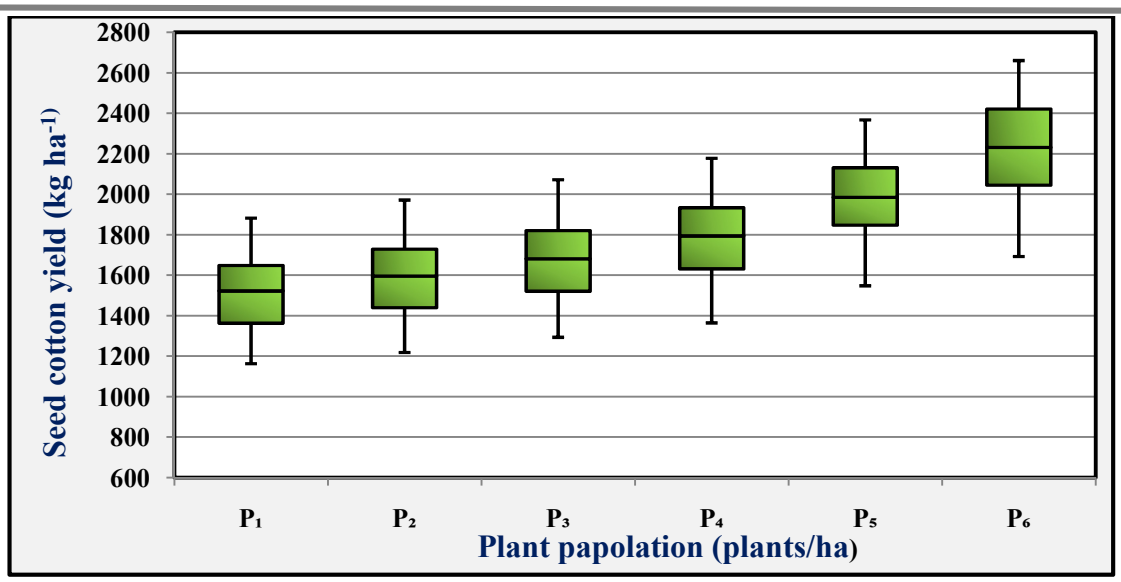


Fig. 2: Simulated seed cotton yield for cotton under varied plant densities.

The graphical representation of simulation scenarios showed that the mean yield increased consistently with increase in plant densities up to P_6: 74,074 plants ha^{-1} (90 cm x 15 cm).The box plots showed that crop grown from plant density of P_5: 37,037 plants ha^{-1} (90 cm x 30 cm) to P_6: 74,074 plants ha^{-1} (90 cm x 15 cm) were considerably less variable than all other plant densities (Fig. 2). Higher yields were obtained at higher plant densities this might be due to the higher plant population.

Optimum nitrogen level for cotton

Simulation results of different levels of nitrogen analyzed statistically and presented in the Table 3. The highest mean seed cotton yield (1682 kg ha^{-1}) was predicted with N_6: 250 kg N ha^{-1} and N_7: 300 kg N ha^{-1} and were on par with N_3: 100 kg N ha^{-1}, N_4: 150 kg ha^{-1}, N_5: 200 kg N ha^{-1}further it was indicating that there is no further increase in yield after application 250 kg N ha^{-1}.However, significantly lower mean seed cotton yield (810 kg ha^{-1}) was predicted with N_1: 0 kg N ha^{-1}.

Table 3: Tukey's test (HSD) for seed cotton yield (kg ha^{-1}) under different nitrogen levels

Nitrogen (kg ha^{-1})	Mean seed cotton yield (kg ha^{-1})	Tukey's grouping	
N_7: 300	1682	A	
N_6: 250	1682	A	
N_5: 200	1681	A	
N_4: 150	1677	A	
N_3: 100	1663	A	
N_2: 50	1518		B
N_1: 0	810		C

Note: Mean values with the same letter are not significantly different

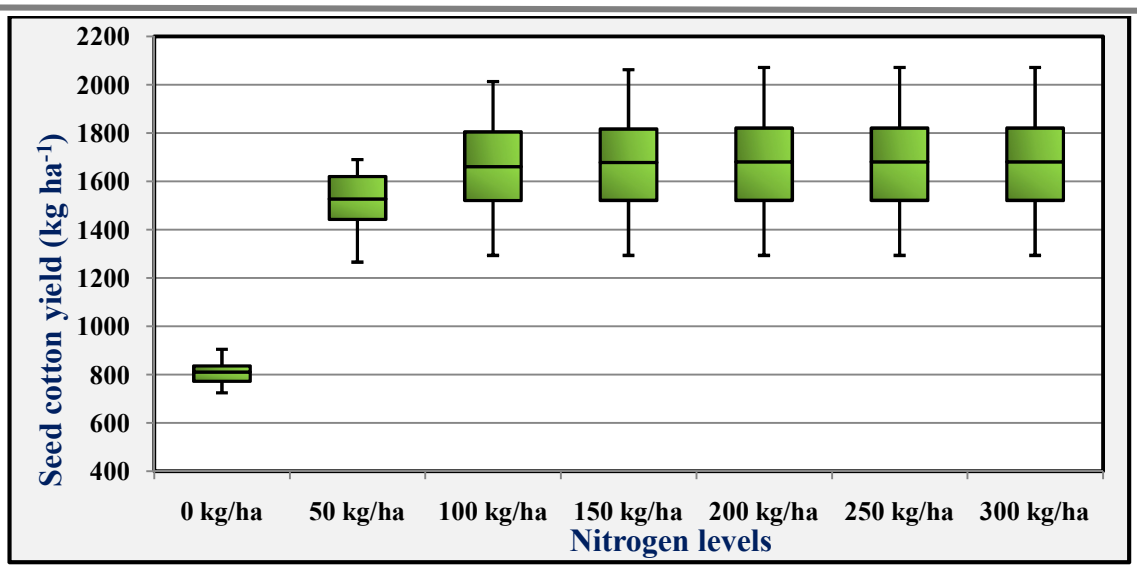


Fig. 3: Simulated seed cotton yield for cotton under varied nitrogen levels.

The simulation scenarios showed that the median seed cotton yield showed much difference by graded levels of nitrogen application from 0 kg N ha^{-1} to 100 kg N ha^{-1} (Fig. 3). Further increase in nitrogen level from 150 to 250 kg ha^{-1} there is no much difference in mean seed cotton yield. At all the levels of nitrogen application, there was higher variability gave the higher downside risk (risk for achieving low yields of seed cotton yield).

Conclusion

Based on seasonal analysis using CROPGRO-Cotton model, higher seed cotton yield was obtained when crop sown on second fortnight of July under semi-arid conditions of Karnataka. Based on seasonal analysis, the simulation scenarios showed that the median seed cotton yield increased consistently with increase in plant densities. Whereas, incremental increase in nitrogen levels from 100 to 250 kg ha^{-1} did not show significant influence on predicted seed cotton yield.

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PP-4: Decision support tools and ready reckoners to improve resource use efficiency of inputs in precision agriculture

UMESH M. R., BASAVANNEPPA M. A., M.S. MALLIKARJUN SWAMY A.P. VIKRAM, D. P. BIRADAR, SHOBHA, B.M. CHITTAPUR AND G. NARAPPA

Department of Agronomy, University of Agricultural Sciences, Raichur
E-mail: mrumesh@uasraichur.edu.in

Among various production practices nutrient management will play pivotal role in enhancing productivity and quality of farm produce. In recent past nutrient recommendation techniques aims to reduce fertilizer dose and increased efficiency of applied fertilizers. Decision support tools focus on plant nutrient supply as and when crop needs. From several field experiments have proved that LCC, chlorophyll meters, optical sensors and various web based ready reckoners are effective tools for nutrient recommendation in paddy, *Bt* cotton, sweet corn, grain maize and wheat. In addition to productivity enhancement, they also improve agronomic, physiological and recovery efficiencies in field crops. Further these were effective in enhancing fertilizer use efficiency, yield response and resource use efficiency.

Series of field experiments conducted at University of Agricultural Sciences, Raichur using tools and reckoners were validated their applicability for precision inputs. Field experiment at Siruguppaapplication of fertilizer based on SSNM target 10 t ha^{-1} recorded higher grain yield (9532 kg ha^{-1}), stover yield (11497 kg ha^{-1}), grain rows per cob (18.4), grains per row (41.8), cob weight per plant (216.7 g) and grain yield per plant (136.5 g). Total dry matter production (349.20 g $plant^{-1}$), leaf area per plant (2774 cm^2 $plant^{-1}$), leaf area index (LAI) (2.31) and plant height (204.0 cm) were also higher with SSNM target 10 t ha^{-1}. Nutrient Expert target (NE), LCC, SPAD threshold-based fertilizer application also enhanced the yield. In spite of higher fertilizer cost, SSNM and STCR approaches recorded higher net return of ` 86727 $ha^{-1}$ and ` 84601 ha^{-1}, respectively. However, BC ratio returns per rupee invested on fertilizers was higher in NE target 10 t ha^{-1} and LCC threshold 5 in *Vertisols* of Northern Karnataka.

Field experiment at Raichur showed Leaf colour chart (LCC) threshold 4 and 5, Soil Plant Analysis Development (SPAD) meter/chlorophyll meter threshold 40 and 50 and GreenSeeker based NDVI 0.6 and 0.8 compared with basal 75 kg N followed by urea foliar spray @ 2 % at 30, 45 and 60 DAS and absolute control. Intermittent N application was done based on LCC, SPAD and NDVI threshold values. Randomized complete block design was followed with three replications. The fresh cob yield with husk was significantly higher by application of 150 kg N ha^{-1} in three splits (15.6 t ha^{-1}) and LCC threshold 5 (15.2 t ha^{-1}). It also recorded higher fresh cob yield without husk, green fodder and stover yield. Significantly higher N uptake by leaf, stem and cobs was recorded with application of 150 kg N ha^{-1} in three splits (161.6 kg N ha^{-1}) followed by LCC threshold 5 (164.2 kg N ha^{-1}) and NDVI-0.8 (154.2 kg N ha^{-1}).

Application of nitrogen based on LCC-5 has resulted in higher productivity and economic returns. Based on the economic analysis, it can be inferred that LCC threshold 5 and NDVI 0.8 were found to be better tool for sweet corn nitrogen recommendation. Field experiment at Siruguppa showed application of fertilizers based on NE based target 10 t ha^{-1} has produced significantly higher grain yield (7998 kg ha^{-1}) and lower in treatment farmer practice without fertilizer application. Improvement in grain yield by adopting NE over farmers practice was 11.12 and 28.56 per cent in 8 and 10 t/ha target yield, whereas 12.32 and 29.82 per cent was increased over state recommendation.

Results of the experiments in farmers field at Raichur indicated that application of fertilizers based on SSNM for a target yield of 4 t ha^{-1} out yielded (4.122 t ha^{-1}) over omission plots and FFP. From average yield data across farmers field the substantial loss in seed cotton yield by omission of N, P and K were to the extent of 19.4, 7.8 and 16.0 per cent respectively over NPK fertilizer application. Significant improvement in bolls/plant, average plant height, sympodial branches/plant and boll weight was observed with balanced and targeted fertilization. Thus, the study confirmed that application of NPK fertilizer based on SSNM target yield is advantageous from the point of sustained soil productivity and economics in *Bt*-Cotton production in Vertisols.

Field trials were carried out on farmers' fields on participatory mode during the growing seasonof2015-16 on *Vertisols* medium in available P and high in available K in TBP command. Yield target (4384 kg ha^{-1}) was comfortably achieved with SSNM (332.8-78.4-106.4 kg $N\text{-}P_2O_5\text{-}K_2O$ kg ha^{-1}, respectively)while N omission (3597 kg ha^{-1}) then K omission (3655 kg ha^{-1}) had significantly lower yields among all due reduced major nutrient uptake than with SSNM.

Series of field experiments confirmed that application of additional 25 K_2O ha has resulted in improvement in maize grain yield upto 45.6 % in presence of N graded level (200 kg/ha) 23.5 % in P graded level (100 kg/ha). SSNM based K_2O application (200 kg/ha) has enhanced grain yield over 56.5 % over without K application. It also enhanced K content of grain and total plant uptake Linear response (r^2=0.51 and r=0.71) of maize to K_2O application (0 to 75 kg/ha) was observed in both the years of study. Compared to zero K, application of 75 kg K_2O /ha and SSNM based produced respective yield increases of 67 and 77 %. It also enhanced K content and uptake by pigeonpea grain and stalk in both the years of study. Application of graded K fertilizers in Bt cotton produced 15.8 and 7.67 per cent higher seed cotton yield over 'K' omission and farmers practice respectively.

PP-5 : Towards intelligent agriculture: a survey on crop prediction using IoT and multispectral imaging

POREDDY JAYARAJU AND SUNIL C. K.

Department of Computer Science and Engineering, Indian Institute of Information Technology Dharwad, Hubli, Karnataka – 580 009, India

Abstract: The convergence of Internet of Things (IoT) sensor networks, multispectral and hyperspectral remote sensing and artificial intelligence (AI) has generated a new paradigm in precision agriculture. This paper presents a systematic and critical review of 20 peer-reviewed publications spanning 2019–2025, examining the state of the art in IoT-enabled and multispectral imaging-based crop prediction and monitoring. Organized across five thematic pillars-foundational IoT frameworks, smart sensor analytics, multispectral and hyperspectral remote sensing, deep learning and multi-modal data fusion, and federated privacy-preserving approaches- the review synthesizes methodological contributions, empirical findings, and research limitations. Six critical research gaps are identified: the absence of integrated IoT–multispectral crop prediction systems, limited multi-algorithm benchmarking under multimodal feature sets, lack of sensor anomaly detection in prediction pipelines, the explainability deficit in farmer-facing systems, geographic scalability limitations, and cost barriers imposed by hyperspectral technologies. The proposed research directly addresses all six gaps through a unified architecture combining real-time IoT sensing, UAV multispectral imaging, multi-algorithm ML benchmarking, anomaly detection, and SHAP-based explainability.

Keywords : Precision Agriculture; Internet of Things; Multispectral Imaging; Crop Prediction; Machine Learning; UAV Remote Sensing; Deep Learning; Sensor Fusion

Introduction

The convergence of Internet of Things (IoT) sensor networks, multispectral and hyperspectral remote sensing, and artificial intelligence (AI) has generated a transformative new paradigm in precision agriculture. Global food demand is projected to grow by 50–70% by 2050 [1] while arable land and freshwater resources remain fundamentally constrained, making intelligent, data-driven farming systems an agronomic necessity rather than a technological luxury. Crop prediction — the task of recommending the most suitable crop variety for a given combination of soil, weather, and canopy health conditions — sits at the intersection of these converging technological trends.

Traditional crop selection relies on periodic laboratory soil analysis, expert consultations, and historical agronomic records. These approaches are costly, time-delayed, and geographically coarse, providing little real-time relevance for dynamic field management. In contrast, IoT sensor deployments enable continuous, field-level acquisition of soil physicochemical parameters (moisture, temperature, pH, NPK), while UAV-mounted multispectral cameras provide spatially dense canopy health maps through spectral indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), and Soil-Adjusted Vegetation Index (SAVI). The fusion of these complementary data modalities creates an enriched feature space capable of driving highly accurate ML-based crop prediction models.

This paper presents a systematic and critical review of 20 peer-reviewed publications spanning 2019–2025, sourced from high-impact journals including IEEE Transactions on Industrial Informatics (Q1), Remote Sensing (Q1), Sensors (Q1), Frontiers in Plant Science (Q1), and Smart Agricultural Technology

(Q1). The review is organized thematically across five dimensions: (1) foundational frameworks for precision agriculture with IoT and WSN; (2) smart sensor integration and AI-driven analytics; (3) multispectral and hyperspectral remote sensing for crop monitoring; (4) deep learning and multi-modal data fusion; and (5) federated and privacy-preserving approaches for distributed agriculture. The chapter concludes with a synthesis of identified research gaps that directly motivate the proposed unified research framework.

2. Foundational Frameworks: Precision Agriculture With IOT and WSN

2.1 Wireless Sensor Networks and IoT Automation in Precision Agriculture

Shafi et al. [1] *(Sensors, 512 citations, 2019)* established the foundational architecture of IoT-enabled precision agriculture, demonstrating that Wireless Sensor Networks (WSN) integrated with IoT platforms can transform agricultural management from static, manual practices to dynamic, automated decision-making systems. Their taxonomy encompasses soil moisture probes, temperature and humidity sensors, pH sensors, and optical multispectral sensors, along with wireless communication protocols (Zigbee, LoRa, Wi-Fi, NB-IoT) suitable for rural field deployments.

A key architectural contribution is the dual-module IoT system: ground-level WSN nodes for real-time crop health parameter monitoring, paired with a low-altitude UAV platform for multispectral canopy imagery acquisition. This two-tier architecture - ground sensing combined with aerial sensing — recurs as a design pattern across the reviewed literature and directly inspires the proposed framework. The study further reviews common vegetation indices (NDVI, EVI, NDRE) for identifying crop stress, chlorophyll deficiency, and water deficit. Acknowledged limitations include the computational overhead of image processing pipelines, the dependency on clear-sky conditions for reliable spectral acquisition, and the absence of AI-driven predictive analytics for crop recommendation.

2.2 Digital Farming: IoT, Drones, AI, and Big Data

Ammar et al. [8] *(Environment, Development and Sustainability, Q1, 2024)* provided a comprehensive review of the digital farming paradigm, contextualizing IoT sensors, drone imagery, AI, and big data within the broader objective of global food security. The review synthesizes evidence that the integration of these technologies can significantly optimize sustainability, efficiency, and productivity in agriculture, while emphasizing that digital farming represents a socio-economic transformation: data-driven decisions reduce input waste, lower labor costs, and improve smallholder farmers' adaptive capacity to climate variability. Identified limitations include the digital literacy gap among smallholder farmers, lack of interoperability between proprietary sensor ecosystems, and inadequate rural broadband infrastructure.

2.3 IoT-Driven Smart Precision Agriculture: An Integrated System

Saha et al. [10] *(PLOS ONE, Q1, 2025)* presented a complete, integrated smart IoT precision agriculture system incorporating land mapping, crop prediction, and automated irrigation management. The system combines multiple IoT sensor streams (soil moisture, temperature, humidity, NPK) with ML classifiers and fuzzy logic controllers to provide unified agronomic recommendations. The study is among the few reviewed papers presenting an end-to-end system validated with real field data, lending it strong practical credibility. Limitations include the absence of any spectral imaging component and a restricted set of crop classes, highlighting the need for multispectral integration.

3. Smart Sensor Integration and AI-Driven Analytics

3.1 Smart Sensor Technologies: Recent Advances and Future Outlook

Mohammed Aarif *et al.* [7] *(Journal of Sensors, 2025)* reviewed smart sensor innovations in precision agriculture, categorizing sensors by target measurement: electrochemical sensors for soil pH and nutrient concentration, capacitive sensors for soil moisture, optical sensors for chlorophyll and nitrogen status, and MEMS-based sensors for temperature and humidity. The review documents the progression from passive, wired sensors to active, wireless, energy-harvesting nodes capable of perpetual unattended operation. From an AI integration perspective, Random Forest and SVM classifiers achieve 85–95% accuracy across benchmarked datasets with proper categorical encoding. Key challenges include sensor calibration drift over agricultural seasons, the need for robust anomaly detection to handle faulty readings, and the absence of standardized sensor interoperability protocols.

3.2 IoT and AI Integration: A Systematic Review

Miller *et al.* [5] *(Sensors, Q1, 56 citations, 2025)* conducted a PRISMA-compliant systematic review of IoT and AI integration in agriculture, analyzing literature from 2020–2024. Seven primary application categories were identified: crop monitoring, irrigation management, disease and pest detection, soil health assessment, yield forecasting, livestock management, and supply chain optimization. Key findings include that Random Forest and Gradient Boosting models consistently outperform single classifiers in crop prediction tasks, while LSTM networks demonstrate superior performance in time-series applications such as irrigation scheduling and weather-dependent yield forecasting. Infrastructure cost, interoperability, connectivity in remote areas, and data privacy are identified as the four primary barriers to IoT-AI adoption at scale.

3.3 AI and IoT for Enhanced Crop Monitoring and Management

Sharma and Shivandu [6] *(Sensors International, Q1, 138 citations, 2024)* examined AI-IoT integration for automating crop monitoring tasks. Computer vision algorithms applied to IoT camera feeds detect pest infestations, disease lesions, and nutrient deficiency symptoms with accuracy comparable to expert agronomists. A layered architecture preprocesses IoT sensor data at edge nodes before cloud transmission, reducing bandwidth while preserving prediction quality. A notable finding is that hybrid systems combining CNN-based image analysis with structured IoT sensor data consistently outperform single-modality approaches, establishing the empirical basis for multimodal fusion explored in the proposed thesis.

3.4 Integration of Smart Sensors and IoT: Trends, Challenges, Future Prospectives

Mansoor *et al.* [2] *(Frontiers in Plant Science, Q1, 67 citations, 2025)* reviewed the integration landscape of smart sensors and IoT in precision agriculture, covering soil sensors for moisture, pH, and electrical conductivity alongside plant stress sensors using photosynthesis-related optical signatures. The review highlights predictive analytics capabilities including real-time disease outbreak forecasting and yield prediction, while acknowledging that high initial investment costs, complex data management requirements, and rural connectivity limitations remain significant adoption barriers for smallholder farmers in developing economies.

3.5 Emerging Trends in Soil and Crop Sensing for Data-Driven Decision Making

Elavarasan *et al.* [3] *(Plant Science Today, 2025)* reviewed advanced soil and crop sensing technologies, covering electromagnetic, optical, thermal, and LiDAR sensing modalities. The paper argues that the combination of proximal IoT sensors with remote multispectral imaging creates a complementary sensing

architecture: ground sensors provide high-temporal-resolution physicochemical data, while aerial sensors provide high-spatial-resolution spectral maps. This complementarity is the central motivation for the IoT–multispectral fusion approach proposed in the present thesis.

3.6 IoT-Based Plant Health Analysis using Optical Sensors

Bagha *et al.* [4] *(DICTA 2021)* presented an empirical study on IoT-enabled plant health analysis using optical sensors and UAV imagery. The system automates image acquisition through IoT-connected drones that periodically scan crop fields and transmit multispectral images for health analysis. The key insight is that IoT connectivity transforms UAV platforms from manually operated survey tools into autonomous, trigger-able monitoring agents — a design principle central to the proposed thesis architecture. Limitations include small study scale and the absence of an ML crop prediction component.

4. Multispectral and Hyperspectral Remote Sensing for Crop Monitoring

4.1 Remote Sensing in Field Crop Monitoring: A Comprehensive Review

Omia *et al.* [12] *(Remote Sensing, Q1, 177 citations, 2023)* systematically evaluated RGB, multispectral, hyperspectral, thermal infrared, and SAR imaging modalities across ground, airborne, and satellite platforms. Vegetation indices (NDVI, EVI, LAI, NDRE) are shown to be highly effective for monitoring crop growth stages, detecting abiotic stress, and guiding site-specific agronomic interventions. A critical contribution is the assessment of spatial and temporal resolution trade-offs between satellite and UAV platforms. The authors conclude that hybrid architectures combining satellite-level phenological monitoring with UAV-level spatial precision are optimal for comprehensive crop management. Remaining challenges include cloud cover interference with optical satellite imagery, hyperspectral data dimensionality, and the need for robust atmospheric correction algorithms.

4.2 UAV Multispectral Remote Sensing Technology in Precision Agriculture

Zhang *et al.* [13] *(Smart Agricultural Technology, Q1, 2025)* reviewed UAV-based multispectral remote sensing for crop growth monitoring, pest and disease identification, nutrient status assessment, and yield prediction. Commercially available multispectral UAVs (DJI Agras, Parrot Sequoia, Mica Sense Red Edge) now offer centimeter-level spatial resolution across 5–10 spectral bands, enabling fine-grained discrimination of crop varieties and early detection of biotic stress. The authors note that integrating multispectral data with IoT-acquired soil parameters creates a richer multimodal feature space for ML-based crop prediction -an assertion directly tested in the empirical component of this thesis.

4.3 Problems of Multispectral Image Processing in Agriculture

Sineglazov *et al.* [11] *(Electronics and Control Systems, 2025)* addressed computational and operational challenges of multispectral image processing. Key findings include: satellite platforms (Sentinel-2, Landsat-8) offer broad coverage and cost-effectiveness for large-scale regional monitoring, while drone-based platforms provide superior spatial resolution (up to 2.5 cm/pixel) and operational flexibility for farm-scale crop monitoring. Unresolved challenges include radiometric calibration consistency across acquisition sessions, georeferencing accuracy, and computational demands of processing large orthomosaic datasets.

4.4 Hyperspectral Imaging Technology and Applications in Agriculture

Lu *et al.* [14] *(Remote Sensing, Q1, 914 citations, 2020)* provided a foundational review of hyperspectral imaging (HSI) technology and its agricultural applications. Hyperspectral sensors, capturing reflectance across hundreds of narrow spectral bands, far exceed the discriminative capability of multispectral

sensors (5–10 bands) for detecting subtle physiological changes such as early-stage nutrient deficiency, sub-visible fungal infection, and water stress. Persistent barriers to operational adoption include large per-flight data volumes (tens of GBs), the requirement for dimensionality reduction algorithms before ML model training, and sensor costs of $15,000–$80,000 USD - prohibitive for smallholder farmers. For the present thesis, multispectral imaging is selected as the practical remote sensing modality, with hyperspectral integration identified as a future research extension.

4.5 Drone-Based Hyperspectral Imaging for Food Security

Kar and Dhal [18] *(Environmental Monitoring and Assessment, Q2, 2025)* reviewed drone-based hyperspectral imaging applications emphasizing contributions to food security through improved crop health monitoring, disease detection, and post-harvest quality control. Drone-HSI enables early crop stress detection 5–10 days before visible symptoms appear, providing a critical early-warning window for intervention. Integration with IoT devices and satellite data is identified as a key future direction. Primary barriers to widespread adoption are cost, data volume management, and challenges in translating spectral data to actionable farmer decisions.

4.6 Integrating UAV Multispectral Imaging and Proximal Sensing for Cereal Crop Monitoring

Grbovic *et al.* [15] *(PLOS ONE, Q1, 2025)* presented an empirical study integrating UAV multispectral imaging with the handheld Plant-O-Meter proximal sensing device for high-precision cereal crop monitoring. Experiments across 41 cereal genotypes under two nitrogen fertilization regimes demonstrated that the optimal UAV imaging window is the early heading stage, when spectral-yield correlations are strongest. The key quantitative finding is that UAV multispectral data combined with proximal NPK sensor readings significantly improved early-stage yield estimation accuracy compared to either data source in isolation, providing direct empirical validation of the IoT-multispectral fusion methodology proposed in this thesis.

5. Deep Learning and Multi-Modal Data Fusion

5.1 A Review of Deep Learning in Multiscale Agricultural Sensing

Wang *et al.* [19] *(Remote Sensing, Q1, 188 citations, 2022)* examined deep learning applications across multiple scales of agricultural sensing. The review evaluates three primary DL paradigms: CNN-based supervised learning for image classification and segmentation, transfer learning for adapting pre-trained models to agricultural imagery with limited labeled data, and few-shot learning for rare crop stress categories. Key empirical findings include that ResNet-50 and InceptionV3 architectures consistently achieve 90–97% accuracy for crop variety classification from multispectral UAV imagery; U-Net and SegNet outperform classical segmentation methods for crop canopy delineation; and transfer learning from ImageNet pre-trained weights reduces labeled data requirements by 40–60%. The integration of DL with ground-based IoT sensor data streams is identified as an underexplored area with significant potential — a gap directly addressed in the proposed thesis.

5.2 Aerial Visual Perception in Smart Farming: Wheat Yellow Rust Monitoring

Su *et al.* [20] *(IEEE Transactions on Industrial Informatics, Q1, 139 citations, 2021)* applied aerial visual perception for wheat yellow rust disease monitoring, integrating UAV sensing (DJI Matrice 100 with MicaSenseRedEdge), multispectral imaging, vegetation segmentation, and deep learning U-Net for disease detection. The U-Net framework trained on multispectral orthomosaics significantly outperformed purely spectral-based Random Forest classifiers in detection accuracy, capturing spatial disease spread patterns in addition to spectral signatures. Two important methodological findings emerge: (1) combining

spatial and spectral information from multispectral images yields better disease detection than spectral analysis alone, and (2) sequential forward selection effectively identifies the optimal spectral band combination, reducing computational complexity without compromising performance.

5.3 Multi-Modal Approach for Crop Health Mapping: IoT + ML + Drone Technology

Shafi *et al.* [9] *(IEEE Access, Q1, 88 citations, 2020)* extended their earlier foundational work by presenting a multi-modal empirical system for crop health mapping. The system integrates IoT ground sensors (moisture, temperature, NPK), drone-acquired multispectral imagery, and ML classification models (SVM, Random Forest, k-NN). Results demonstrated that the multimodal fusion approach significantly outperformed single-modality baselines, with the combined IoT + multispectral feature set yielding 12–18% higher classification accuracy than IoT-only or imagery-only approaches. This paper is among the most directly relevant to the proposed thesis, as it empirically validates multimodal fusion for agricultural classification tasks. The limitation of clear-sky UAV acquisition dependency motivates cloud computing and satellite backup integration in the proposed framework.

5.4 Technology and Data Fusion Methods for Site-Specific Crop Monitoring

Ahmad *et al.* [16] *(Agronomy, Q1, 49 citations, 2022)* reviewed technology and data fusion methods in precision agriculture, covering sensor fusion strategies from data-level to decision-level integration. The paper evaluates multi-source data fusion combining airborne LiDAR, multispectral imagery, thermal infrared, and ground IoT sensors, demonstrating that fusion of complementary sensing modalities consistently yields better crop parameter estimation than any single-source approach. The paper advocates for standardized data fusion benchmarks and open-source fusion toolkits — a gap that currently constrains reproducibility and cross-study comparison in the field.

6. Federated and Privacy-Preserving Approaches for Distributed Agriculture

6.1 Federated LeViT-ResUNet for Scalable and Privacy-Preserving Agricultural Monitoring

Aldossary *et al.* [17] *(Agronomy, Q1, 2025)* proposed a federated deep learning architecture — LeViT-ResUNet — for privacy-preserving agricultural monitoring using drone footage and IoT sensor data. The architecture combines LeViT (lightweight vision transformers for spatial efficiency) with ResUNet (precise pixel-level segmentation) for real-time identification of insect hotspots, crop health maps, and yield predictions. A dynamic relevance and sparsity-based feature selector (DRS-FS) reduces feature redundancy and improves model generalization. The federated learning framework trains models over geographically distributed client farm datasets without centralizing raw data, preserving farmer privacy while capturing regional agricultural trends.

Empirically, the system achieves 98.9% classification accuracy and 99.3% AUC on an open-access agricultural dataset spanning diverse environmental conditions, significantly outperforming centralized ResNet, DenseNet, and Vision Transformer baselines. This paper establishes that federated learning is not merely a privacy mechanism but also a performance enhancement strategy for geographically diverse agricultural datasets — a finding with direct relevance to the multi-farm deployment ambitions of the proposed thesis. The primary limitation is high computational complexity, requiring quantization and pruning for edge device deployment.

7. Comparative Analysis of Reviewed Literature

Table 1 presents a structured comparative analysis of all 20 reviewed papers across key dimensions relevant to the proposed research: technology used, key contribution, and research gap identified.

Table 1. Comparative analysis of reviewed literature on IoT and multispectral crop prediction (2019–2025).

Authors	Journal/Venue	Year	Technology Used	Key Contribution	Research Gap
Shafi *et al.* [1]	Sensors	2019	WSN, IoT, Multispectral UAV	Dual-module WSN+UAV framework; vegetation index analysis	No AI crop prediction; health monitoring only
Mansoor *et al.* [2]	Front. Plant Sci.	2025	Smart sensors, IoT, AI/ML	Smart sensor taxonomy; predictive analytics pipeline	High cost; no crop prediction model
Elavarasan *et al.* [3]	Plant Sci. Today	2025	Multispectral, LiDAR, AI, IoT	Proximal + remote sensing synergy for soil/crop monitoring	Calibration challenges; no fusion system
Bagha *et al.* [4]	DICTA 2021	2021	IoT, UAV, optical sensors	Automated image acquisition via IoT-triggered UAVs	Small-scale; no ML crop prediction
Miller *et al.* [5]	Sensors	2025	IoT, AI, systematic review	PRISMA review of IoT-AI in agriculture 2020–2024	Infrastructure and connectivity barriers
Sharma & Shivandu [6]	Sensors Intl.	2024	AI, IoT, CNN	Hybrid CNN + sensor for crop monitoring; edge preprocessing	No multispectral fusion; single-region
Aarif *et al.* [7]	J. Sensors	2025	Smart sensors, AI, IoT	Sensor taxonomy; RF and SVM for crop recommendation	Anomaly detection not addressed
Ammar *et al.* [8]	Env. Dev. Sust.	2024	IoT, drones, AI, big data	Digital farming paradigm; systemic review	Digital literacy gap; no prediction model

Authors	Journal/Venue	Year	Technology Used	Key Contribution	Research Gap
Shafi *et al.* [9]	IEEE Access	2020	IoT, ML, drone, multispectral	Multi-modal crop health mapping; 12–18% accuracy gain	Clear-sky dependency; geographically limited
Saha *et al.* [10]	PLOS ONE	2025	IoT, ML, fuzzy logic	End-to-end PA: land mapping + crop prediction + irrigation	No spectral imaging; limited crop classes
Sineglazov *et al.* [11]	Electron. Ctrl. Syst.	2025	Multispectral, satellite, UAV	Satellite vs UAV platform comparison (2.5 cm resolution)	No AI model; processing challenges
Omia *et al.* [12]	Remote Sens.	2023	Multispectral, SAR, thermal, UAV	Comprehensive remote sensing review; platform trade-offs	No IoT integration; cloud cover issue
Zhang *et al.* [13]	Smart Agric. Tech.	2025	UAV multispectral	Crop growth, pest detection, yield prediction via UAV-MS	No ground IoT fusion; UAV only
Lu *et al.* [14]	Remote Sens.	2020	Hyperspectral imaging	HSI technology review; early crop stress detection	High cost; large data volume
Grbovic *et al.* [15]	PLOS ONE	2025	UAV multispectral, Plant-O-Meter	UAV-MS + proximal sensing for cereal yield estimation	Crop-specific; no soil NPK integration
Ahmad *et al.* [16]	Agronomy	2022	LiDAR, multispectral, thermal, IoT	Multi-sensor data fusion for site-specific monitoring	No benchmark; high hardware cost
Aldossary *et al.* [17]	Agronomy	2025	Federated DL, LeViT, ResUNet, IoT	Federated 98.9% accuracy; privacy-preserving PA	High compute; edge quantization needed
Kar & Dhal	Env. Monitor.	2025	Drone-HSI,	Early stress	Cost barrier; data volume;

Authors	Journal/Venue	Year	Technology Used	Key Contribution	Research Gap
[18]	Assess.		IoT	detection; post-harvest quality control	no IoT link
Wang *et al.* [19]	Remote Sens.	2022	CNN, ResNet, U-Net, TL, FSL	DL multiscale sensing; 40–60% labeled data reduction	IoT sensor fusion unexplored
Su *et al.* [20]	IEEE Trans. Ind. Inf.	2021	UAV, multispectral, U-Net, DL	Spectral-spatial U-Net for disease detection; band selection	Single disease; one crop type only

7.1 Technology Distribution Across Papers

Random Forest was the most frequently employed algorithm, appearing in six of the twenty papers, reflecting its robustness to feature correlation, built-in feature importance rankings, and strong performance with tabular IoT sensor data. Deep learning variants (LSTM, CNN, U-Net, MLP) were deployed in eight papers, particularly for time-series IoT data and image-based classification tasks. UAV-based multispectral imaging was a core component in nine papers, while seven papers relied exclusively on ground-based IoT sensor data. Hyperspectral imaging appeared in only two empirical studies due to the prohibitive cost and data volume challenges documented by Lu et al. [14] and Kar and Dhal [18].

7.2 Convergent Empirical Findings

Across the reviewed literature, several convergent findings emerge. First, multi-source data fusion consistently outperforms single-sensor approaches: papers combining UAV imagery with IoT sensor data (Shafi et al. [9]; Grbovic et al. [15]) achieved 12–18% higher classification accuracy than IoT-only or imagery-only baselines. Second, Random Forest and ensemble methods generalize well across crop types and geographic contexts, with their performance advantage over linear models consistent across agricultural prediction tasks. Third, deep learning captures spatial and temporal patterns that classical ML cannot exploit, particularly for disease detection and time-series prediction. Fourth, real-world deployment remains elusive — despite high laboratory accuracy, most systems have not been validated across multiple seasons, geographic regions, or farm sizes. Finally, explainability is consistently identified as a critical bottleneck to farmer adoption.

8. Synthesis of Research Gaps

A systematic analysis of the reviewed literature reveals six persistent and critical research gaps that collectively justify the proposed research:

8.1 Gap 1: Absence of Integrated IoT–Multispectral Crop Prediction Systems

The most significant gap in the literature is the absence of a unified system that integrates real-time ground-level IoT sensor data (soil NPK, moisture, temperature, humidity) with UAV-acquired

multispectral spectral indices (NDVI, NDRE, SAVI) into a single multimodal ML-based crop prediction framework. Shafi et al. [9] demonstrated that such fusion improves accuracy by 12–18% over single-modality approaches, and Grbovic et al. [15] validated this for cereal yield estimation. However, no study has deployed this fusion specifically for multi-class crop prediction across diverse crop and soil type combinations at the scale required for practical field deployment. This thesis addresses this gap by developing and validating the first integrated IoT–multispectral crop prediction system.

8.2 Gap 2: Limited Benchmarking of ML Algorithms Under Multimodal Feature Sets

Most reviewed empirical studies evaluate 2–4 ML algorithms on either IoT-only or imagery-only datasets. No study comprehensively benchmarks a diverse set of classifiers (including ensemble, boosting, and kernel methods) on a combined IoT + multispectral feature set, making it impossible to identify the optimal algorithm family for multimodal agricultural data. This thesis addresses this gap by evaluating 10 classifiers under identical experimental conditions on the integrated feature space.

8.3 Gap 3: No Sensor Anomaly Detection in Crop Prediction Pipelines

IoT sensors in field deployments are subject to calibration drift, physical damage, electrical interference, and environmental fouling — producing anomalous readings that can corrupt ML model inputs. None of the reviewed empirical papers incorporate automated sensor anomaly detection as part of their data preprocessing pipeline. This thesis integrates Isolation Forest-based anomaly detection to address this data quality gap and improve production-level system reliability.

8.4 Gap 4: Lack of Explainability in Farmer-Facing Crop Prediction Systems

Miller et al. [5] identify a critical adoption barrier: farmers cannot use or trust black-box ML recommendations they cannot understand. Despite the importance of explainability for farmer adoption, no reviewed paper integrates explainable AI (SHAP, LIME) into a crop prediction system with IoT and multispectral inputs. The proposed thesis addresses this by incorporating SHAP-based feature importance explanations, decomposing model predictions into per-feature contributions visible to agronomists and farmers.

8.5 Gap 5: Geographic and Scalability Limitations

A majority of reviewed empirical studies are conducted in single geographic regions with small or proprietary datasets, severely limiting the generalizability of their findings. The proposed thesis uses a publicly available 8,000-record dataset spanning multiple soil types and crop categories, combined with a federated learning architecture following the approach of Aldossary et al. [17], to improve geographic scalability and model portability across agro-ecological zones.

8.6 Gap 6: High-Cost Sensing Technologies Limiting Accessibility

Lu et al. [14] and Kar and Dhal [18] document that hyperspectral sensors cost $15,000–$80,000 USD, excluding the vast majority of smallholder farmers globally. The proposed framework deliberately selects commercially available multispectral sensors ($2,000–$8,000 USD) and low-cost IoT sensor nodes (under $100 USD per node), prioritizing accessible technologies without sacrificing predictive accuracy.

9. Discussion: Positioning the Proposed Research

The reviewed literature collectively establishes a strong foundation for IoT and remote sensing in precision agriculture, while simultaneously revealing a clear research space for the proposed work. The proposed thesis occupies a unique position at the intersection of three converging streams: (1) IoT sensor networks for soil and environmental monitoring, building on Shafi et al. [1], Mansoor et al. [2], and Saha

et al. [10] to establish a reliable ground sensing layer; (2) UAV multispectral imaging for crop canopy analysis, building on Zhang et al. [13], Omia et al. [12], and Grbovic et al. [15] to generate spatially dense spectral features for crop prediction; and (3) ML-based multimodal fusion for crop prediction, building on Shafi et al. [9] and Ahmad et al. [16] to develop and rigorously benchmark ML models on the integrated IoT + multispectral feature space.

The proposed system advances the state of the art in four specific ways: (1) integrating IoT and multispectral features in a single crop prediction pipeline not previously demonstrated in the literature at multi-class scale; (2) comprehensively benchmarking 10 classification algorithms under identical experimental conditions; (3) incorporating sensor anomaly detection for production-quality data reliability; and (4) integrating SHAP-based explainability for farmer-interpretable recommendations. Comparison with the closest related work — Shafi et al. [9] and Grbovic et al. [15] — reveals that while these studies validate the fusion principle, neither deploys a complete, multi-algorithm benchmarked, anomaly-detected, and explainability-equipped system. The proposed framework represents a holistic integration of these independently validated components into a single, deployable precision agriculture pipeline.

Conclusion

This paper presented a systematic, thematically organized review of 20 peer-reviewed publications on IoT-enabled and remote sensing-based precision agriculture, focusing on the intersection of ground-level sensor networks, multispectral UAV imaging, and ML-based crop prediction. The reviewed literature spans high-impact journals (IEEE Transactions on Industrial Informatics, Remote Sensing, Sensors, Frontiers in Plant Science, PLOS ONE) and covers publications from 2019 to 2025, capturing both foundational frameworks and the most recent state of the art.

The synthesis identified six critical research gaps: the absence of integrated IoT–multispectral crop prediction systems, limited multi-algorithm benchmarking under multimodal feature sets, no sensor anomaly detection in existing pipelines, the explainability deficit in farmer-facing systems, geographic and scalability limitations, and the cost barriers imposed by hyperspectral technologies. The proposed research directly addresses all six gaps through a unified system architecture combining real-time IoT sensing, UAV multispectral imaging, multi-algorithm ML benchmarking (10 classifiers), Isolation Forest-based anomaly detection, and SHAP-based explainability — contributing a novel, practically deployable precision agriculture system for real-time crop prediction.

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PP-6: Artificial intelligence in plant disease detection and their limitations

SHRIPAD KULKARNIAND SANJEEV B. K. AND NANDINI K. S.

[1]Professor (Plant Pathology), Dean, Student Welfare, UAS Dharwad-580 005, Karnataka, India.
[2]Research scholar, Department of Plant Pathology, UAS Dharwad-580 005, Karnataka, India.
[3]Department of Agronomy, University of Agricultural Sciences, Dharwad-580 005, Karnataka, India.

Abstract: Plant diseases pose a serious threat to global agricultural productivity by significantly affecting both crop quality and yield. Early and accurate detection of these diseases is essential to minimize losses and ensure sustainable food production. Traditional disease identification methods, which rely heavily on visual inspectisson and farmer expertise, are often time-consuming, less accurate and often ineffective in detecting subtle symptoms. In this context, Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), has emerged as a powerful tool for automated plant disease detection. This paper presents a comprehensive overview of AI-based approaches for plant disease identification, including key steps such as image acquisition, pre-processing, segmentation, feature extraction, and classification. Various ML and DL techniques, especially Convolutional Neural Networks (CNNs), are discussed for their effectiveness in detecting diseases in major crops such as tomato, chilli, potato, and cucumber. The study also highlights the practical applications of AI in precision agriculture, smart farming, and real-time disease monitoring using IoT and remote sensing technologies. Despite promising advancements, challenges such as limited availability of datasets, environmental variability, high computational requirements, and lack of model interpretability remain significant barriers to widespread adoption. The paper further outlines future research directions, emphasizing the need for robust, lightweight, and explainable AI models. Overall, AI-driven plant disease detection systems offer a reliable and efficient solution for improving agricultural productivity and ensuring food security.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Plant Disease Detection, Precision Agriculture

Introduction

Plant diseases significantly affect both the quality and quantity of crop production. Early detection and accurate prediction of these infections are crucial to minimize crop losses and improve yield. In India, agriculture contributes approximately 17% to the national GDP (Agarwal *et al.,* 2019). The country holds a leading position in the production of major crops such as tomatoes, potatoes, and pepper (Tm *et al.,* 2018; Thapa and Subash, 2019; Zunjare *et al.,* 2023). The occurrence and spread of plant diseases are influenced by several factors, including environmental conditions and cross-contamination (Kodama and Hata, 2018). A wide range of crops are cultivated globally, each susceptible to various infections, making them important subjects for study. Pest infestations alone are responsible for an annual reduction in crop productivity of about 30–33% (Kumar *et al.,* 2019). Plant diseases are primarily caused by fungal, bacterial, and viral pathogens. Due to the diversity of infections and their contributing factors, farmers often find it difficult to shift effectively between different disease management strategies. This complexity directly impacts overall crop productivity and quality. Despite rapid technological advancements, many farmers still rely on traditional methods for disease identification, primarily through visual inspection based on personal experience (Ayoub Shaikh *et al.,* 2022). Such conventional approaches present several limitations in agricultural research and practice. In severe cases, failure to detect infections at an early stage can lead to total crop loss, thereby reducing yield significantly. Moreover, some plant diseases exhibit subtle or unclear symptoms, making it difficult to determine the correct diagnosis and appropriate intervention. These challenges highlight the need for advanced and

comprehensive research in this field (Munjal *et al.,* 2023). Therefore, it becomes essential to conduct advanced andcomprehensive research (Munjal *et al.,* 2023).

Methods for Plant Disease Detection

AI-based plant disease detection systems typically follow a systematic framework that involves several interconnected stages, beginning with image acquisition and culminating in disease classification. The initial stage involves capturing images of plant leaves using various devices such as digital cameras, smartphones, or advanced sensors deployed in agricultural fields. The quality and diversity of these images are critical, as they directly influence the performance and accuracy of the detection system. Once the images are acquired, they undergo pre-processing to enhance their quality and remove noise or distortions. Techniques such as filtering, contrast adjustment, and normalization are commonly used to ensure that the images are suitable for further analysis.

Following pre-processing, the images are subjected to segmentation, a process that isolates the region of interest, typically the infected portion of the leaf. Segmentation is essential for focusing the analysis on relevant areas and eliminating background interference. Various techniques, including thresholding, clustering, and edge detection, are employed to achieve accurate segmentation. After isolating the diseased regions, the next step involves feature extraction, where important characteristics such as colour variations, texture patterns, and shape features are identified. In traditional Machine Learning approaches, these features are manually designed and selected based on domain knowledge, whereas Deep Learning models automatically learn these features from the data.

The final stage in the framework is classification, where the extracted features are used to determine whether a plant is healthy or diseased and, in some cases, to identify the specific type of disease. This classification is performed using various ML and DL algorithms, which are trained on large datasets to recognize patterns associated with different plant diseases. The effectiveness of this framework lies in its ability to systematically process complex image data and provide accurate and timely predictions.

a. Machine Learning Methods

Machine Learning is a subset of Artificial Intelligence that focuses on developing algorithms capable of learning from data and making predictions without explicit programming. In the context of plant disease detection, ML techniques are widely used to analyse features extracted from plant images and classify them into different categories. One of the fundamental aspects of Machine Learning is the type of learning approach employed, which can be broadly categorized into supervised, unsupervised, and semi-supervised learning.

In supervised learning, the model is trained using labelled data, where each input is associated with a corresponding output. For example, images of plant leaves labelled as healthy or diseased are used to train the model to recognize similar patterns in new data. This approach is highly effective for classification tasks, as it enables the model to learn the relationship between input features and output classes. In contrast, unsupervised learning deals with unlabelled data, where the model attempts to identify hidden patterns or structures within the dataset. This approach is useful for exploratory analysis and identifying unknown disease patterns. Semi-supervised learning combines elements of both supervised and unsupervised learning, utilizing a small amount of labelled data along with a large amount of unlabelled data to improve model performance.

b. Deep Learning Methods

Deep Learning represents an advanced subset of Machine Learning that utilizes multi-layered neural networks to automatically learn hierarchical representations of data. Unlike traditional ML approaches,

which rely on manually engineered features, DL models can directly process raw image data and extract relevant features without human intervention. This capability makes Deep Learning particularly well-suited for image-based plant disease detection. One of the most widely used Deep Learning architectures in this domain is the Convolutional Neural Network (CNN), which is specifically designed for image processing tasks. CNNs use convolutional layers to capture spatial features such as edges, textures, and patterns, enabling them to accurately identify disease symptoms in plant leaves. Other DL models, such as Deep Neural Networks and autoencoders, are also used for various tasks, including feature extraction and anomaly detection. Transfer learning has further enhanced the applicability of DL models by allowing pre-trained models to be adapted for specific tasks, thereby reducing the need for large datasets and extensive training.

The evolution of Deep Learning can be divided into two major phases. The early phase, spanning from the 1940s to the late 1990s, focused on the development of foundational concepts such as neural networks and backpropagation. The modern phase, which began in the mid-2000s, has been characterized by significant advancements in computational power, availability of large datasets, and the development of sophisticated architectures such as CNNs. A notable milestone in this evolution was the success of the Alex Net model in the 2012 ImageNet competition, which demonstrated the superior performance of Deep Learning in image classification tasks.

Case studies

a. Automated tomato disease detection

The tomato, scientifically known as *Solanum Lycopersicum*, is an important agricultural crop cultivated throughout Asia for human use. Some of the most prominent nutrients in this crop include vitamin E, vitamin C, and beta-carotene. These crops are rich in potassium, a crucial mineral for health. Because of its popularity and nutritional value, this vegetable is grown worldwide. The tomato crop is vulnerable to several diseases brought on by bacterial infections, microbes, and pest infestations (Lal, 2021). In contrast, the disease name, diseased image, and unique symptoms.

Previous research (Francis and Deisy, 2019) proposed a CNN model to discriminate between healthy and diseased tomato and apple leaves. The proposed model comprises four convolutional layers, followed by equivalent pooling layers. The model also uses a sigmoid activation function and two dense layers that are fully coupled. A total of 3663 image samples were used during training and testing, all carefully selected from the extensive PlantVillage dataset. The system's output demonstrates an impressively high accuracy rate (87%). Similarly, researchers (Basavaiah and Anthony, 2020) observed the practice of various ML approaches to identify tomato plant disease.

b. Automated Chilli disease detection

One of India's most important agricultural products is the chilli, a crop with a pungent flavor widely used in regional and international cuisines. Chilli pepper, also known as Lanka and Mirchi, has several names. Many varieties can be used as seasonings, dyes, oils, and medicinal compounds. Approximately 45 different viruses are known to infect chilli plants. Only 24 are known to occur naturally; the rest may be brought on through vaccination or other ways (Duranova *et al*, 2022). Various chilli diseases such as Down curl, gemini virus, cercospora, leaf spot etc. are caused by bacteria, virus, and fungus causative agents. Disease identification is based on leaf images and characteristic symptoms.

This study (Naik *et al*, 2022) examines the effectiveness of DL and ML techniques for classifying chilli leaf disease. Twelve pre-trained DL networks were employed, and the dataset features images of five critical diseases. Without augmentation, VGG19 had the highest accuracy (83.54%), whereas DarkNet53

performed exceptionally well with augmentation. A unique squeeze-and-excitation-based convolutional neural network (SECNN) model outperformed the rest, obtaining 98.63% accuracy without augmentation and 99.12% with augmentation, respectively.

c. Automated potato disease detection

The authors (Patil *et al.,* 2017) compared three ML methods, RF, SVM, and ANN, for spotting blight disease in potato leaf images. These techniques were trained and tested using the PlantVillage dataset and from the University of Agricultural Sciences India. The dataset consisted of 892 images depicting healthy leaves, leaves with early blight, and leaves with late blight. Applying the fuzzy c-mean clustering technique to each image helped identify and distinguish healthy and diseased categories. Thesimulation showed that the ANN was the most accurate ML technique for detecting diseases. ANN has an impressive 92% accuracy, followed by SVM at 84% and RF at 79%.

d. Automated cucumber disease detection

Cucumbers, a widely consumed and refreshing vegetable, belong to the prestigious Cucurbitaceae family of plants. The crop is well-known for its high-water content, making it a refreshing and hydrating choice even during the hottest times. In addition, cucumber plants are susceptible to several ailments, such as anthracnose and angular leaf spots, which cause various leaf problems (Vishnoi *et al*, 2021).Cucumber plants are particularly susceptible to powdery mildew in their later stages of development.

A study (Lin *et al.,* 2019) presents a novel CNN-based U-Net semantic segmentation approach to overcome these obstacles. Over twenty test samples, the model correctly segments images of cucumber leaves damaged by powdery mildew with an averagepixel accuracy of 96.08%, an intersection over union score of 72.11%, and a dice accuracy of 83.45%. The proposed method shows tremendous potential in pixel-level segmentation of powdery mildew in cucumber leaf diseases.

Applications of AI in Agriculture

The application of Artificial Intelligence in plant disease detection has significantly transformed agricultural practices by enabling more efficient and precise crop management. One of the key applications is precision agriculture, where AI systems provide real-time insights into crop health, allowing farmers to apply fertilizers, pesticides, and water resources more efficiently. This targeted approach not only improves crop yield but also reduces environmental impact.

AI-based systems are also integrated into smart farming technologies, where sensors and IoT devices continuously monitor environmental conditions and crop health. These systems can detect early signs of disease and provide timely alerts to farmers, enabling proactive intervention. Mobile-based applications have further increased the accessibility of AI technologies, allowing farmers to diagnose plant diseases using smartphone cameras. Additionally, remote sensing technologies, such as drones and satellite imagery, are used to monitor large agricultural areas and detect disease outbreaks at an early stage.

5. Limitations and Challenges

Despite the significant advancements in AI-based plant disease detection, several challenges hinder their widespread adoption. One of the primary limitations is the lack of largeand diverse high-quality datasets that accurately represent real-world conditions. Many existing datasets are limited in size and diversity, which can affect the generalizability of the models. Environmental variability, such as changes in lighting, background, and weather conditions, further complicates the detection process and can reduce model accuracy.

Another major challenge is the interpretability of Deep Learning models, which are often considered "black boxes" due to their complex internal structures. This lack of transparency can reduce trust among users and hinder adoption in practical applications. Additionally, AI models require significant computational resources, making it difficult to deploy them on low-cost devices commonly used in rural areas. Data privacy and security concerns also pose challenges, particularly when dealing with centralized data storage and sharing.

Future Directions

Future research in AI-based plant disease detection should focus on addressing these challenges by developing more efficient and robust models. Future efforts should focus on to create large and diverse datasets that capture real-world variations in crop conditions. The development of lightweight models that can operate on edge devices will facilitate real-time applications in resource-constrained environments. Enhancing model interpretability through Explainable AI techniques will improve user trust and adoption.

Conclusion

Artificial Intelligence has emerged as a powerful tool in transforming agricultural practices, particularly in the detection and management of plant diseases. By leveraging Machine Learning and Deep Learning techniques, AI systems can provide accurate, efficient, and automated solutions for disease diagnosis. While significant progress has been made, challenges such as data limitations, environmental variability, and computational constraints must be addressed to fully realize the potential of AI in agriculture. Continued research and innovation in this field will play a crucial role in ensuring sustainable food production and improving global agricultural productivity.

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PP-7: Efficacy of UAV (drone)-based herbicide application for weed management in soybean

SANTOSHKUMAR TANVASHI, NOOLI S. S. AND SOURABH MUNNOLLI

[1]PG Student (Agronomy), College of Agriculture, Vijaypur, UAS, Dharwad
[2] Scientist (Agronomy), AICRP-Sugarcane, ARS, Sankeshwar
[3]Assistant Professor (Agronomy), KLE College of Agricultural Sciences, Tenikolla
E-mail: santoshtanvashi8686@gmail.com
Mobile: 95917 13665

Abstract: The study entitled "Efficacy of UAV (drone)-based herbicide application for weed management in soybean" was carried out during *kharif*-2025 at Agricultural research station, Hukkeri, Belagavi. The primary objective was to evaluate the efficacy of drone sprayer in controlling weeds in soybean and to standardise the herbicide dose for drone sprayer. The experiment was laid out in a Randomized block design (RBD) included 10 treatments with 2 different herbicides, Sulfentrazone 28% + clomazone 30% WP ready mix (RM) (1250 g ha^{-1} Recommended dose -RD) and Diclosulam 84% WDG (31 g ha^{-1} RD) (applied at three doses of 100, 75 and 50% of RD), along with weed free and weedy check treatments. The herbicides were sprayed with UAV and knapsack sprayers. The efficacy of the sprayers was evaluated based on weed control efficiency (WCE), Weed index (WI), seed yield and economics.Among herbicide treatments the 100% RD of Sulfentrazone 28% + clomazone 30% WP (RM) applied using knapsack sprayer showed the superior performance with higher WCE (98.76, 92.06 and 85.57 % @ 10, 20 and 30 DAS respectively), lower WI (5.86 %), higher seed yield (2427 kg ha^{-1}) and higher B:C ratio (2.69). Application of 100% RD of Sulfentrazone 28% + clomazone 30% WP (RM) using a drone sprayer was found to be on par with knapsack spraying, recording WCE values of 96.85%, 89.02% and 84.19% at 10, 20 and 30 DAS, respectively, WI of 8.96%, seed yield of 2350 kg ha^{-1} and B:C ratio of 2.61. The results indicated that, the scope for adoption of the modern technologies like use of UAV for weed management will perform on par with conventional methods.

Key words: UAV spray, Knapsack spray, Herbicides, Weeds and Soybean.

PP-8: Use of UAV in application of new generation ready mix pre-emergence herbicides ssin Sugarcane

NOOLI S. S. AND SOURABH MUNNOLLI

[1]ssScientist (Agronomy), AICRP-Sugarcane, ARS, Sankeshwar
[2]Assistant Professor (Agronomy), KLE College of Agricultural Sciences, Tenikolla
E-mail: nooliss@uasd.in/ssnooli@gmail.com
Mobile: 09448752119

Abstract: A field experiment was conducted at the Agriculture Research Station in Hukkeri, during 2023-24. The experiment was laid out in RCBD design with three replications. The treatments were *viz.*, Pre emergence (PE) application of Clomazone 22.5 % + Metribuzine 21 % WP (ready mix) @ 2.5 kg ha^{-1} using drone (T1), PE application of Clomazone 30 % + Sulfentrazone 28 % WP (ready mix) @ 2.5 kg ha^{-1} using drone (T2), PE application of Atrazine 80% WP @ 2.5 kg ha^{-1} using drone (T3), PE application of Metribuzine 70% WP @ 1.25 kg ha^{-1} using drone (T4), PE application of Clomazone 22.5 % + Metribuzine 21 % WP (ready mix) @ 2.5 kg ha^{-1} using knapsack sprayer (T5), PE application of Clomazone 30 % + Sulfentrazone 28 % WP (ready mix) @ 2.5 kg ha^{-1} using knapsack sprayer (T6), PE application of Atrazine 80% WP @ 2.5 kg ha^{-1} using knapsack sprayer (T7), PE application of Metribuzine 70% WP @ 1.25 kg ha^{-1} using knapsack sprayer (T8), Weedy check (T9) and Weed free (T10). The results indicated that, Pre emergence (PE) application of Clomazone 22.5 % + Metribuzine 21 % WP (ready mix) @ 2.5 kg ha^{-1} using drone (T1) recorded significantly higher yield (164.5 t ha^{-1}), net returns (Rs. 3.84.388 ha^{-1}) and B; C (4.52) and it was on was with PE application of Clomazone 30 % + Sulfentrazone 28 % WP (ready mix) @ 2.5 kg ha^{-1} using drone(T2) (157. 4 t ha^{-1}, Rs. 3,64,588 ha^{-1} and 4.39, respectively). There was no phytotoxicity effect on the sugarcane crop.

Key words: Pre emergence, Knapsack sprayer, Drone and Phytotoxicity.

PP-9: Machine Learning based Prediction of sucking pest dynamics in Cotton under Semi-arid conditions of Northern Karnataka, India: A 10-Year Longitudinal Study

POORNIMA MATTI, SHANWAD U. K., RAJESH PATIL, KULKARNI V. R., KARIKATTI S. R., SMD AKBAR, SUMA, SAJJANAR AND SHRUTHI S. M.

[1-8]Agricultural Research Station, Dharwad, University of Agricultural Sciences Dharwad
E-mail: mattipv13511@uasd.in

Abstract: As agriculture faces increasing challenges due to climate change and pest pressures, advanced technologies are crucial for effective pest management. The integration of machine learning based predictionand computational models is essential to forecast pest occurrence in advance. Thus this study aims to predict the dynamics of Leaf hopper, Thrips and Aphids based on key local weather parameters, including maximum and minimum temperature, relative humidity and rainfall to identify the most accurate and reliable model for pest prediction. Correlation analysis between pest population and weather factors showed that leafhopper populations were positively correlated with maximum temperature, indicating that higher daytime temperatures favor their multiplication. Thrips populations were positively associated with minimum temperature and relative humidity, suggesting that warm nights and humid atmospheric conditions provide favorable conditions for thrips development. In contrast, aphid populations showed strong negative correlations with minimum temperature and relative humidity, indicating that cooler and drier conditions are conducive to aphid population buildup.Among the machine learning algorithms tested, the Random Forest model with 500 decision trees showed the best overall predictive performance for all three pest species. Random Forest models are particularly well suited for ecological datasets because they can handle nonlinear relationships, interactions among variables, and noisy data. The model achieved moderate predictive accuracy, with R^2 values of 0.078 for leafhoppers, 0.134 for thrips, and 0.114 for aphids.

Key Words: Machine learning, leafhopper, thrips, aphids, Cotton, Karnataka

Introduction

Agriculture continues to play a pivotal role in ensuring global food security by supplying the essential resources required to sustain the ever-increasing human population. Despite its importance, the sector is confronted with numerous challenges, including climate variability, limited natural resources, and increasing pest pressures. Fluctuating weather patterns, environmental disturbances, and the rising incidence of extreme climatic events significantly influence the behavior, distribution, and population dynamics of agricultural pests.Among sucking pests, such as leaf hopper (*Amrascabiguttulabiguttula*), Thrips (*Thrips tabaci*) and Aphids (*Aphis gossypii*) have the potential to cause substantial damage to crops like cotton, okra, and horticulturalproduce, leading to severe economic losses and jeopardizing food security on a global scale (Zhou *et al.,* 2024). The urgency for more accurate, data-driven pest management strategies has never been greater, especially in the face of the unprecedented challenges posed by climate change (Kaushal et al 2025).

The impacts of climate change on agriculture are far-reaching and multifactorial. Rising temperatures, altered precipitation regimes, and more frequent extreme weather events have direct and indirect effects on pest ecology (Kirui et al 2025). Warmer temperatures can accelerate pest life cycles, leading to multiple generations in a single growing season, increasing the likelihood of infestations. Changes in humidity and rainfall further enhance pest survival rates and affect their distribution, complicating the task of pest control (Zhou et al. 2023). These climate-induced changes necessitate a proactive, dynamic approach to pest management, one that can adapt to rapidly changing conditions. Understanding weather-pest linkages and using predictive models to anticipate pest outbreaks are critical in this new climate

reality, offering the potential for more precise, timely interventions and more resilient agricultural systems (Lu and Xiao 2024). Furthermore, predictive models contribute significantly to improving agricultural efficiency by optimizing input use, lowering production costs, and enhancing crop productivity with the economic viability of farming systems and promote resilience against climate-related uncertainties (Jiang *et al.,* 2023).

Materials and Methods

Long term study was undertaken to analyze the population dynamics of major sucking pests of cotton and to forecast their future occurrence using advanced statistical and artificial intelligence techniques. Historical major sucking pests and weather data were collected for ten cropping seasons on non Bt cotton cultivar DCH-32 from 2013–14 to 2022–23, comprising 244 weekly observations recorded according to Standard Meteorological Weeks (SMW). Among major sucking pests included viz.,leafhoppers, thrips, and aphids, which frequently afflict cotton leading to substantial yield losses worldwide. This study integrates machine learning (ML) models to predict pest incidence based on key meteorological attributes, including maximum temperature, minimum temperature, maximum relative humidity, minimum relative humidity, and rainfall were used to model pest populations and forecast their occurrence for the next three cropping seasons (2023–24 to 2025–26).

Results and Discussion

Descriptive statistical analysis was conducted to summarize the overall pest population characteristics across the ten-year study period. The results indicated that leafhoppers had a mean population of 6.13 insects per leaf, with a maximum recorded value of 31.20 per 3 leaves. Thrips exhibited the highest variability among the three pests, with an average population of 15.84 insects per leaf and a maximum peak level of 231 per 3 leaves, indicating the occurrence of extreme population explosions under favorable environmental conditions. Aphids showed a mean population of 12.34 insects per leaf with a peak population of 46.75 per 3 leaves, suggesting moderately high infestation levels during certain seasons. Correlation analysis between pest population and weather factors showed that leafhopper populations were positively correlated with maximum temperature, indicating that higher daytime temperatures favor their multiplication (Table 1). Thrips populations were positively associated with minimum temperature and relative humidity, suggesting that warm nights and humid atmospheric conditions provide favorable conditions for thrips development. In contrast, aphid populations showed strong negative correlations with minimum temperature and relative humidity, indicating that cooler and drier conditions are conducive to aphid population buildup. Rainfall generally showed weak or negative correlations with pest populations, implying that heavy rainfall may suppress pest populations by washing insects off the plants or by creating unfavorable environmental conditions.

Among the machine learning algorithms tested, the Random Forest model with 500 decision trees showed the best overall predictive performance for all three pest species. Random Forest models are particularly well suited for ecological datasets because they can handle nonlinear relationships, interactions among variables, and noisy data. The model achieved moderate predictive accuracy, with R^2 values of 0.078 for leafhoppers, 0.134 for thrips, and 0.114 for aphids. Although these values are relatively modest, they are typical for biological systems where pest populations are influenced by many factors beyond weather, such as crop growth stage, natural enemies, and management practices. Using the optimized Random Forest model, pest populations were forecast for three future cotton seasons: 2023–24, 2024–25, and 2025–26. The forecast results indicated that leafhopper populations are expected to remain relatively stable at moderate levels across all three seasons, with predicted mean populations between 7.50 and 7.80 insects per 3 leaves. Thrips populations are predicted to show a gradual increase over the forecast period, with mean values rising from approximately 19.44 insects per 3 leaves in 2023–24 to 22.44 insects per

leaves in 2025–26, indicating a possible long-term upward trend. Aphid populations are expected to remain consistently high across the three forecast seasons, with peak values around 30.64 insects per 3 leaves, suggesting that aphids may pose the greatest threat to cotton production during the forecast period (Fig 4). Study on machine learning-based models for predicting pest infestations, specifically Jassid and Thrips, using key meteorological parameters viz., maximum and minimum temperature, relative humidity, wind speed, sunshine hours, and evaporation, successfully identified the most relevant factors influencing pest dynamics. Through rigorous evaluation of multiple classifiers, this study found that the Stacking ensemblemodel outperformed individual models, achieving an accuracy of 90.38%(Rubab Shafique *et al.,* 2025).

Conclusion

Weather-based warning signals can be used to alert farmers about potential pest outbreaks, allowing timely implementation of control measures such as biological control, botanical insecticides, or selective chemical treatments as part of an integrated pest management strategy. As forecast based on weather can predict pest problems weeks in advance, which provides valuable support for integrated pest management strategies.

Figure 1: Average Pest Population by Standard Meteorological Week (10-year mean ±1 SD band). Arrows mark peak SMW for each pest.

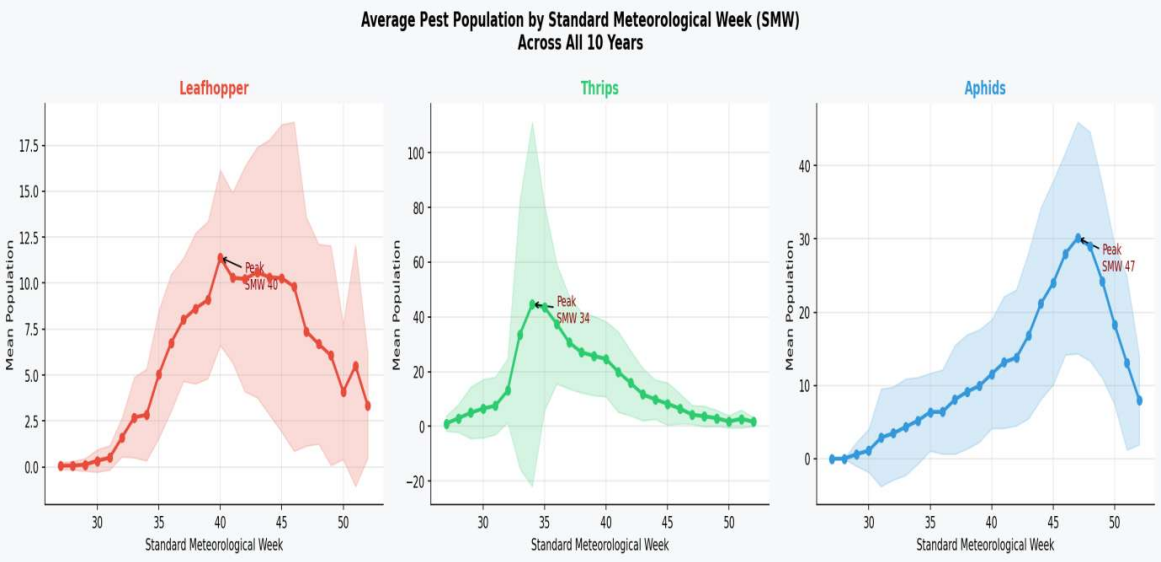


Table 1: Pearson Correlation Coefficients between Pest Populations and Weather Parameters. (* p<0.05, ** p<0.01, *** p<0.001)

Weather Parameter	Leafhopper (r)	Thrips (r)	Aphids (r)
Max Temperature (°C)	+0.382***	-0.047 ns	+0.309***
Min Temperature (°C)	-0.067 ns	+0.330***	-0.467***
RH Max (%)	-0.100 ns	+0.283***	-0.449***
RH Min (%)	-0.161*	+0.277***	-0.444***
Rainfall (mm)	-0.090 ns	+0.044 ns	-0.231***

Figure 2: Full Model Comparison — LOYO R² (top) and MAE (bottom) for allalgorithms. Gold border = winner per pest.

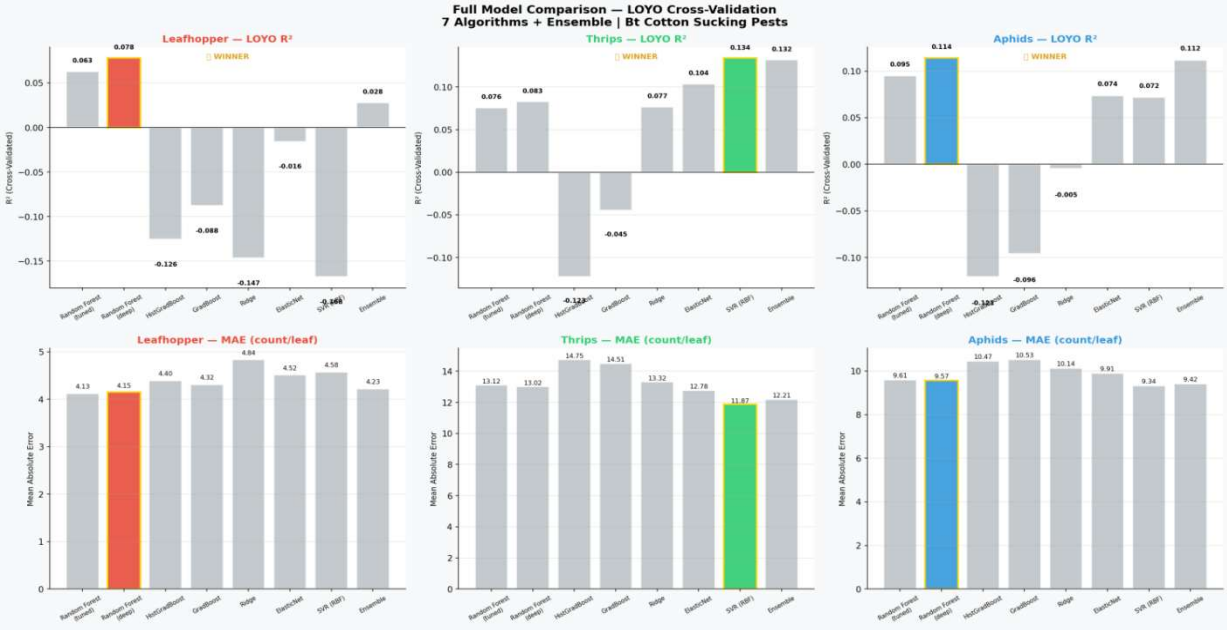


Figure 3: Actual vs Predicted scatter plots (LOYO CV) for best models. Points near the diagonal = good accuracy.

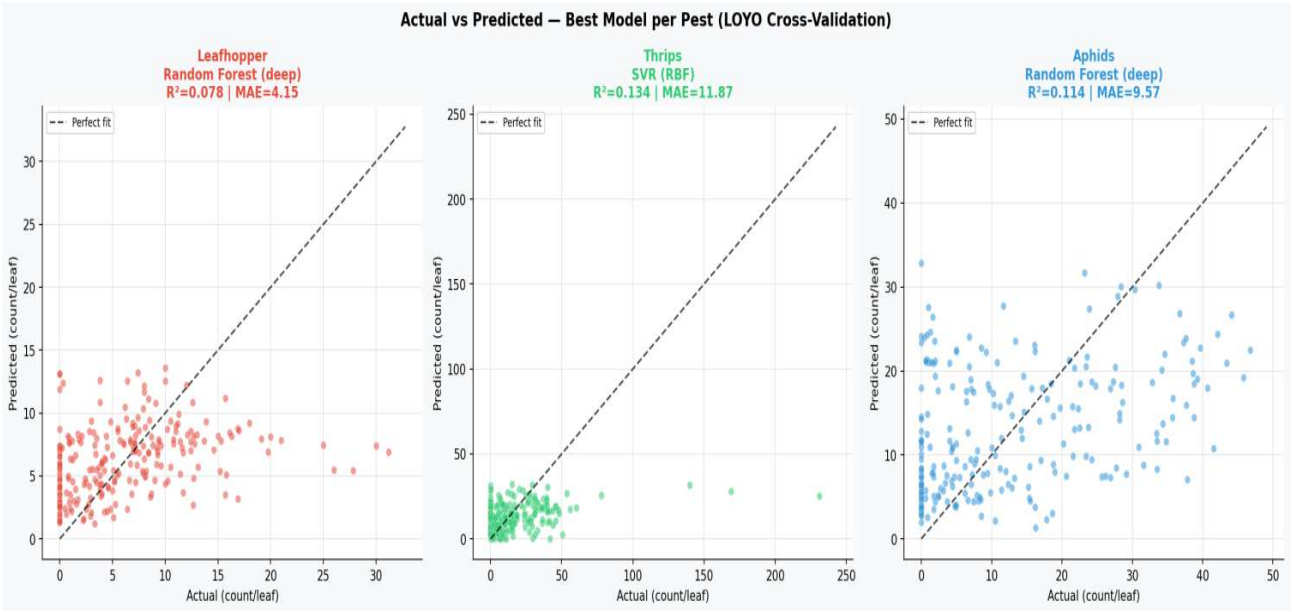
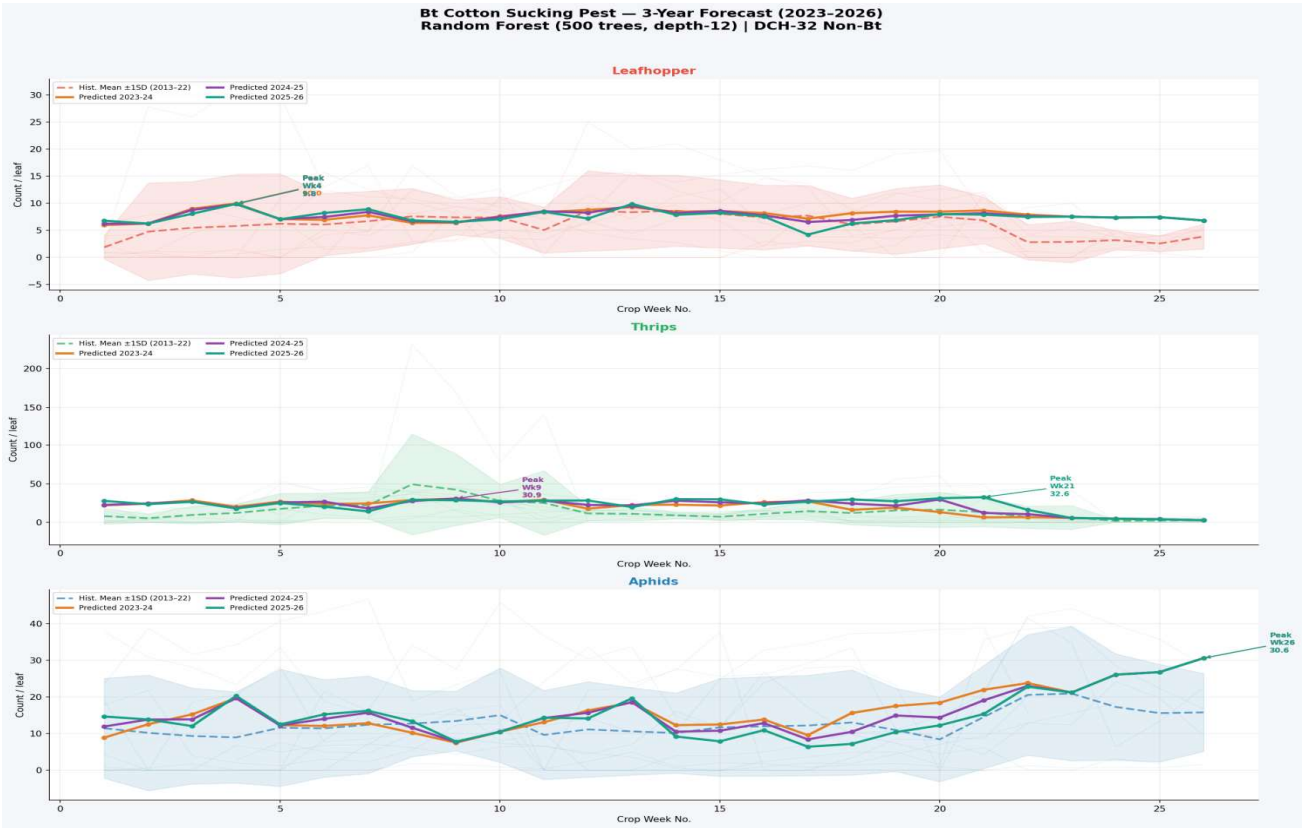


Figure 4: Predicted weekly pest profiles 2023–26 overlaid on 10-year historical mean ±SD. Peak annotations shown.



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PP-10: Use of AI; Soil Health and Nutrient Management

NAGARAJ, SUBHASH KANDAKUR AND SUDEEP KUMAR E.

[*1]Assistant Professor (Agril.Extn Educ) & Officer In-Charge, ARS, Konnur,
UAS, Dharwad-580005, Karnataka, India,
[2]Assistant Professor (Agriculture Entomology), MARS, UAS, Dharwad-580005, Karnataka, India
[3]Assistant Professor (Seed Science & Technology), COA, Vijayapur - 586101, Karnataka, India.
E-mail: nagu4146@gmail.com

Abstract: Artificial Intelligence (AI) is transforming the agriculture sector by enabling more precise and efficient soil health and nutrient management. Soil Health AI involves using AI technology to monitor, analyse, and optimise soil conditions, ensuring enhanced crop yield, reduced costs, and sustainable farming practices. Spark Emerging Technologies is at the forefront of this innovation, offering advanced AI solutions that revolutionise soil health management. Benefits of AI provide real-time monitoring of soil conditions, enabling quick identification and resolution of issues and AI optimises the use of water, fertilisers, and soil amendments, reducing waste and lowering costs and it improves crop yield by providing precise recommendations for soil management.AI uses historical data and current metrics to predict potential soil health issues and recommend preventative measures.AI supports sustainable farming by minimizing environmental impact and promoting efficient resource use.Soil Health AI is transforming the landscape of farming practices by providing real-time monitoring, predictive analytics, and optimised resource usage. With the innovative solutions from Spark Emerging Technologies, farmers can enhance their soil health management practices, improve efficiency and achieve better crop health and productivity. Explore our Soil Health AI solutions today and join us in revolutionising agricultural practices.AI for soil health transforms farm management by giving early warnings, optimizing resource use, and protecting yields against unpredictable threats.

Key words: AI, Precision Agriculture, Soil Health and Nutrient Management

PP-11: Application of remote sensing and GIS to study the influence of soil depth on profile characteristics in nukapur micro-watershed, Karnataka.

VIJAYAKUMARI RAVEENDRA CHANNAVAR, JAGADEESH B R, SADANAND RAMCHANDRARAO INAMDAR, PATIL P. L., MILIND P POTDAR AND CHANDRASHEKHAR S S

Department of Soil Science and Agricultural Chemistry, College of Agriculture,
University of Agricultural Sciences, Dharwad, Karnataka, India
E-mail: jagadeeshbr@uasd.in

Abstract: Soil depth is an important physical property which significantly influences various soil properties in general and soil profile characteristics in particular. Soil depth also affects soil fertility, plant growth and overall ecosystem health. The study was supported with RS and GIS applications in dealing the influence of soil depth on physico-chemical properties and soil profile characteristics in Nukapur micro-watershed. Based on the toposheets and satellite imagery; LISS-IV (Linear Imaging Self-Scanning Sensor-4) is a high-resolution, multi-spectral camera operated by ISRO on Resourcesat-2/2Afrom NRSC, Hyderabad was used forprofile sampling and the samples were categorized into upland, midland and lowland. Results revealed that upland soils characterized by a moderate depth of 85-100 cm and very gently sloping gradients of 1-3 percent, exhibit slight erosion and slow runoff. These soils have over 15-35 percent gravel coverage and possess sandy clay loam texture. In contrast, midland soils are moderately shallow deep, exceeding 50 cms in depth, with very gentle slopes of 1-3 percent. These soils experience slight erosion and slower runoff, with 15-35 percent gravels and sandy clay loam texture. Lowland soils, which were shallow (33+ cms) and have very gentle slopes of 1-3 percent, show slight erosion and slow runoff. Gravel coverage in lowland soils was less than 15 percent, and they exhibit a clay texture. The pH of upland soils (6.92-7.26) was lower compared to that of midland (8.20-8.27) and lowland soils (8.66-8.98). Electrical conductivity (EC) values vary across horizons 0.20-0.12 dSm^{-1} in upland, 0.43-0.38 dSm^{-1} in midland and 1.39-1.86 dSm^{-1} in lowland. Calcium content ($cmolkg^{-1}$) increase (35.79-36.26) with depth in upland and decreased (19.34-18.34) in midland and lowland(27.86-23.46). Whereas, magnesium content ($cmolkg^{-1}$) decreased with depth in upland (11.32-10.87) and lowland (11.14-10.89) and increased in midland (7.62-8.34) soils. Potassium content decreased with depth. Sodium concentration consistently increased with depth. The cation exchange capacity (CEC) increased from upper to lower horizons and from upland to midland positions but was lower in lowland soils. In general the Nukapura Micro watershed soils were distributed as medium fertility soils with slope and depth constraints but are suitable for many field crops and perennials.

Key words: Soil depth, Soil texture, Cation exchange capacity, Toposheets, RS and GIS

PP-12: Application of artificial intelligencein entomology

ROHINI SUGANDHI, PUNITHA B C AND BANGAREMMA S WADEYAR

Institute of Organic Farming, University of Agricultural Sciences, Dharwad

E-mail: sugandhirr@uasd.in

Agricultural pests cause 20-40 per cent loss of global crop production every year as reported by the Foodand Agriculture Organization (Shaik and Gollapelly, 2022). Smart agriculture presents the best option for farmers to apply artificial intelligence (AI) techniques integrated with modern information and communication technology to manage these harmful insect pests. AI is a broad term encompassing Machine Learning (ML), deep learning, computer vision etc. AI in entomology are helpful in taxonomic studies (identification and classification of insects, phenotype quantification, understanding evolutionary variations in traits), pest detection,prediction and identification thereby helping in timely pest management (pest identification, classification, monitoring, developing pest warning, prediction systems and biosecurity) & ecological studies(Spatial and temporal distribution of insects understanding changes in insect biomass, abundance and diversity, analysing nutritional ecology of insects, estimating microhabitat characters).

Applications *viz*., Plantix, Leaf-Byte, Bioleaf, Cotton Ace, Apizoometc have been developed to diagnose and identify insect pests to manage them. Chen *et al.*, 2020 developed an AIoTbased smart agricultural system for *Tessaratomapapillosa* (lychee giant stink bug) detection with 90 per cent accuracy. Karar *etal*., 2021 developed a mobile application for the detection of five groups of insect pests *viz*., aphids, leafhoppers, flax budworm, flea beetles and red spider mites with 99.0 per cent accuracy for all tested pest images. As monitoring the insect pests is a crucial component in pheromone-based pest management systems, Ding and Taylor (2016) developed an automatic moth detection method using AI with images collected from pheromone traps for timely pest management unlike the conventionalcounting methods. Liu *et al.,* 2019 using an AI developed an autonomous robotic vehicle in natural farm scene for the recognition of pyralidae insects with 94.3 per cent recognition accuracy. Potamitis and Rigakis (2015) developed a smarttrap for automatic remote monitoring of *Rhynchophorus ferrugineus*to take necessary steps for controlling it based on ETLs. Selvaraj *et al*., 2019 developed a model based on AI for early banana diseases and pests detection with significant high success rate.

Some successful usage of AIin pest management

i. Pest control in forests: Stevens Institute of Technology researchers recently developed and tested new technology thatcombines highly-sensitive vibration sensors, vibro-acoustic insect libraries and artificial intelligence toroot out emerald ash borer and the Asian longhorn beetle hidden inside the trees. In forests, the sensors are strapped around the trees, collecting tiny vibrations produced by woodboringinsect larvae. They carefully recorded the vibrations produced by the two species of woodboring pests with high-quality vibration sensors.Thus, the plants infected with wood borersproduces vibrations and only the affected plants can be treated with pesticides thereby helping inprecision control of the pest(Shaik and Gollapelly, 2022).

ii. Bug traps with AI & WI-FI: Trap is placed in different locations throughout the farmer's field. Once the insects enter the trap, the trap uses a combination of LEDs, optical sensors(flight sensor), and other

electronic devices (including microprocessors) to identify thetype and number ofinsects captured.The collected data, along with the GPS coordinates of each trap, is sent over Wi-Fi to a cloudbasedserver.Instead of simply spraying large amounts of general-purpose pesticides across the farmland, farmerscan strategically use specific amounts of specific pesticides to address the problem. Hence, integrating AI with entomology will help ineffective & timely management and forecasting of pests and diseases.It helps us to manage the crop from pests and diseases right from sowing to till harvest. However, inturn helps the farmers and extension workers when they trained regarding the use of this technology in order to reap the benefits of AI(Shaik and Gollapelly, 2022).

Key words: Artificial intelligence, machine learning, insect pest management

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PP-13: Validation of leaf area index of rabi sorghum genotypes using conventional and artificial intelligence techniques

KIRAN NAIK , POTDAR M. P., ARAVINDA KUMAR B. N., GURUPADA BALOL

Department of Agronomy, Department of Pathology,College of Agriculture, Dharwad
University of Agricultural Sciences, Dharwad- 580 005

*Rabi*sorg*hum* (*Sorghumbicolor* (L.) Moench) is avitaldryland crop cultivated widely in semi-arid regions of India, particularly in Maharashtra, Karnataka and Andhra Pradesh. It plays a crucial role in ensuring food security and supporting the livelihoods of farmers under rainfed conditions. The crop is well adapted to harsh environments, exhibiting tolerance to drought, high temperature and soil salinity. Recent advances in breeding have resulted in improved varieties suchas M35-1, SPV 2217 and CSVseries, which combine higher yield potential with enhanced stress tolerance and adaptability to diverse agro-ecological conditions.

Leaf area is a fundamental parameter influencing photosynthesis, transpiration and biomass productionin crops. The Leaf Area Index (LAI), defined as the total leaf area perunit ground area, is widely used to assess canopy structure, light interception and crop productivity. In sorghum, large and alternately arranged leaves provide an efficient canopy system for radiation capture, making LAI a key indicator of crop growth and yield potential.

LAI typically follows a dynamic pattern during crop growth, increasing during vegetativestages, reaches apeak at floweringand declining thereafterdue to senescence.The ability of certain genotypes to maintain higher LAI during grain filling (stay-green trait) is associated with improved drought to leranceandyield stability. Therefore, accurate estimation of LAI is essential for crop growth analysis and agronomic management. Various methods area vailable for measuring leaf area and LAI, ranging from traditional manual techniques to advanced digital and remote sensing approaches. Conventional methods, although reliable are of ten labor intensive and time-consuming. Incontrast, moderntechniques such as canopy analyzer and UAV-based imaging combined with machine learning offerrapid, non-destructive and scalable solutions. This study aims to evaluate different methods of LAI estimation and assess the performance of machine learning models for accurate prediction in *rabi* sorghum.

Methodology

Afield experiment was conducted during *rabi* season 2025-2026 at Main Agricultural Research Station, UAS, Dharwad under rainfed condition in split plot design with three *rabi* sorghum varieties (*i.e.* M35-1, SPV2217 and CSV29R) asmainplot and four Leaf area index estimation methods (*i.e.* Length and Breadth method, Leaf area meter, Canopy analyzer and UAV based AI method) with three replications.

Theprimaryobjectiveof theexperimentwas

To validate leaf area index of *Rabi* Sorghum genotypes using conventional and artificial intelligence techniques.

Leaf Area index data were recorded by both **direct and indirect methods** to estimate LAI in *rabi* sorghum.

Direct Methods

The **length × breadth method (l× b method)** used as a reference, where leaf length (base to tip) and maximum breadth (widest point) were measured and multiplied by acorrection factor (0.747) to estimate leaf area.

The leaf area was calculated by using the formula

Leaf area=Length ×Breadth ×0.747 (Stickler *etal*.,1961)

Theleafareaper plantwascalculatedby usingthe formula

Leaf areaper plant= Leaf area (cm^2)× Numberofleavesperplant

Then, LAI is calculated by dividing Leaf area per plant (cm^2) toLand area (cm^2) occupied by single plant (Watson, 1947)

LAI= Leaf area perplant (cm^2)Ground area (cm^2)

A **leaf area meter:** The BioVis PSM-L300 (IDSuEye-XSsoftware) equipped with aconveyor belt was used to measure the leaf area of plants. The cleaned leaves were placed on the conveyor belt, which moved each leaf smoothly and steadily into the scanning area**.** As the conveyor belt moved, each leaf was automatically positioned flat on the scanning surface ensuring complete coverage within the scanning area and avoiding any overlapping edges. During scanning process, the IDSu Eye-X Ssoftware display the intensity of each color channel (red, green and blue) on ahistogram derived from scanned image. Aseachleafmoves through the scanning area, the software captures the RGB color intensity data, which is then used to calculate the leaf area. Once the scan is complete, the calculated leaf area is displayed on the screen and the measurement is recorded**.**

Then, LAI is calculated by dividing Leaf area per plant (cm^2) to Land area (cm^2) occupied by single plant (Watson, 1947)

Indirect Methods

The **LAI-2200 C Plant Canopy Analyzer** used to estimate LAI non-destructively based on light interception (gap fraction method), a non-destructive approach for assessing canopy characteristics. This method involvedopticalsensorto measure light transmission through the canopy at various zenith angles (0°, 15°, 30°, 45° and 60°) providing insights into canopy structure, density and light interception. Despite the availability of multiple view caps (10°, 45°, 90°, 180° and 270°) for these azimuthal angles, 45° view cap was chosen. Observations include above canopy (base line of maximum light availability) and below canopy (5 cm above from Ground surface) readings taken along a diagonal transect to capture canopy variability. Aftercollectingtheaboveandbelow-canopyreadings, the canopy analyzercalculatedthe LAI by comparing the light transmission data which directly gives LAI

Anadvanced **UAV-basedimagingapproach** was the RGB cameramountedona UAVwill be used to capture 15-second video segments of crop plots from a height of 15 meters at a resolution of 1920 x 1080 pixels. The camera's RGB sensor capturesred, green and blue light intensities, which are combined to form full-color images. After conducting pre-flight checks, the UAV will capture videos that will belater transmitted for analysis. These videos that will be later converted into JPEG images, manually cropped into four plot frames per video and labelled according to treatment. All images will be resized to 256 x 256 pixels using Python 3.14.3 to ensure uniformity for analysis.

Twelve vegetation indices will be extracted from the cropped RGB images and analyzed using greycorrelation analysis. The indices Excess Green Index (ExG), Green Leaf Index (GLI) and Red Green Blue Vegetation Index (RGBVI) showing the highest correlation with Leaf Area Index (LAI) will be selected for further analysis. These selected indices, along with ground truth LAI data, will be used to train machine learning models such as **Support Vector Regression (SVR)**, **Random Forest (RF)**, **K-Nearest Neighbors (KNN)** and **Extra Tree (ET)**. A total of nearly 6000 images were used, split into 4200 for training (70%), 900 forvalidation (15%) (totunehyperparameters) and 900 for testing (15%) the model performance across the growth stages and to evaluate the performance of each model, the following metrics were used: Mean Absolute Error (MAE) tomeasuretheaverage magnitude of errors, Root Mean Squared Error (RMSE) to interpret the errors in the same units as the output variable and R^2 Score to determine how well the model explains the variability of the target variable.

To validate the LAI measurements obtained from different methods against the l×b method, the percentage deviation for each alternative method was calculated. This percentage deviation quantified how much the LAI values obtained from the othermethods deviated from the l × b method, which was used as a reference.

Percentagedeviationformula

$$\text{Percentage deviation} = \frac{|(LAI_{Method} - LAI_{l \times b})|}{|LAI_{l \times b}|} \times 100$$

Where,

- LAI_{Method} is the Leaf Area Index measured by theme thod being compared (e.g.,disc method, leaf area meter, canopy analyzer, AI).
- $LAI_{l \times b}$ is the Leaf Area Index measured by the l×bmethod. Note:
  - Low percentage deviationindicates method closer to l× b method and reliable alternative for measuring LAI.
  - High percentage deviation indicates method deviated significantly froml×bmethod and potential issues or inaccuracy for alternative LAI estimation.

Resultsa nd Discussion

Performanceof Machine Learning Models

Table1: Performancee valuation of machine learning model

Models	R^2	RMSE	MAE
SVR	0.92	0.47	0.32
ET	0.89	0.55	0.34
RF	0.88	0.75	0.29
KNN	0.87	0.80	0.35

The performance evaluation of machine learning models indicated that **SVR** was the best-performing model, with the highest R^2 (0.9242), lowest RMSE (0.4712) and low MAE (0.32). This demonstrates its superior ability to capture nonlinear relationships between vegetation indices and LAI.

The **Extra Trees model** also showed strong performance (R^2 = 0.8935), followed by **Random Forest**, which exhibited the lowest MAE (0.29), indicating consistent predictions. The **KNN model** showed comparatively lower accuracy, due to limitations in handling complex canopy variations.

The superior performance of SVR highlight sits effectiveness for LAI prediction under varying growth conditions of *rabi* sorghum.

LAI Variation across Methods and Growth Stages

Table 2: Leaf Area Index (LAI) of *Rabi* sorghum genotypes at different growth stages by different methods

Varieties	Methods	V_5	R_0	R_1	R_3
M35-1	L×B method	1.92	5.43	5.93	4.21
	LeafAreameter	1.55	7.95	5.83	4.26
	Canopyanalyzer	3.41	4.22	3.72	4.17
	AI method	2.61	5.25	6.17	4.31
SPV2217	L×B method	2.20	6.72	6.36	4.89
	LeafAreameter	1.75	7.58	7.26	5.56
	Canopyanalyzer	3.64	4.25	4.05	4.50
	AI method	3.01	6.2	6.17	3.48
CSV29R	L×B method	1.82	6.65	6.33	4.61
	LeafAreameter	1.56	7.20	6.08	4.67
	Canopyanalyzer	2.74	4.14	3.53	4.20
	AI method	2.83	5.54	5.20	4.13

(V_5-Fiveleafstage, R_0-Bootingstage, R_1-Flowering (full) stage, R_3 Physiologicalmaturity stage)

Leaf Area Index (LAI) shows a characteristic growth pattern across all genotypes, increasing from the vegetative stage (V5) to reproductive stages (R0and R1), followed by a decline at physiological maturity (R3) due to leaf senescence. SPV2217, LAI increased from 2.20 at V5to 6.72 at R0 and 6.36 at R1, before declining to 4.89 at R3.A similar trend was observed in CSV29R (1.82→6.65→6.33→4.61) and M35-1(1.92→5.43→5.93→4.21), represents typical canopy development patternsin sorghum.

Among the different genotypes, SPV 2217 consistently maintained higher LAI values, particularly at reproductive stages, it shows superior canopy development and greater potential for light interception and biomass accumulation compared to CSV29R and M 35-1.

The percentage deviation of LAI varied among estimation methods across different growth stages and genotypes, because differences in measurement consistency and reliability.

Table 3: Percentvariation in LAI of *rabi* sorghum genotypes by all methods of estimation from length and breadth method

Varieties	Methods	V_5	R_0	R_1	R_3
M35-1	LeafArea meter	19.27	45.87	3.36	16.07
	Canopy analyzer	49.56	27.61	31.74	12.09
	AI method	41.08	4.54	7.30	6.68
SPV2217	Leaf Area meter	17.45	14.84	12.55	14.16
	Canopy analyzer	45.01	38.67	38.16	3.22
	AI method	46.11	7.04	9.53	7.40
CSV29R	Leaf Area meter	26.76	22.65	5.92	18.82
	Canopy analyzer	42.70	30.18	36.73	3.22
	AI method	46.63	9.77	12.01	5.05

Among the methods, the **canopy analyzerexhibited the highest deviation** across all growth stages (V5 stage, deviation values reached up to **49.56%inM35-1**,**45.01% in SPV2217** and **42.70%in CSV29R**) this indicatesgreatervariabilityassociatedwithlight-basedestimation. This trend continues across all stages, which indicates sensitivity of the method to canopy structure and light transmission.

The **leaf area meter showed moderate deviation**, particularly at reproductive stages (at R0reached **45.87% in M 35-1)** indicates variability under dense canopy conditions, due to destructive sampling and handling of leaves.

Incontrast, the **AI-based method demonstrated relatively lower and more stable deviation compared to other methods**. Although higher deviation was observed at early stages (e.g., **41.08% in M 35-1 atV5**), the values decreased across subsequent stages, indicates improved estimation as canopy development increases. Similarly, in SPV2217 and CSV29R,AI-based deviation remained comparatively lower than the canopy analyzer and more stable across growth stages.

Conclusion

The study highlights the importance of accurate LAI estimation for understanding crop growth and improving productivity in *rabi* sorghum. LAI showed a consistent trend of increasing up to flowering and declining thereafter, with SPV2217 exhibiting superiorcanopydevelopment among the tested genotypes.

Among the different methods evaluated, the **SVR-based AI approach** provedtobethe most effective, providing accurate and reliable LAI estimates with lesspercentage variationin comparison with conventional methods such as the length × breadth method which used as a reference, which is less suitable for large-scale applications. The leaf area meter and canopy analyzer showed limitations in overestimation and underestimation, respectively.

The integration of **UAV-based imaging and machine learning techniques** offers a promising, non-destructive and scalable solution for LAI estimation. This approach helps for precision agriculture, improve crop monitoring and enhance decision-making for sustainable management of *rabi* sorghum under dryland conditions.

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PP-14: Digital weed management: Integrating AI, robotics, and precision innovations for sustainable agriculture

PRIYA P., BINDU CHOWDARY M. S., BABU P., VIJAY KUMAR C, DARSHAN H. P. AND NOOR NAWAZ A. S.

[1] Department of Agronomy, University of Agricultural Sciences, Dharwad – 580 005
[2] Department of Horticulture, University of Agricultural Sciences, Dharwad – 580 005
[3] Department of Soil Science, University of Agricultural Sciences, Dharwad – 580 005
[3]Department of Microbiology, University of Agricultural Sciences, Dharwad – 580 005
E-mail: priyap@uasd.in

Identifying weeds with precision is essential for sustainable crop management. Traditional weed observation and management methods are increasingly constrained by labour shortages and rising operational costs. Moreover, the excessive and repeated use of herbicides has resulted in significant environmental risks and has accelerated the emergence of herbicide-resistant weed species. Consequently, intelligent technologies based on artificial intelligence (AI), machine learning (ML) and advanced image analysis have gained considerable attention as promising alternatives. These technologies enable accurate and timely weed detection and form the basis for site-specific weed management strategies that minimize chemical inputs while protecting soil health and human safety. Image processing constitutes a fundamental component of AI-driven weed detection systems. High-resolution imagery is typically acquired using unmanned aerial vehicles (UAVs), satellite platforms or ground-based imaging systems. Pre-processing techniques are applied to correct for illumination variability, sensor noise and geometric distortions, followed by the creation of annotated datasets for model training.

Deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated notable success in weed detection tasks. CNNs automatically learn hierarchical feature representations from large, labelled datasets of crop and weed images, thereby reducing dependence on manually engineered features. Remote sensing technologies add another dimension by capturing spectral information beyond the visible range. Multispectral and hyperspectral imaging can identify subtle differences in reflectance between crops and weeds. Peña *et al.* (2013) used UAV based hyperspectral imaging in wheat fields in Spain and achieved classification accuracies between 85 and 90 per cent. In rice systems, UAV multispectral imaging combined with machine learning achieved 88 per cent accuracy in weed classification and reduced herbicide use by 25 per cent (Huang *et al*., 2018). These examples highlight the synergy between UAVs and AI, where aerial imagery provides large scale coverage and machine learning ensures accurate classification.

Digital Weed Management Technologies in India

India has recently caught the new wave of innovation in weed science with digital technologies. These tools use artificial intelligence, robotics, sensors and decision support systems to make weed control more intelligent, precise and sustainable. One such example is the Rakshak laser weeding robot that was developed under NITI Aayog's Frontier

Technologies programme. Rakshak employs GPS and AI-enabled vision to spot weeds in cotton fields and zap them with laser beams, rather than applying herbicides. The ICAR

Directorate of Weed Research has also developed mobile applications for farmers, namely ICAR DWR Weed Manager and Weed ID, which assist the farmers in identification of weed species and provide management advisory (CLFMA, 2024).

Other technologies are also having an effect. Targeted precision sprayers such as See and Spray have been trailed in soybean fields and reduced herbicide input by more than 59 per cent (Avent *et al*., 2024). Combining drones with driverless robots in trials has demonstrated how aerial mapping can then inform site-specific spraying in cotton and rice (Vijayakumar *et al*., 2025). Ultra-precise smart sprayers in the global perspective, such as ARA, have already reduced herbicide use by 95 per cent in vegetable crops, and similar methods are now under pilot testing at select horticulture clusters of India (Anne *et al*., 2024). Beyond spraying, innovations such as electric pulse weeding systems rupture plant cells with high voltage currents, offering eco-friendly alternatives to chemical control (Slaven *et al*., 2023).

Together, these technologies signal a decisive shift toward eco-friendly and data driven weed management tailored to Indian farming conditions. By integrating AI vision, robotics and precision spraying, India is moving closer to sustainable agriculture that reduces chemical dependency, protects soil health, and empowers farmers with modern tools.

Socio-Economic Impacts

For small landholders, shared use through custom hiring centres and farmer producer organizations have shown to be essential in alleviating and giving solution to capital constraints (Das *et al*., 2025). They offer access for farmers to lease high-tech machinery at low cost, so digital tools are not just for wealthier land owners. In India, manual weeding is usually done by women labours and this physical burden is greatly reduced with digital automation. Concurrently, new professions become available in drone piloting, robotics operation and data processing (Menpadi*et al*., 2025). Rakshak in Telangana is a deployment that demonstrates how service-based models can enable rural youth to run sophisticated robotics and create new livelihood trajectories. This way, digital weed management keeps powering the farm economy and also changes rural labour dynamics for good as it minimizes drudgery while providing opportunities for skilled employment.

Environmental Impacts

Herbicide-free alternatives like laser, steam and electric pulse systems can replace all herbicides to promote soil health and biodiversity (Slaven *et al*., 2023). Novel weed detection methods contribute to prevention of off-target drift and reduce greenhouse gas emissions through optimization of spray application (Sreeja *et al*., 2024). Trials with UAV weed mapping systems demonstrated that targeted spraying could in some cases replace blanket applications, thus reducing diesel use and CO_2 emissions and other pollutants (Vijayakumar *et al*., 2025). Leveraging AI-based decision support systems implemented on mobile devices, farmers can have only selective herbicidal sprays and avoid environmental consequences while still achieving close to maximum output per hectare.

Barriers to Digital Weed Management in India

While digital weed control technologies are proving themselves in the field, they still face many challenges for wider acceptance in Indian farms. The most obvious impediment is cost. Custom hiring centers facilitate shared use leading to cost savings, but affordability and timely availability remain issues. Land fragmentation adds another difficulty. Adoption is also constrained by the digital divide. Farmers, especially women and marginalized groups, often lack the training or confidence to use

sophisticated digital tools. In addition, cloud-based decision support systems are constrained by infrastructure gaps like poor internet connectivity and unreliable electricity in rural areas. Data scarcity is another obstacle. Weed detection models demand large labelled datasets for Indian crops and regions, which are currently scarce. Institutional and policy gaps also slow progress.

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PP- 15 : Drone-based application of insecticides for the management of major maize pests: Bio-efficacy, economics and ecological impact

SADANAND R. INAMDAR, KAMBREKAR D. N. AND NAVEEN V.

[1]Department of Statistics, University of Agricultural Sciences, Dharwad- 580 005, Karnataka, India
[2]Department of Entomology, University of Agricultural Sciences, Dharwad- 580 005, Karnataka, India
E-mail: inamdars09@gmail.com

Introduction

Maize is a vital cereal crop cultivated across diverse agro-ecological regions, serving as a key source of food, feed, and industrial raw material. However, its productivity is severely affected by major insect pests such as fall armyworm (*Spodoptera frugiperda*) and stem borer, which cause significant yield losses. Conventional pest management primarily relies on insecticide application using knapsack sprayers, which involve high water usage, labour intensity, and uneven spray coverage. In recent years, drone-based spraying has emerged as an innovative approach offering precision, reduced input use, and improved efficiency. However, field-level validation of drone-assisted insecticide application in maize ecosystems remains limited. Therefore, this study was undertaken to evaluate the bio-efficacy, economic feasibility, and ecological impact of drone-based insecticide application for managing major maize pests.

Materials and Methods

Field experiments were conducted during the cropping seasons of 2024-25 and 2025-26 using a Randomized Block Design with appropriate replications. The treatments included chlorantraniliprole 18.5% SC (75 and 100 ml/ha) and spinetoram 11.7% SC (188 and 250 ml/ha), applied through drone sprayers using a spray volume of 20-25 L/ha. These were compared with conventional knapsack spraying using 500 L/ha, along with an untreated control. Plot sizes were maintained at 500 m² for drone treatments and 100 m² for knapsack applications. Observations on pest incidence were recorded one day before spraying and at 1, 3, 7 and 10 days after spraying for both applications. Additional parameters recorded included grain yield, cost of cultivation, gross and net returns, benefit–cost ratio, natural enemy population (coccinellids and *Chrysoperla*), and phytotoxicity symptoms. Data were statistically analysed after square root transformation, and treatment means were compared using Duncan's Multiple Range Test.

Results

Drone-based insecticide application proved highly effective in managing maize pests. Higher doses of chlorantraniliprole and spinetoram significantly reduced fall armyworm larval populations, bringing them to negligible levels within 7–10 days after spraying. The efficacy was comparable to or better than conventional knapsack spraying despite using substantially lower spray volumes. Similar results were observed for stem borer control, where near-complete suppression was achieved at higher doses. Economic analysis indicated that drone-applied treatments produced higher grain yields (exceeding 30 q/ha) compared to untreated control (20 q/ha). The benefit–cost ratio was also higher in drone treatments due to reduced labour, lower water usage, and faster operation, making it suitable for large-scale farming. The impact on natural enemies showed a moderate reduction in populations of coccinellids and *Chrysoperla* in treated plots, with relatively lesser impact observed in drone applications, suggesting improved selectivity. No phytotoxic effects were observed in any treatments, confirming the safety of the insecticides when applied via drones.Overall, the study demonstrates that drone-based insecticide application is an efficient, economical, and environmentally safer alternative to conventional spraying for maize pest management, with strong potential for integration into sustainable agriculture practices.

PP-16: Integrated Application of AI, GIS and RS techniques for improved soil resource assessment data generation.

VIJAYAKUMARIR. CHANNAVAR, JAGADEESH B. R., SADANAD R. INAMDAR, MILIND P. POTDAR, PATIL P. L. AND CHANDRASHEKHAR S. S.

Department of Soil Science and Agricultural Chemistry, College of Agriculture,
University of Agricultural Sciences, Dharwad, Karnataka, India
E-mail: jagadeeshbr@uasd.in

Soil resource assessment data has been generated for Chikka Aralahalli micro-watershed (4D4C2J2d), covering a total geographical area of 477 ha. The study aimed to evaluate the morphological, physical and chemical characteristics of soils using integrated Artificial Intelligence (AI) methodology for effective land evaluation and sustainable agricultural planning.In order to categorize soil types and detect characteristics like erosion or compaction, computer vision models in particular, Convolutional Neural Networks (CNN) analyse high-resolution digital imagery from drones or smartphones. GIS tools combine satellite data (Landsat 8, Sentinel-2) and terrain characteristics (elevation, slope) to give the point source data a more comprehensive spatial framework. For high level property prediction from spectral data, Artificial Neural Networks (ANN) and deep frameworks like RDNet are employed that outperforms conventional techniques. High-resolution maps illustrating the spatial variability of soil fertility produced by applying the trained models to the integrated geospatial database. This comprehensive strategy offers vital and economically viable data for agricultural decision-makers, enabling them to enhance resource utilization, reduce environmental effects, and maintain soil health over the long term. The soil test results of the micro-watershed were predominantly very deep (257 ha, 53.88%) and deep (212 ha, 44.46%), indicated favourable conditions for root proliferation and moisture storage. The texture was mainly clay (402 ha, 84.35%) followed by sandy clay (67 ha, 13.99%) with gravelly characteristics. The entire area fell under very gently sloping, suggested minimal erosion risk. Soil reaction (pH) indicated that 232 ha (48.58 %) of the area is strongly alkaline, 162 ha (34.04 %) moderately alkaline and a small portion slightly alkaline to neutral and slightly acidic, reflected variations influenced by parent material and management practices. The soils were non-saline across the watershed, implying no restriction for crop growth due to salinity. Organic carbon (OC) content was medium in 413 ha (86.68 %). Nutrient status assessment showed that nitrogen was uniformly low throughout the micro-watershed, available phosphorus was medium in 444 ha (93.08 %), potassium availability varied, with 200 ha (41.91 %) under medium and 269 ha (56.44 %) under high status. Sulphur content was medium in 388 ha (81.38 %) and low in 78 ha, suggesting localized deficiencies. Micronutrients (Fe, Mn and Cu) were found sufficient indicated no immediate concern for these elements. However, zinc deficiency was widespread, with only 68 ha showed sufficiency and 401 ha (84.14%) deficient, emphasized the need for Zn-application for balanced nutrition. Finally, Chikka Aralahalli micro-watershed werecharacterized by good depth, heavy texture and moderate fertility but constrained by alkalinity, nitrogen and zinc deficiencies. It can be concluded that proper soil fertility management involving the application of organic manures, green manuring and micronutrient supplementation, especially zinc, along with appropriate cropping systems, would enhance soil productivity and ensure sustainable agricultural development in the micro-watershed.

PP- 17: On applicability of AI in land resource interpretation and soil water conservation

SUNIL MASKE, R. SRINIVASAN, M. CHANDRAKALA, R. VASUNDHARA, C. RADHIKA, N. MADILETTI AND S. DHARMARAJAN

ICAR-NBSS&LUP, RC, Bangalore – 560024

Soil survey of Dawanagere district at 1:10,000 scale is accomplished by using SOP methodology developed by National Bureau of Soil Survey and Land Use Planningin 2021. SOP methodology utilises DEM, LULC imagery and GIS modelling to delineate Terrain Mapping Units (TMU). Broad landforms are described on the basis of landform patterns at the broader scale (e.g. hill land, mountain land, piedmonts, plains) and delineated DEM. District resource maps of Geological Survey of India (GSI) shall be used as a base to delineate the broad geological formations of the district. For delineation and mapping of landform at 1:10,000 scale, open-source ALOS PALSAR 12.5m DEMs were used. The cloud-free open-source recent Sentinel-2A and 2B data products of 10m spatial resolution is used in landform mapping at 1:10,000 scale.Thederived slope and LULC is to be integrated with landform units in GIS to identify the distinct TMUs. TMUs were delineated using DEM and Sentinel imagery (2Aor 2B) and modelling in GIS (pixel and multipixel). While finalizing the TMU boundaries, the delineated landform units need to be superimposed on latest Google Earth image as .kml file to verify its boundaries and correctness to improve the map accuracy.Infield, after necessary geometrical and attribute corrections in TMUs, if any, TMUs maps shall be finalized and used to conduct the land resource inventory at 1:10,000 scale. The proposed conditional Latin Hypercube Sampling (cLHS) model further improves the LHS model by including landform/TMUs as strata. The *c*LHS criterion is a stratified random sampling procedure that provides an efficient way of sampling variables from their multivariate distributions and adopted in the task. Soil survey was done accordingly.

Davangere district, known as the "Manchester of Karnataka" and located in central Karnataka, is a major commercial and agricultural hub, famous for its textile industry, food processing, and butter dosa. The district lies in 13°5′ N to 14°50′ N latitude and 75°30′ E to 76°30′ E longitude. Dawanagere district consists of 5 talukas namely Dawanagere, Harihar, Honnali, Channagiri and Jagalur and has 4.51 lakh ha total geographical area (TGA). Davangere district has a tropical savanna climate, generally warm and dry with distinct summer, monsoon, and winter seasons. Summers (March-May) are hot, reaching over 40°C, while winters (November-February) are pleasant, with lows around 15°C. The region receives an average annual rainfall of 644 mm, with the rainy season occurring from June to October. Major crops grown in the area are cotton, maize, cheakpea, sunflower, rice etc. Arecanut is the commonly grown plantation crop in the district. Davangere district's geology is dominated by Archaean-aged granites, granitic gneisses, and metamorphic rocks, with significant red sandy and black soil coverage. The region, situated in the heart of Karnataka, features notable mafic-ultramafic complexes, particularly the Channagiri

segment, which hosts platinum-group elements. Soil survey of the district using the SOP methodology revealed 17 soil series and 47 soil phases.

Use of AI in land resource interpretation:

1. AI can linked with GIS output employed to know soil types in the area
2. Interpretation of red soils, black soils and intermediate soils
3. Soil depth linked with soil slope
4. Problematic soils and their severity interpretation
5. Interpretation of vegetation cover and its effect on desertification

Use of AI in soil and water conservation:

1. Integration of soil type, slope and soil water conservation measures for particular rainfall frequency
2. Integration of problematic soils with its amelioration/ reclaimation
3. AI enhances soil water conservation by optimizing irrigation and managing resources through data-driven insights, reducing water waste by up to 25%
4. AI algorithms, combined with IoT sensors and satellite imagery, provide real-time monitoring of soil moisture, predict, and automate irrigation
5. Use of AI can be emphasized in soil health management

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PP-18: Smart surveillance: machine learning approaches for invasive pest detection in agriculture

KALAVATHI K KAMBALI, ROHINI SUGANDHI AND BANGAREMMA S WADEYAR
University of Agricultural Sciences, Dharwad-580005
[1]Department of Entomology and 2Department of Genetics and Plant Breeding
E-mail: kambalikk@uasd.in

Abstract: Invasive insect pests pose a serious challenge to global agriculture, particularly in tropical regions where favorable climatic conditions accelerate pest establishment and spread. Conventional pest detection methods are often inadequate due to their labor-intensive nature and limited spatial and temporal resolution. In recent years, machine learning (ML) has emerged as a powerful tool for improving pest detection, monitoring, and forecasting. This review synthesizes current advancements in ML-based pest detection, including computer vision, IoT-enabled monitoring systems, remote sensing, acoustic detection, and predictive modeling. These approaches enable early diagnosis, real-time surveillance, and data-driven decisionmaking, contributing to precision pest management. Despite promising results, challenges such as data scarcity, variability in field conditions, and limited accessibility remain. Addressing these issues is essential for large-scale adoption and sustainable agricultural development.

Key words: Machine learning, invasive, monitoring, *Spodoptera frugiperda,*remote sensing.

Introduction

Insect pests are responsible for substantial agricultural losses worldwide, with estimates indicating 20–40% reduction in crop yields annually (Oerke, 2006; FAO, 2019). In India, crop losses due to insect pests range between 15–25%, with significantly higher damage observed during invasive pest outbreaks (Dhaliwal *et al*., 2015).

India has experienced several invasive insect pests that have caused significant crop losses across different agro-ecosystems. Among the most destructive is the fall armyworm (*Spodoptera frugiperda*), which affects maize and can lead to yield losses of 30–60% under severe infestation. The tomato leaf miner (*Tuta absoluta*) is another major invasive pest damaging tomato crops, often causing 80–100% loss if unmanaged. In cotton and other crops, the pink bollworm (*Pectinophoragossypiella*) has resurged as a serious problem due to resistance development. The papaya mealybug (*Paracoccus marginatus*) has caused widespread damage in fruit crops, while the rugose spiraling whitefly (*Aleurodicusrugioperculatus*) has affected coconut, banana, and ornamental plants. Additionally, the coconut rhinoceros beetle (*Oryctes rhinoceros*) and the invasive thrips (*Thrips parvispinus*) have emerged as important threats in plantation and vegetable crops (Sharanabasappa*et al*., 2018; Navas-Castillo *et al*., 2011). These examples highlight the need for efficient pest detection systems capable of identifying infestations at an early stage.Traditional pest monitoring techniques, including manual scouting and visual identification, are constrained by limited coverage, delayed detection, and reliance on expert knowledge (Pedigo and Rice, 2014).

Machine learning (ML) provides advanced analytical capabilities for processing large agricultural datasets. By integrating image data, environmental variables, and historical pest records, ML models can classify pests and predict outbreaks with high accuracy. Deep learning models such as Convolutional Neural Networks (CNNs) have demonstrated classification accuracies exceeding 90% (Ferentinos, 2018).

Machine Learning Approaches in Pest Detection

1. Computer Vision and Deep Learning

Computer vision-based approaches utilize image data to detect and classify insect pests. CNNs automatically extract features such as shape, color, and texture, enabling accurate pest identification (LeCun *et al*., 2015). Real-time detection models such as YOLO allow rapid field-level identification (Redmon *et al*., 2016).These methods have been successfully applied for detecting fall armyworm damage and estimating whitefly populations in field crops.

2. IoT-Based Smart Monitoring Systems

IoT-enabled smart traps integrate sensors and cameras with ML algorithms to automate pest monitoring. These systems provide continuous data on pest populations and enable threshold-based decision-making (Wang *et al*., 2020). Applications include monitoring of *Helicoverpa armigera* and *Pectino phoragossypiella* in cotton ecosystems.

3. Remote Sensing and UAV Applications

Remote sensing technologies, including UAVs and satellite imagery, enable large-scale pest monitoring. Multispectral data capture crop stress signals, which ML models analyze to detect infestation patterns (Zhang and Kovacs, 2012).

4. Acoustic Detection Techniques

Acoustic sensing detects pests based on feeding-generated vibrations. ML algorithms classify these signals to identify hidden infestations, such as borers (Mankin *et al*., 2011).

5. Predictive Modeling and Pest Forecasting

ML algorithms such as Random Forest and Support Vector Machines are widely used for pest forecasting. These models integrate climatic variables with historical pest data to predict outbreaks (Cutler *et al*., 2007; Zhang *et al*., 2019).

6. Time-Series Analysis

Time-series models analyze temporal patterns in pest populations, enabling identification of peak infestation periods and improving intervention timing (Box *et al*., 2015).

7. Decision Support Systems and Mobile Applications

Mobile-based decision support systems integrate ML models with user interfaces, enabling real-time pest identification and advisory services (Patel and Patel, 2020).

8. Data Integration and Multi-Source Analytics

Data fusion approaches combine multiple datasets such as images, weather data, and trap counts to improve prediction accuracy and robustness (Kamilaris and Prenafeta-Boldu, 2018; Liakos *et al*., 2018).

Advantages of ML-Based Pest Detection

- Early detection of infestations
- High classification accuracy
- Real-time monitoring capabilities
- Reduced labor dependency

- Optimized pesticide application (20–30% reduction)
- Enhanced precision agriculture practices

Challenges and Limitations

- Requirement for large annotated datasets
- Variability in field conditions
- High cost of advanced technologies
- Limited accessibility for smallholder farmers
- Model generalization issues

Future Perspectives

Future developments in machine learning (ML) for invasive pest detection are moving toward systems that are not only accurate but also practical under real field conditions. Newer deep learning approaches, such as transformer-based models and hybrid frameworks, are improving the ability to detect pests even in complex environments with varying light, crop stages, and background noise. At the same time, techniques like transfer learning and few-shot learning are helping reduce the need for large labeled datasets, making it easier to identify newly emerging invasive pests with limited data. The use of advanced remote sensing tools, including hyperspectral imaging and high-resolution satellite data, is also opening up possibilities for detecting pest-related stress in crops before visible symptoms appear. In addition, combining weather data with pest history through spatio-temporal models is strengthening forecasting systems, allowing farmers to take preventive action rather than reacting after damage occurs.

At the field level, the integration of ML with IoT devices, edge computing, and automation is making pest detection faster and more accessible. Smart traps, drones, and handheld devices can now analyze data directly on-site, reducing delays caused by poor internet connectivity in rural areas. Bringing together different types of data, such as images, weather information, acoustic signals, and trap countsimproves the reliability of detection systems. Efforts to make ML models more transparent through explainable AI are also important, as they help farmers and extension workers trust and understand the recommendations provided. When combined with user-friendly mobile applications and government advisory platforms, these technologies can reach a wider farming community. Looking ahead, the use of autonomous systems for precise interventions, like targeted pesticide application, has the potential to reduce chemical use, lower costs, and support more sustainable and climate-resilient agriculture.

Conclusion

Machine learning has significantly improved invasive pest detection by enabling accurate, rapid, and large-scale monitoring. Its integration with digital agriculture technologies supports early warning systems and sustainable pest management. Continued advancements and improved accessibility will play a crucial role in enhancing agricultural productivity and environmental sustainability.

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PP-19: AI-based soil analysis system for crop recommendation

SUMAN YALIGAR, RAJESHWARI V PATIL, LEENA I SAKRI, KIRAN ARAVADI , NISARG SHETTAR, SANJANA SHIDRAMANI AND VANDANA GURUWODEYAR

Assistant professor, Dept of AIML SDMCET Dharwad
Students, Dept of AIML SDMCET Dharwad
Department of Artificial Intelligence & Machine Learning
Shri Dharmasthala Manjunatheshwara College of Engineering and Technology

Abstract: Choosing the right crop for a particular piece of land is something farmers have always done based on experience passed down through generations. But with changing weather patterns and increasingly unpredictable rainfall, that traditional approach is becoming harder to rely on. This project builds a simple, practical tool that uses machine learning to suggest the most suitable crop based on basic soil and climate measurements. We used a publicly available dataset containing readings for nitrogen, phosphorus, potassium, pH, temperature, humidity, and rainfall across 22 different crop types. After comparing multiple classification algorithms, Random Forest turned out to be the most reliable, achieving an accuracy of 99.5%. The final model is wrapped in a web application where a farmer or agricultural worker can enter their soil values and instantly receive a crop recommendation. The goal is to make data-driven farming accessible without needing any technical background.

Introduction

Soil is essentially the foundation of farming — it determines what crops can grow, how well they grow, and how much yield a farmer can expect at the end of the season. Soil analysis is the process of measuring the chemical and physical properties of soil to understand its condition. The key properties that matter most for agriculture are the levels of nitrogen (N), phosphorus (P), and potassium (K) — nutrients that plants directly absorb — along with the soil's pH level, which controls how available these nutrients actually are to plants. Climate factors like temperature, humidity, and rainfall interact with these soil properties to either support or limit crop growth.

The reason soil analysis matters so much is that a mismatch between what the soil offers and what a crop needs leads to poor yield, wasted inputs like fertilizers and water, and financial loss for the farmer. In India especially, where agriculture supports a huge portion of the population, these inefficiencies add up significantly at a national scale. Traditionally, crop selection was guided by what worked in previous seasons or what neighbors were growing — not by scientific soil data.

This is where artificial intelligence becomes genuinely useful. ML models can learn the complex relationship between soil parameters and which crops thrive under those conditions. Instead of a farmer needing to understand agronomy at a technical level, they can simply enter their soil test readings into a system and get a reliable recommendation in seconds. Our project does exactly that — it builds a classification model trained on real agricultural data and deploys it as a web application anyone can use.

Comparative Analysis

3.1 Traditional Methods and Their Limitations

Before ML-based systems existed, crop selection depended on a few conventional approaches. Soil testing through government agricultural labs would give farmers NPK and pH readings, but interpreting those results and matching them to the right crop still required expert agronomists, who are not always accessible in rural areas. Extension workers would visit farms periodically and advise based on regional

crop calendars. Another common approach was simply following what worked historically on the same land.

These methods have real limitations. Lab testing is slow — results can take weeks — and affordable advisory services are not always available to small farmers. Regional crop calendars don't account for variation between individual plots of land. And relying on last season's success doesn't account for soil degradation over time or shifts in rainfall patterns due to climate change.

3.2 How Our AI-Based System Improves on This

Aspect	Traditional Method	Our AI System
Speed	Days to weeks for lab results and expert advice	Instant prediction once soil values are entered
Accessibility	Requires access to labs or extension workers	Available online, works on any device
Personalisation	General regional advice, not plot-specific	Based on exact NPK, pH, climate values
Consistency	Varies with the expert's experience	Same model gives consistent results every time
Cost	Lab fees and consultation charges	Free to use once deployed

Applications

The system has practical uses across several areas of agriculture:

- Farm-Level Decision Support: Individual farmers can enter their soil test results and get a crop recommendation without needing to consult an agronomist. This is especially useful in areas where expert access is limited.
- Government Agricultural Programs: State agriculture departments can use the tool to provide data-driven advisory to farmers through Krishi Vigyan Kendras or mobile outreach programs.
- Agri-Tech Startups: The trained model can be integrated into precision farming platforms that combine soil sensing, weather data, and market price information for comprehensive advisory.
- Educational Use: The project demonstrates a complete ML pipeline that students and researchers can study, extend, or adapt for related problems like fertilizer recommendation or yield prediction.
- Future IoT Integration: With soil sensors becoming cheaper, the system could eventually take live readings directly from the field and give real-time recommendations without the farmer needing to manually enter values.

Conclusion

This project shows that a relatively simple machine learning approach — a Random Forest classifier trained on seven soil and climate parameters — can recommend the right crop with very high accuracy. The 99.5% test accuracy and consistent cross-validation results suggest the model is reliable and not just fitting noise in the data. More importantly, the system is practical: we wrapped it in a web application where anyone can use it without any ML knowledge.

What we found most interesting during the project was that dataset quality matters more than model complexity. When we tried a more complex dataset with 29 features but severe class imbalance, accuracy dropped to around 46% even with oversampling techniques like SMOTE. The simpler, well-balanced dataset gave far better results. This taught us that good data preparation is arguably more important than choosing a fancy algorithm.

Going forward, we plan to integrate a real-time weather API so farmers don't need to manually enter climate values, and to explore adding fertilizer recommendations alongside crop predictions. We also hope to eventually incorporate Indian Soil Health Card data to make recommendations more specific to Indian agricultural conditions.

PP-20: Multi-image fusion and context-aware deep learning frame work for reliable plant disease detection in real-world agricultural environments

RAJESHWARI V PATIL, SUMAN YALIGAR, KARAN NAVALAGUND
Department of Artificial Intelligence and Machine Learning
SDM College of Engineering and Technology, Dharwad, Karnataka, India

Abstract: Deep learning classifiers for plant disease detection routinely exceed 99% accuracy on controlled laboratory benchmarks but fall to 70–85% when deployed in real field conditions. This paper presents MIF-CADNet (Multi-Image Fusion Context-Aware Detection Network), a framework designed specifically to close that gap. The system collects three to five field photographs of the same plant, fuses them through a shared EfficientNet-B4 backbone and a learned attention mechanism, and passes the result through a two-stage hierarchical classifier that resolves crop identity before predicting disease. GPS and weather metadata condition the final probability output to reflect geographic and seasonal disease prevalence, uncertain predictions are with held ratherthan reported with falseconfidence, and all accepted diagnoses are converted in top lain-language advisory messages for non-expert farmers. On a 14,200-image Field Validation Corpus assembled across India and Ghana, MIF-CADNet achieves 89.7% field accuracy and 95.4% on the PlantVillage benchmark -11.5 percentage pointsahead of the best single-image baseline in field conditions-while fitting within 19 MB for mobile deployment.

Keywords: Plant disease detection, multi-image fusion, context-aware deep learning, EfficientNet, precision agriculture, explainable AI, PlantVillage, PlantDoc

Introduction

Plant pathogens destroy an estimated 20–40% of global food output annually, with the FAO placing total losses above USD 220 billion [1]. Smartphone-based AI diagnostic tools hold genuine promise for smallholder farmers who lack access to trained agronomists.Mohanty et al. [2] demonstrated in 2016 that a deep convolutional network could classify 26 plant diseases at above 99% accuracy on the PlantVillage dataset, catalyzing a wave of architectural refinements [3], [4]. Yet the same models consistently drop to 70–85% accuracy when evaluated on images taken in real fields [5].

Two factors account for most of this degradation. Environmental variability-uneven lighting, cluttered agricultural backgrounds, and the inconsistent imaging pipelines of consumer smartphones-creates a distributional gap that neither augmentation nor architectural tuning has fully closed. Equally important, though less discussed, is the single-image assumption: virtually every published model treats each photograph as an independent inference event, ignoring the multi-observation reasoning that experienced plant pathologists apply naturally. MIF-CADNet addresses both.

Relatedwork

Benchmark studies by Mohanty et al. [2], Ferentinos [3], and Too et al. [4] confirmed that deep networks can match expert-level classification under controlled conditions — DenseNet201 reaching 98.99% in the most systematic comparison to date [4] — but each study acknowledged that controlled training data limits real-world applicability. Singh *et al.* [6] reviewed over 100 published studies and found near-universal reliance on PlantVillage as the sole benchmark. The PlantDoc dataset [5], built specifically to measurereal-world generalization across 13 speciesand 17 disease categories, revealed that standard classifiers achieved only 70.5–83.7%on open-field images. Domain adaptation [8] and generative augmentation [9] have partially narrowed this gap but retain the single-image assumption. Multi-image aggregation — standard practice in medical imaging [12] and face recognition [11] — has not previously been formalized in an end-to-end plant disease pipeline.

Proposed Methodology

A. *Multi-Image Preprocessing*

Each image undergoes CLAHE histogram equalization, bilinear resize to 224×224, and ImageNet normalization. Structured bursts of the same leaf use lightweight ORB-based keypoint alignment to correct minor perspective shifts; unordered photographs skip alignment when matching confidence is low. N=3 images is the default, validated by ablation experiments.

B. *Attention-WeightedFusion*

A shared EfficientNet-B4 backbone (ImageNet pretrained) processes each image independently, yielding a 1792-dimensionalfeature vector h_i. An attention module assigns weights $\alpha_i = \text{softmax}(W_a \cdot h_i + b_a)$, and the fused representation $h_{fused} = \Sigma_i \alpha_i \cdot h_i$ up-weights images that best expose diagnostic features while down-weighting those degraded by shadow or motion blur. A regularization term prevents one image from dominating regardless of actual image quality.

C. *Two-StageHierarchical Classifier*

Rather than mapping hfused directly to a 60-class flat disease space, the model first predicts crop species. Crop confidence ≥ 0.85 activates the corresponding disease head exclusively; below that threshold the top-2 crop heads are blended by weighted averaging. This eliminates documented cross-species confusion — bacterial spot on tomato misclassified as pepper leaf curl — and allows individual disease heads to be updated independently as new crop data becomes available.

D. *Context-AwareRe-weighting*

A priorvectorq encodes expected disease prevalence at the GPS location, calendarmonth, andambient weather, drawn from CABI epidemiological records [18] and a corpus-learned seasonal frequency model. The adjusted output is $p_adj = 0.75 \cdot p_visual + 0.25 \cdot \text{softmax}(q)$. The 0.75 weight keeps the visual model dominant while context resolves borderline cases. When GPS is unavailable, the context module is bypassed and inference runs on visual evidence alone.

E. *ConfidenceFilteringandAdvisoryOutput*

Predictions with max (p_adj) <0.70 enteradvisorymode, returning the top-3 candidate diseases and prompting the farmerto capture additional images. The empirical accuracy of these withheld cases is 61.3% on the FVC test set, confirming the filter identifies genuinely difficult examples rather than beingover-conservative. Accepted predictions drive180 disease-specific NLG templates in English, Hindi, Swahili, and Tamil, each covering disease name, causal agent, symptom confirmation checklist, locally available treatments, and an urgency rating.

Datasetsan dtraining

Three datasets support the experiments. PlantVillage [2] (54,309 images, 38 classes, 14 crops; 70/15/15 split) provides the primary laboratory training corpus. Plant Doc [5] (2,598images) is reserved entirely forreal-world evaluation and never seen during training. The Field Validation Corpus (FVC) was assembled over two growing seasons across15 districts inIndia and Ghana: 14,200 images of six crops captured with seven smartphone models, annotated by two certified plant pathologists with consensus resolution, and critically including 3–5 images per plant specimen to enable genuine multi-image evaluation.

Augmentation bridges the studio-to-field gap through background replacement, JPEGcompression artifacts, brightness and contrast jitter, and CutMix. Training uses AdamW (weight decay 1×10^{-4})

with a cosine learning rate schedule from 5×10^{-5}; the backbone is frozen for 30 epochs then fully fine-tuned for 50 on 4× NVIDIA A100 GPUs with FP16 precision (~18 hours total).

Results and Discussion

F. *AblationStudy*

Table I shows each component's independent contribution on the FVC test set. Multi-image fusion delivers the largest single gain (+5.3 pp), consistent with the intuition that individual field photographs are noisy and aggregating multiple views substantially reduces variance. Hierarchical classification adds 3.1 pp independently; their combination reaches 86.4%. Context re-weighting contributes a further 2.1 pp, and the full system reaches 89.7%. Expected Calibration Error falls from 0.112 to 0.047, confirmingthat confidence scores are reliable rather than inflated.

TABLEI—Ablation Study on Field ValidationCorpus

Config	Description	FVCAcc.	MacroF1	ECE
A0	Single-imageEfficientNet-B4(baseline)	78.2%	0.769	0.112
A1	A0+Multi-imagefusion(N=3)	83.5%	0.824	0.091
A2	A0+Two-stage hierarchy	81.3%	0.806	0.098
A3	Fusion+Hierarchy combined	86.4%	0.858	0.078
A4	A3+Context-awarere-weighting	88.5%	0.879	0.061
A5	**FullMIF-CADNet**	**89.7%**	**0.892**	**0.047**

G. *Comparisonwith Baselines*

Table II reveals that PlantVillage accuracy is a poor proxy for field utility: Mohanty et al. score highest on the benchmark (99.3%) yet lowest in the field (74.8%). Fine-tuning on PlantDoc narrows the gap but still falls 8.3 pp short of MIF-CADNet on FVC, confirming that dataset-level adaptation without architectural change cannot replicate structural gains from fusion and context conditioning. MIF-CAD Net's Plant Village accuracy of 95.4% is modestly below the highest baselines — a small, justified cost that the 11.5 pp field improvement more than offsets.

Table II—Performance Comparison (PV=Plant Village, PD=Plant Doc, FVC=Field Validation Corpus)

Method	PV Acc.	PD Acc.	FVCAcc.	MacroF1
Mohantyetal.[2]—AlexNet	99.3%	70.5%	74.8%	0.731
Ferentinos[3]—VGGCNN	99.5%	72.4%	76.1%	0.748
Tooetal. [4] — DenseNet201	98.9%	76.3%	79.6%	0.783
EfficientNet-B4(single-image)	97.8%	75.8%	78.2%	0.769
PlantDoc-FTDenseNet201	96.1%	83.7%	81.4%	0.805
MIF-CADNet(Ours)	**95.4%**	**84.6%**	**89.7%**	**0.892**

Mobile Deployment

INT8 quantization reduces model size from 74 MB to 19 MB at a cost of only 0.4 pp accuracy on the FVC. Inference for N=3 images completes in ~3.6 seconds on a Snapdragon 888 — confirmed

acceptable through field testing. Context API responses are cached for 24 hours to support intermittent rural connectivity; offline inference runs on visual evidence alone. The Android UI was refined through participatory design sessions with 24 smallholder farmers in Karnataka and Ghana, incorporating leaf-positioning overlays, color-coded urgency indicators, and audio readout for limited-literacy users.

II. Conclusion

The lab-to-field accuracy gap in plant disease detection is not a ceiling imposed by deep learning — it is a consequence of withholding information that is genuinely available at inference time. MIF-CADNet restores that information through multi-image fusion, crop-conditioned disease prediction, and regional disease priors, reaching 89.7% field accuracy against 74–81% for comparable single-image baselines while remaining deployable on mid-range smartphones. The broader implication is that closing this gap may require less architectural innovation than clearer thinking about what information a farmer actually brings to the moment of diagnosis. Future work will explore video-based inference for temporal symptom tracking, continuously updated epidemiological priors, and federated learning to improve the model from field data without centralizing sensitive agronomic information.

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PP-21: Data driven prediction of soil organic carbon using machine learning algorithms

PUNITHA B. C., ROHINI SUGANDHI., SAVITA, B., VIDYAVATI G.Y. AND AKKAMAHADEVI D. AGASIMANI

Institute of Organic Farming, UAS, Dharwad, Department of Soil Science and Agril. Chemistry, UAS, Dharwad, AICRP on Dryland Agriculture, Department of Horticulture, College of Agriculture, UAS, Dharwad – 580005 (Karnataka). India
E-mail: punithabc@uasd.in

Introduction

Soil is the largest terrestrial ecosystems sink of organic carbon and changes with atmospheric composition, climate and land cover transformation. Soil organic carbon (SOC) is a critical component of soil health, ecosystem functioning and the global carbon cycle. It plays a key role in nutrient cycling, water retention and climate change mitigation through carbon sequestration. Accurate estimation and spatial prediction of SOC are therefore essential for sustainable land management and environmental monitoring. However, SOC exhibits high spatial and temporal variability, making its prediction challenging using conventional fieldbased methods.Evaluating SOC provides information about soil fertility, levels of sequestration of carbon, recovery of degraded soil, and the impact of land use change (Bonfatti*et al.,* 2016).
Recent advances in artificial intelligence (AI) and machine learning (ML) have significantly improved the ability to predict SOC by leveraging large datasets and modeling complex nonlinear relationships between SOC and environmental covariates.

Machine learning models for soil organic carbon prediction

Machine learning (ML) models have been widely applied in the prediction of soil organic carbon (SOC) due to their ability to capture complex, nonlinear relationships between environmental variables and soil properties. Among these, ensemble methods, kernel-based approaches, and neural networks are the most commonly used, each with distinct strengths and limitations as listed below;

Random Forest (RF) is widely used in soil organic carbon (SOC) prediction due to its ability to handle nonlinear relationships and high-dimensional data. As an ensemble method, it combines multiple decision trees, making it robust to noise and resistant to overfitting while also providing insights into variable importance. However, RF has limitations in extrapolating beyond the range of the training data.

Arthur*et. al.* 2025 conducted a systematic literature review using Systematic Review and Meta-Analysis (PRISMA) approach, the study highlights the application of deep learning, traditional neural networks and other machine learning models for estimating soil organic carbon (SOC).Sentinel satellite data (Sentinel-2) along with key inputs *viz.,* vegetation indices (NDVI, SAVI, EVI) and digital elevation models showed strong correlations with SOC

Support Vector Machines (SVM) are effective for modeling soil organic carbon (SOC) in small to moderately sized datasets, as they can capture nonlinear relationships using kernel functions and perform well in high-dimensional spaces. However, they require careful hyperparameter tuning, are computationally intensive, and are less interpretable than tree-based methods.

Anis Ben *et al.* 2025 proposed integrating the Ninja Optimization Algorithm (NiOA) for simultaneous feature selection and hyperparameter tuning to improve model accuracy and efficiency. This approach reduced the SVM model error from an MSE of 0.00513 to 7.52×10^{-7}, achieving a 99.98% reduction in prediction error.

Gradient Boosting Machines (GBM), including XGBoost and LightGBM, are widely used for soil organic carbon (SOC) prediction due to their high accuracy and ability to capture complex feature interactions through sequential tree building. However, they require careful parameter tuning and proper regularization to avoid overfitting.Nguyen (2021) reviewed leveraging algorithms like Random Forests and XGBoost and showed that this approach enhances accuracy for monitoring soil health and supporting carbon sequestration initiatives.

Artificial Neural Networks (ANNs) are powerful models for capturing complex nonlinear relationships among soil, climate, and terrain variables, especially in large datasets. However, they require substantial data and computational resources, and their black-box nature limits interpretability. Emadi *et al*., (2020) compared multiple machine learning models (SVM, ANN, regression tree, RF, XGBoost, and DNN) for soil organic carbon (SOC) prediction. The deep neural network (7 hidden layers, size 50) showed the highest accuracy and lowest uncertainty at the provincial scale due to its ability to effectively utilize large auxiliary datasets.

k-Nearest Neighbors (k-NN) is a simple, instance-based method for predicting soil organic carbon (SOC) based on similarity between observations, but it is sensitive to distance metrics and scaling, and its performance declines with large or high-dimensional datasets, limiting its suitability for complex DSM applications.

Deep Learning models, *viz.,* Convolutional Neural Networks (CNNs), are powerful tools for soil organic carbon (SOC) prediction, excelling at capturing spatial patterns from remote sensing data, but they require large datasets, high computational resources and specialized expertize.

Kumar *et al.* (2023) compared four machine learing models *viz*., Random Forest (RF), Cubist, Extreme Gradient Boosting (XGBoost) and Support Vector Machine (SVM) and found that RF had the best accuracy and the lowest uncertainty for predicting the regional SOC compared to other models. Additionally, shortwave infrared bands and hyperspectral data were identified as critical for SOC estimation, with future hyperspectral satellite missions and multispectral data fusion offering strong potential for global SOC monitoring.

Conclusion

In comparative studies, ensemble methods such as Random Forest and Gradient Boosting consistently demonstrate strong and stable performance across different datasets and environmental conditions. Deep learning models often achieve higher accuracy when sufficient data are available, whereas simpler models like SVM and k-NN may perform adequately in smaller or less complex datasets. Overall, the choice of machine learning model for SOC prediction depends on factors such as dataset size, computational resources, required interpretability, and the complexity of the study area.

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PP-22: Validation of leaf area index of maize for graded levels of fertilizers using conventional and artificial intelligence techniques

BINDU M., POTDAR M.P., RAJKUMARA S., ARAVINDA KUMAR B.N. AND RAJAKUMAR G. R.

Department of Agronomy, Department of Soil Science & Agri. Chemistry,
College of Agriculture, Dharwad
University of Agricultural Sciences, Dharwad – 580 005

The production of maize in food systems and their potential to contribute to national food security, there is a direct need to explicitly generate monitoring frameworks for spatially optimizing assessments of maize. Field phenotyping poses challenges due to its labor-intensive, time-consuming nature, low efficiency and susceptibility to bias and inaccuracies (Araus and Cairns, 2014). As a C_4 plant, maize possesses a high yield potential of nearly 10 t ha^{-1}, to achieve this yield potential and maximize dry matter production, maize requires a healthy leaf area that effectively harnesses solar radiation, contributing to optimal growth and yield. Hence there is an urgent need for a method to efficiently, accurately, non-destructively and affordably monitor and measure the biophysical parameters of crops. Biophysical crop traits encompass essential variables used to quantify phenotypic characteristics, including biomass, leaf area index (LAI) and fractional vegetation cover (FVC). Among these traits, the LAI has been widely used as an important indicator reflecting crop canopy structure and growth.

LAI is defined as the photo synthetically active leaf area per unit of horizontal ground surface area (Watson, 1947). It is a determinant factor in many physiological and agronomic processes, particularly in terms of growth, photosynthesis, transpiration, water and nutrients use and productivity (Gao *et al.,* 2012, Pandey and Singh, 2011).

There are two methods for LAI measurement, the direct measurement and the indirect LAI estimation. Direct methods are the most accurate and helpful to validate indirect measurements, but they remain extremely time-consuming and prohibitively expensive when applied to large crop areas (Sonnentag *et al.,* 2007).

Artificial Intelligence (AI) has revolutionized various sectors, including agriculture, by enhancing the precision and efficiency of monitoring and managing crop growth. AI technologies, such as machine learning (ML) and computer vision, have significantly contributed to agricultural research by enabling the analysis of complex datasets. These technologies facilitate non-destructive, rapid and cost-effective assessment of critical crop traits, making them highly suitable for large-scale crop production monitoring. The integration of AI in agriculture, particularly through the use of UAV and advanced imaging techniques, has paved the way for innovative approaches to estimate key biophysical parameters like the LAI. AI-based methods for estimating the LAI offer several advantages over traditional approaches. By utilizing advanced machine learning algorithms, these methods provide increased precision in LAI estimation through the analysis of high-resolution data. Hence, the present study focuses on the estimation of LAI by integrating AI with UAV technology, utilizing RGB imagery to assess LAI across varying fertilizer levels and growth stages of maize.

LAI is being influenced by several factors irrespective of crops. Nutrient plays an important role in growth and yield. Graded levels of fertilizer have been used in the present investigation to create variation in growth parameter visa-vis leaf area of maize at different growth stage of maize with the following

Objectives:

1. To validate leaf area index of maize using conventional and artificial intelligence techniques.
2. Response of maize to growth and yield parameters to varied levels of recommended dose of fertilizers.

Methodology

A field study was conducted during *kharif* 2023 at Main Agricultural Research Station, UAS, Dharwad. The Hybrid Maize (NK 6668 plus) with sixteen treatments laid out in split plot design comprised of three different ferlilizer levels i.e. F_1: 50 % RDF (50: 25: 12.5 kg N: P_2O_5: K_2O ha^{-1}), F_2: 100 % RDF (100: 50: 25 kg N: P_2O_5: K_2O ha^{-1}) and F_3: 150 % RDF (150: 75: 37.5 kg N: P_2O_5: K_2O ha^{-1}) in main plots and five leaf area index estimation methods i.eL_1: LAI estimation by length (l) x breadth (b) x correction factor,L_2: LAI estimation by disc method, L_3: LAI estimation by leaf area meter, L_4: LAI estimation by canopy analyzer, L_5: LAI estimation by artificial intelligence (AI): RGB camera mounted UAV in sub-plot and one Control: Without fertilizers

Methods to measure and estimation of leaf area index (LAI)

The present study focuses on measurement of LAI with different methods as per subplot treatments. LAI was recorded at V_8 **(Knee-high stage)**, V_T **(Tasseling stage)**, R_1 **(Silking stage)** and R_3 **(Grainfilling stage)** stage.

The five methods include both direct and indirect method as follows:

- Length × breadth× correction factor (l × b method) } Direct methods
- Disc method
- Leaf area meter
- Canopy analyzer } Indirect methods
- Artificial intelligence (AI): RGB camera mounted UAV

1. Direct methods

a) Length × breadth method

The length of fully opened leaf lamina was measured from the base of the lamina to the tip. Leaf breadth was taken at the widest point of lamina. The product of the leaf length and breadth was multiplied by the factor 0.75 (Saxena and Singh, 1965) and multiplied with the number of leaves per plant and expressed as leaf area in dm^2 $plant^{-1}$.

Leaf area was measured by following formula

$$\text{Leaf area} = \text{Length} \times \text{Breadth} \times \text{Correction factor (0.75)}$$

Then, LAI is calculated by dividing the leaf area per plant by land area occupied by single plant (Watson, 1947).

$$\text{LAI} = \frac{\text{Leaf area per plant } (cm^2)}{\text{Ground area } (cm^2)}$$

b) Disc method

The leaves were separated from the plant. Fifty discs of known size were prepared through cork borer from leaves. The discs and the remaining leaf blades were dried separately at 65° C to a constant weight and leaf area was calculated by using following formula (Vivekananda *et al*., 1972).

$$LA = \frac{Wa \times A}{W_d}$$

Where,

LA = Leaf area (dm^2)

W_a = Weight of all leaves (including 50 discs in g)

W_d = Weight of 50 discs (g)

A = Area of 50 disc (dm^2)

Then, LAI is calculated by dividing the leaf area per plant by land area occupied by single plant (Watson, 1947).

c) Leaf area meter

The BioVis PSM-L300 (IDS uEye-XS software) was used to calculate leaf area. The cleaned leaves placed on a conveyor belt for scanning. The device capture images and the software calculate leaf area based on RGB color intensity data.

Then, LAI is calculated by dividing the leaf area per plant by land area occupied by single plant (Watson, 1947).

2. Indirect methods

a) LAI-2200C Plant Canopy Analyzer

This optical sensor measured light transmission through the canopy at various zenith angles (0°, 15°, 30°, 45° and 60°). Above-canopy readings established a baseline, followed by below canopy readings along a diagonal transect to capture canopy variability.After collecting the above and below-canopy readings, the canopy analyzer calculated the LAI by comparing the light transmission data which directly gives LAI

b) AI: UAV-Based Data Collection and Image Processing

The RGB camera mounted on the Phantom UAV was utilized to capture steady 15-second video segments of crop plots from a height of 15 meters, with a resolution of 1920x1080 pixels (also known as Full HD, providing a detailed and clear image) using an RGB sensor. An RGB (Red, Green and Blue) sensor captures color information in three channels corresponding to the primary colors. Each pixel in the sensor detects red, green and blue light intensities, which are then combined to produce a full-color image. Each segment recorded four plots at a time and fifteen passes were required to cover the entire study area.

Before the flights, pre-flight checks were conducted, All observations were conducted on the same date as the LAI measurements, which was between 7:00 AM and 8:00 AM. Video recording commenced at the designated start points. This early morning timeframe offered soft, warm light, ideal for photography and avoided the harsh light of midday, which could result in the loss of highlights and shadows. After each 15-second segment, the UAV continued to the next segment at the same altitude.

Post-flight, the video files were transferred to a system for analysis. Each segment was labeled with the corresponding plot numbers.

The videos were then disassembled into JPEG image format. Following this, the images were manually cropped into individual plot frames using the crop image option, which results in four frames from each video. Each plot frame was labeled with the corresponding treatment name. All cropped images were resized to a uniform size of 128x128 pixels using Python 3.12.3. This resizing maintained consistency in the dataset and facilitated better analysis of the treatments.

TheExtraction of Vegetation Indices

Indices Calculation: Twelve vegetation indices were extracted from the cropped RGB images. These indices were analyzed for their correlation with Leaf Area Index (LAI) using grey correlation analysis. Based on the highest correlation with LAI, three indices-Excess Green Index (ExG), Green Leaf Index (GLI) and Red Green Blue Vegetation Index (RGBVI) - were selected for further analysis.

The formulas for three vegetation indices are given below:

- **ExG (Excess Green Index)**: ExG was calculated by the formula as outlined by Pocas*et al.* (2020).

$$ExG = 2G - R - B$$

- **GLI (Green Leaf Index)**: GLI was calculated by the formula as outlined by Tumlisan (2017)

$$GLI = \frac{2G - R - B}{2G + R + B}$$

- **RGBVI (Red Green Blue Vegetation Index)**: RGBVI was calculated by the formula as outlined by Bendig *et al.*(2015)

$$RGBVI = \frac{(G \times G) - (R \times B)}{(G \times G) + (R \times B)}$$

These indices were computed from the red (R), green (G) and blue (B) channels of the 128 ×128-pixel images. The extracted vegetation indices, along with ground truth data for LAI, were used as inputs for the machine learning models.

Model Training and Evaluation

Support Vector Machine (SVM): SVM is a powerful supervised learning model commonly used for regression tasks. It works by identifying a hyperplane in the feature space that best fits the data while maintaining a margin of tolerance.The SVM model was trained on the features ExG, GLI and RGBVI, which were selected for their strong correlation with LAI. After training, the model was applied to the test dataset for prediction.

Random Forest (RF): Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and robustness. By averaging the predictions of individual trees, the model reduces variance and is less prone to overfitting compared to a single decision tree. The model was trained using the same set of features (ExG, GLI and RGBVI) to maintain consistency across all models. During prediction, the final output is derived by averaging the predictions from all the individual trees, ensuring a more stable and reliable prediction.

K-Nearest Neighbors (KNN): KNN is a non-parametric, instance-based learning method that makes predictions by considering the proximity of data points in the feature space.The prediction for each test instance is then made by averaging the target values of these nearest neighbors. As an instance-based method, KNN does not explicitly learn a model during training; instead, it essentially memorizes the

dataset and relies on the distance between instances to make predictions. This approach allows KNN to capture local patterns in the data, though it can become computationally expensive as the size of the dataset grows.

Decision tree model (DT): A Decision tree model constructs a tree-like model of decisions based on the input features. Each internal node in the tree represents a decision on a particular feature, while each leaf node corresponds to a predicted outcome. This model is highly interpretable and capable of capturing complex interactions between features. For this study, the decision tree was utilized with its default settings, which include automatic selection of splits and tree depth. During training, the model recursively splits the dataset based on the features (ExG, GLI and RGBVI) to maximize information gain or minimize impurity, effectively partitioning the data into subsets that are more homogeneous in terms of the target variable. Once trained, the tree is used to make predictions on the test set by tracing the paths from the root to the leaf nodes, where the final prediction is determined.

Evaluation of models: To evaluate the performance of each model, the following metrics were used: Mean Absolute Error (MAE) to measure the average magnitude of errors, Root Mean Squared Error (RMSE) to interpret the errors in the same units as the output variable and R^2 Score to determine how well the model explains the variability of the target variable.

$$\mathbf{MAE} = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i|$$

Where,

n = Number of observations

yi = Actual value

$\hat{y}i$ = Predicted value

$$\mathbf{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(yi - \hat{y}i)^2}$$

n = Number of observations

yi = Actual value

$\hat{y}i$ = Predicted value

$$\mathbf{R^2} = 1 - \frac{n\sum(yi - \hat{y}i)^2}{\sum_{i=1}^{n}(yi - \bar{y})^2}$$

Where,

n = Number of observations

yi = Actual value

$\hat{y}i$ = Predicted value

$\bar{y}$ is the mean of the actual values

Validation

To validate the LAI measurements obtained from different methods against the l × b method, the percentage deviation for each alternative method was calculated. This percentage deviation quantified

how much the LAI values obtained from the other methods deviated from the l × b method, which was used as a reference.

Percentage deviationformula

$$\text{Percentage deviation} = \frac{|(LAI_{Method} - LAI_{l \times b})|}{|LAI_{l \times b}|} \times 100$$

Where,

- LAI_{Method} is the Leaf Area Index measured by the method being compared (e.g., disc method, leaf area meter, canopy analyzer, AI).
- $LAI_{l \times b}$ is the Leaf Area Index measured by the l × b method.

Note: Low deviations indicated reliable methods, while high deviations suggested potential inaccuracies.

Results and Discussion

Table 1: Leaf area index of maize as influenced by graded levels of fertilizers and methods of estimation of leaf area index (LAI)

Treatments	Leaf area index			
	V8 (Knee-high stage)	VT (Tasseling stage)	R1 (Silking stage)	R3 (Grainfilling stage)
Main plot (Fertilizer levels)				
F_1	0.57^{b}	2.87^{b}	3.40^{b}	3.07^{b}
F_2	0.66^{ab}	3.93^{a}	4.55^{a}	3.92^{a}
F_3	0.75^{a}	4.26^{a}	5.00^{a}	4.19^{a}
S.Em. ±	0.01	0.06	0.10	0.05
Sub plot (Different methods of estimation of leaf area index)				
L_1	0.83^{a}	4.15^{a}	4.93^{a}	4.42^{a}
L_2	0.46^{d}	2.13^{c}	2.90^{c}	2.20^{c}
L_3	0.78^{a}	4.20^{a}	4.91^{a}	4.24^{a}
L_4	0.56^{c}	3.85^{b}	3.85^{b}	3.27^{b}
L_5	0.68^{b}	4.06^{a}	4.99^{a}	4.50^{a}
S.Em. ±	0.01	0.04	0.09	0.07
Interaction (Fertilizer levels × Different methods of estimation of leaf area index)				
F_1L_1	0.76^{de}	3.21^{e}	3.85^{b}	3.55^{d}
F_1L_2	0.41^{k}	1.50^{h}	1.71^{d}	1.49^{h}
F_1L_3	0.63^{g}	3.57^{d}	4.07^{b}	3.36^{de}
F_1L_4	0.46^{jk}	2.88^{f}	3.25^{c}	3.05^{ef}
F_1L_5	0.57^{h}	3.78^{d}	4.09^{b}	3.68^{c}
F_2L_1	0.85^{bc}	4.55^{ab}	5.39^{a}	4.76^{ab}
F_2L_2	0.45^{k}	2.11^{g}	2.86^{c}	2.28^{g}
F_2L_3	0.80^{cd}	4.30^{c}	5.21^{a}	4.52^{b}
F_2L_4	0.52^{hi}	4.27^{c}	4.02^{b}	3.30^{de}
F_2L_5	0.71^{ef}	4.41^{bc}	5.27^{a}	4.73^{ab}
F_3L_1	0.88^{ab}	4.70^{a}	5.46^{a}	4.93^{a}
F_3L_2	0.51^{ij}	2.79^{f}	4.12^{b}	2.84^{f}

F_3L_3	0.91[a]	4.72[a]	5.45[a]	4.85[ab]
F_3L_4	0.69[f]	4.40[bc]	4.27[b]	3.45[d]
F_3L_5	0.75[de]	4.54[ab]	5.62[a]	4.88[a]
S.Em. ±	0.02	0.06	0.15	0.12
Control				
Without fertilizers	0.65	2.63	3.42	2.65
S.Em. ±	0.02	0.15	0.18	0.15
CD at 5%	0.05	0.42	0.53	0.43

F_1: 50% RDF (50: 25: 12.5 kg N: P_2O_5: K_2O ha^{-1})
F_2: 100% RDF (100: 50: 25kg N: P_2O_5: K_2O ha^{-1})
F_3: 150% RDF (150: 75: 37.5kg N: P_2O_5: K_2O ha^{-1})
L_1: LAI estimation by length x breadth x correction factor
L_2:LAI estimation by disc method
L_3: LAI estimation by Leaf area meter
L_4: LAI estimation by Leaf area index meter or Canopy analyzer.
L_5: LAI estimation by AI (RGB camera mounted UAV)
Control: Without fertilizers

Performance of machine learning models

Across all growth stages, random forest model demonstrated the best performance, achieving lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), along with the highest Coefficient of Determination (R^2). At knee-high stage, it had an MAE of 0.02, RMSE of 0.03, and R^2 of 0.67. During the tasseling stage, it recorded an MAE of 0.11, RMSE of 0.26, and R^2 of 0.85. At silking stage, it continued to perform well with an MAE of 0.13, RMSE of 0.25, and R^2 of 0.87 and at the grain filling stage, it achieved an MAE of 0.12, RMSE of 0.19, and R^2 of 0.94. The decision tree model also showed strong performance across all stages, with its MAE ranging from 0.01 to 0.11, RMSE from 0.03 to 0.30 and R^2 values from 0.59 to 0.92. The KNN model showed moderate performance, with higher MAE and RMSE and lower R^2 compared to random forest and decision tree models, particularly at the grain filling stage with an R^2 of 0.64. The SVM model had the weakest performance overall, with the highest errors and lowest R^2 values, particularly at the knee-high and silking stages, where it recorded a negative R^2 (-0.03) and a low R^2 (0.01), respectively.

The random forest model performed best at the grain filling stage with highest R^2 of 0.94, MAE of 0.12 and the lowest RMSE of 0.19. It showed good performance at the silking stage also with an R^2 of 0.87, MAE of 0.13 and RMSE of 0.25. At the tasseling stage, the model showed R^2 of 0.85, MAE of 0.11 and RMSE of 0.26. The lowest performance was observed at knee-high stage where, the R^2 was 0.67, the MAE was 0.02 and the RMSE was 0.03. This performance was attributed to its ensemble nature, which allowed for averaging multiple decision trees, thereby reducing the overfitting and improving predictive accuracy across varying datasets (Breiman, 2001).

Estimation of LAI by different methods

LAI of maize varied across all growth stages and fertilizer levels. The l × b method consistently recorded higher values, ranging from 0.76 at the knee-high stage with 50 per cent RDF to 5.46 at the silking stage with 150 per cent RDF. The disc method recorded lower values, from 0.41 at the knee-high stage with 50 per cent RDF to 4.12 at the silking stage with 150 per cent RDF. This method reliance on weight-to-area

conversion often led to errors due to variations in leaf thickness, moisture content and uniformity.The leaf area meter recorded values between 0.63 at knee-high with 50 per cent RDF and 5.45 at silking with 150 per cent RDF. It provides precise and consistent measurements because of its direct scanning method allowed for accurate quantification of individual leaf areas avoiding the need for indirect assumptions about light interception or canopy structure that could lead to inaccuracies in other methods. The canopy analyzer recorded values from 0.46 at knee-high with 50 per cent RDF to 4.40 at silking with 150 per cent RDF. It shows underestimation of LAI due to their assumptions and limitations. These methods assumed that all light entering the system was either absorbed by leaves or transmitted through them, neglecting the fact that some light was reflected. This reflection led to an overestimation of the gap fraction, resulting in underestimated LAI values. The AI method recorded values from 0.57 at knee-high with 50 per cent RDF to 5.62 at silking with 150 per cent RDF, aligning closely with the l × bmethod and leaf area meter methods across all stages and fertilizer levels. It shows least deviation due to the inclusion of the Random Forest model, which performed robustly. Its ensemble nature, created multiple decision trees and aggregated their predictions, which enhanced both accuracy and robustness

Validation of methods of estimation of LAI

Among various methods validated, the UAV images and leaf area meter methods demonstrated the closest agreement with the l × b method, with deviations ranging from 0.43 to 9.86 per cent and 0.18 to 17.11 per cent, respectively. The disc method showed more deviations, ranging from 24.54 to 58.00 per cent, indicating significant difference compared to the l × b method. The canopy analyzer exhibited moderate accuracy with deviations ranging from 6.2 to 39.5 per cent.

Conclusion

- Destructive methods like the length × breadth × correction factor and leaf area meter methods provide precise and reliable estimates of leaf area index, making them suitable for validating other estimation techniques.
- Maize LAI can optimally estimated by using UAV derived RGB images with random forest model. Since higher accuracy of model and minimum deviation observed from tasseling (VT) and grain filling stage (R3), it can be concluded that R3 stage is the best stage to estimate LAI of maize.

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PP-23: Development of an effective YOLOv5 model for detecting alternaria leaf spot disease in cauliflower

PREMCHAND U, MRS. HEENA M.S, R.K MESTA, SHANKARAPPA K S, SHIVASHANKAREMURTHY M, AND SHAMARAO JAHAGIRDAR

[1]Subject Matter Specialist (Plant Protection), ICAR-KVK, Indi (Vijayapura II)
[2]Scientist (Horticulture), ICAR-KVK, Indi (Vijayapura II)
[3]Director of Extension. KSNUAHS, Shivamogga
[4]Associate Professor & Head, Department of Plant Pathology, COH, Bengaluru, UHS, Bagalkot
[5]Senior scientist and Head, ICAR-KVK, Indi (Vijayapura II)
[5]Registrar, KSNUAHS, Shivamogga

Abstract: Alternaria leaf spot, caused by *Alternaria brassicae* and *A. brassicicola*, is a major foliar disease affecting cauliflower (*Brassica oleracea* var. *botrytis*), leading to significant yield losses under warm, humid conditions. Traditional disease diagnosis through visual inspection is time-consuming, subjective and prone to error. Recent advances in deep learning-based object detection offer promising solutions for automated, real-time plant disease monitoring. In this study, a YOLOv5-based model was developed for detecting Alternaria leaf spot in cauliflower leaves. The YOLOv5 architecture, featuring a CSPDarknet backbone, PANet neck and CSP-based feature aggregation, was employed for its balance of speed and accuracy. A dataset of field-collected cauliflower leaf images was annotated with bounding boxes delineating diseased and healthy regions and a background class was included to represent soil, debris and non-leaf objects. Online data augmentation, including mosaic augmentation, scaling and color adjustments, was applied during training to improve model generalization and address the small-object detection challenge posed by early-stage lesions. The trained model achieved a true positive rate of 0.87 for Alternaria leaf spot, with minimal confusion with the Healthy class (0.1), though substantial misclassification of disease instances as Background (100%) was observed, indicating feature overlap between diseased regions and background artifacts such as soil spots or senescent debris. Healthy leaves were identified with high accuracy (0.96) and no misclassification, demonstrating the model's strong discriminative capacity for asymptomatic tissue. The Background class remained problematic, with zero correct classifications; instead, 13% were misclassified as Alternaria leaf spot and 4% as Healthy, highlighting the challenge of differentiating complex background elements from disease symptoms. The precision–recall analysis yielded an area under the curve of 0.861 for the disease class and 0.980 for the Healthy class, while the F1 score peaked at 0.89 at a confidence threshold of 0.411, balancing precision and recall. The mean Average Precision (mAP) at an IoU threshold of 0.5 reached 0.92, confirming robust overall detection performance. However, recall for Alternaria leaf spot declined steadily with increasing confidence thresholds, reflecting a trade-off between detection sensitivity and prediction certainty. These findings underscore the potential of YOLOv5 for automated cauliflower disease surveillance, while revealing the need for improved background suppression and feature disentanglement to reduce false negatives and enhance field-level reliability. Future work will explore attention mechanisms, synthetic background augmentation, and multi-scale feature fusion to further improve disease classification in complex agricultural environments.

Keywords: YOLOv5; Alternaria leaf spot; Cauliflower disease detection; Object detection; Deep learning

PP- 24: Nutrient imbalance analysis in acid lime orchards of northern karnataka using statistical and machine learning approaches

SAVITA B., HEENA M. S., PUNITHA B. C., SADHANA B BABAR, SYEDA SAMINA ANJUM AND NEGALUR R. B.

[1]AICRP on Dryland Agriculture, RARS, Vijayapura -586101,
[2]ICAR-KVK, Indi -586209
[3]Institute of Organic farming, UAS, Dharwad-580005,
[4]AICRP on Pearl millet, RARS, Vijayapura -586101,
[5]AICRP on Sorghum, MRS, UAS, Dharwad-580005,
[6]Department of Agronomy, UAS, Dharwad-580005, Karnataka, India
E-mail: savitab@uasd.in,

Acid lime (*Citrus aurantifolia* Swingle) is an important fruit crop in India, ranking third after mandarin and sweet orange. The *Kagzi* lime variety from Northern Karnataka has gained recognition for its distinctive aroma, flavour, and juice quality, leading to its Geographical Indication (GI) status (APEDA, 2023). The nutrient requirements of acid lime need to be assessed through soil and leaf analysis to minimize yield losses. In this context, the present investigation was undertaken to develop multivariate diagnostic norms using the Compositional Nutrient Diagnosis (CND) approach, with the aim of improving diagnostic precision and identifying yield-limiting nutrients in low-yielding orchards. The study also aimed to understand nutrient interactions using a machine learning approach, namely Principal Component Analysis (PCA). CND is a multivariate extension of the Critical Value Approach (CVA) and the Diagnosis and Recommendation Integrated System (DRIS), and is fully compatible with PCA (Parent *et al.*, 1994). It considers all possible nutrient interactions simultaneously. CND nutrient indices are derived from two components: one representing differences among nutrient concentrations, and the other representing differences in nutrient balance, defined in terms of geometric means between individual samples and reference populations.

Methodology

During the period 2019-20, a survey was carried out in Vijayapura districts of Karnataka state where acid lime cv. *Khazi* lime is being grown extensively. Leaf samples (n=85) of acid lime (selecting 3-5 months shoot of new growth 1st leaf during June month) collected as out lined by Bhargava and Raghupathi (2005) and analyzed for macro-and micro-nutrient status following standard procedure to develop nutrient diagnostic norms and identification of most yield limiting nutrients in low yielding acid lime orchards. The entire population was divided into two *i.e.* low- and high-yielding population based on cut-off yield of 1500 fruits/tree/year. The dataset comprised 54 orchards in the high-yielding population and

Compositional Nutrient Diagnosis (CND):

The CND norms were developed by adopting the procedure followed by Parent *et al*., (1994). The full composition array for D nutrient proportions in plant tissues can be described by the following simplex S^D contained to 100%.

$$S^D = [(N, P, K....R): N>0, P>0, K>0.....R>0; N+P+K.....+R] = 100\ \%.....(1)$$

Where, 100% was dry matter content; N, P, K were the nutrient concentrations and R was filling value between 100% and sum of the nutrients concentrations. Nutrient concentration was corrected by geometric mean, G of all components including R.

$$G = (N \times P \times K \times .....x\ R)^{1/D} .....(2)$$

The row centered log ratios were generated as follows:

$$V_N = In\ (N/G) .....V_B = In\ (B/G) ..... (3)$$

Expressions such as N/G. ……. B/G are multi-nutrient ratios, since each nutrient is divided by geometric means of all the components (the determined nutrients and the filling value). The row-centered log-ratios are linearized (undistorted) estimates of the original components that are fully compatible with PCA (Parent *et al*., 1994).

Principal Component Analysis (PCA) and CND indices :

The PCA was performed on log transformed data of the original nutrient concentration prior to statistical computation that followed normal distribution. The correlation matrix in PCA generates a linear combination of standardized row centered log-ratios as follows:

$$PC_j = a_{ij}(V_N - V^*_N)/SD^*_N + ... + a_{(D-1)\,j}\,(V_B - V^*_B)/SD^*_B .....(4)$$

Where PC_j is the j^{th} principal component, and a_{ij} to a $_{(D-1)}$ [(D-1) components excluding R as specified above] are PC score coefficients of standardized row centered log-ratios. V^*_N to V^*_{Mo} and SD^*_N to SD^*_B were CND norms (indicated by asterisks) i.e. mean and standard deviation of each row centered log ratio in the high yielding orchards. Standardized variables $(V_N - V^*_N)/SD^*_N$ to $(V_B - V^*_B)/SD^*_B$ were CND nutrient indices. The indices (I) for N to Mo are calculated in low yielding orchard by using the formula

$$I_N = (V_N - V^*_N)/SD^*_N, ..., I_B\ (V_{Mo} - V^*_B)/SD^*_B ..... (5)$$

Independent values of V_N to V_B were introduced in the equation (5) for diagnostic purpose.

The PC loading in eigen vector having values greater than the selection criterion (SC) only were considered significant. For a selection criterion to be declared as significant, PCs must have eigen values >100/P, where P is the total number of varieties under diagnosis. Alternatively, PCs showing eigen values <1 were considered to be not significant. Selection criterion would be computed as follows (Ovalles and Collins, 1988):

$$SC = 0.50 / (\text{PC eigen values})^{0.5} ……... (5)$$

Results

The CND norms in acid lime

The CND nutrient element norms (mean and standard deviation) used to solve equations 3 and 4 are presented in Table 1. CND norms for N (V_N), P (V_P) and K (V_K) were 4.34, 3.77 and 4.07, respectively. Among the macro nutrients, the CND norm derived for N indicated higher requirement of N as compared to P, which might be due to continuous and non-determinate type of vegetative growth in acid lime. In contrast, micronutrients including Fe (V_{Fe}), Mn (V_{Mn}), Zn (V_{Zn}), and Cu (V_{Cu}) showed negative row centered Log-ratios mean values, with zinc(-3.43) and copper(-2.21) being the most deficient. These negative values indicate that these nutrients are present in relatively lower proportions and may be limiting factors for optimal plant growth and productivity. Boron (V_B), with a mean value of -0.60, was closer to neutrality, suggesting a relatively balanced status compared to other micronutrients.

Table 1: Compositional nutrient diagnosis norms (mean and standard deviation), row centered log-ratios of acid lime for the high yielding population.

Row Centered Log-Ratios	Mean	Standard deviation
V_N	4.34	0.19
V_P	3.77	0.29
V_K	4.07	0.25
V_{Ca}	4.25	0.28
V_{Mg}	3.59	0.21
V_S	3.03	0.19
V_{Fe}	-1.69	0.19
V_{Mn}	-1.85	0.23
V_{Zn}	-3.43	0.18
V_{Cu}	-2.21	0.29
V_B	-0.60	0.28

The CND indices in acid lime

The mean CND indices of nutrients in low-yielding acid lime orchards are presented in Figure 1. The analysis revealed considerable variation in nutrient balance, with both negative and positive indices indicating deficiencies and excesses, respectively.Among the macronutrients, S recorded the most negative mean index, followed by P and N, indicating that these nutrients are the most limiting factors in low-yielding orchards. Mg and Zn also showed negative values, suggesting moderate deficiencies. In contrast, K remained close to neutrality, while Ca exhibited slightly positive values, indicating a relatively balanced status.Among the micronutrients, Fe and Cu recorded markedly high positive indices, followed by Mn and boron B, suggesting their relative abundance or excess in plant tissues.

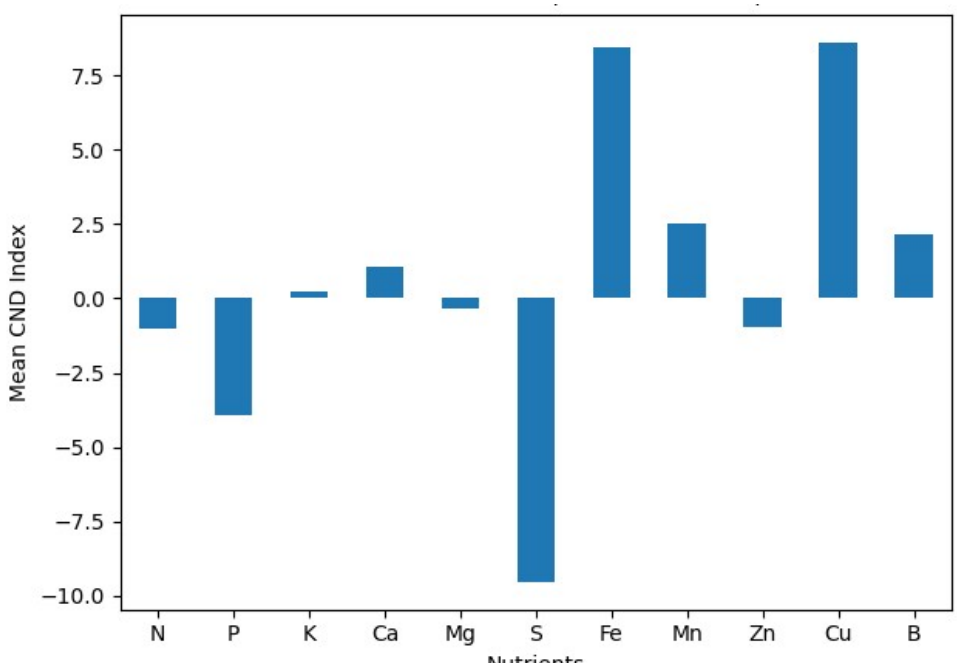


Fig 1. CND indices of low yielding orchards of acid lime

PCA performed on log-transformed nutrient data of acid lime

Principal Component Analysis (PCA) of log-transformed nutrient data in acid lime explained 75.83% of total variability, indicating strong representation of nutrient interactions (Table 2).

- PC1 (19.60%): Dominated by P and Mg (positive) and Ca (negative), indicating a nutrient balance between P–Mg and Ca. Yield showed a positive association, suggesting better productivity with higher P and Mg.
- PC2 (16.71%): Influenced by N, S, and B, representing nutrients important for growth and fruit development, though with limited direct effect on yield.
- PC3 (13.66%): Characterized by K and S (positive) and Fe (negative), indicating interaction between macronutrients and micronutrients, with moderate positive influence on yield.
- PC4 (10.22%): Mainly governed by Zn, highlighting its role in metabolic activities and yield improvement.
- PC5 (8.78%): Dominated by Mn, with a negative association with yield, suggesting possible imbalance or toxicity at higher levels.
- PC6 (6.86%): Shows Zn (negative) and Cu interaction, indicating micronutrient imbalance. Thus, The PCA reveals that both macro- and micronutrients interact complexly, and balanced nutrition rather than individual nutrients is key to improving acid lime yield.

Table 2: PCA loading performed on log-transformed data of Acid lime

Nutrients	PC1	PC2	PC3	PC4	PC5	PC6
N	0.176	0.411*	0.010	-0.313	-0.287	0.129
P	0.532*	0.136	-0.104	-0.185	0.048	0.031
K	-0.138	0.125	0.493*	0.408	-0.182	0.300
Ca	-0.409*	0.314	0.044	-0.272	-0.148	-0.247
Mg	0.508*	-0.067	0.138	-0.190	0.250	-0.268
S	-0.088	0.370*	0.447*	-0.315	-0.085	-0.287
Fe	0.065	0.343	-0.459*	0.203	-0.285	0.311
Mn	-0.126	0.276	0.125	0.369	0.564*	-0.190
Zn	0.184	0.148	-0.209	0.488*	-0.233	-0.634*
Cu	0.268	0.336	0.204	0.122	0.338	0.373
B	-0.115	0.474*	-0.326	-0.014	0.242	-0.024
Yield (Fruits/plant)	0.309	0.056	0.326	0.249	-0.406	-0.059
Eigen Value	2.35	2.00	1.64	1.23	1.05	0.82
%Variation	19.60	16.71	13.66	10.22	8.78	6.86
Selection criteria*	0.326	0.353	0.390	0.452	0.487	0.551

* Significant over selection criteria

Conclusions

CND analysis indicated that low-yielding acid lime orchards are mainly constrained by deficiencies of S, P, Zn, and N, while Fe, Cu, and Mn showed relatively higher indices, suggesting micronutrient imbalance. PCA supported these findings by revealing strong nutrient interactions, with macronutrients (P, Mg, K, and S) positively associated with yield. Overall, S, P, Zn, and N were identified as the key yield-limiting nutrients. The results highlight the importance of balanced and integrated nutrient management to improve productivity and sustain soil health in acid lime orchards of Northern Karnataka.

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PP-25: "Multivariate analysis of nutrient interactions in pomegranate orchards of northern karnataka: a pca-based diagnostic approach"

HEENA M. S., [1]SAVITA B., [2*3]PREMCHAND U, [4]SHIVSHANKARE MURTHY M, [5]SIDHARAM PATIL AND [6]KUMARA B. H.

[1-3AND 4*]ICAR-KVK, Indi -586209, [2]AICRP on Dryland Agriculture, RARS,Vijayapura -586101,
[5]Department of Soil Science, Vijayapura- 586101, [6]AICRP on Water management Arabhavi,
E-mail: heenams@uasd.in,

Pomegranate *(Punica granatum* L.) requires substantial amount of nutrients for maximum yield and quality. Reliable nutrient norms for obtaining adequate nutrient balance is, therefore, required for rationalization of nutrient applications. Nutrient status in plants is diagnosed using nutrient concentration or dual ratios in selected tissues (Walworth and Sumner, 1987). The use of dual ratios as in DRIS instead of nutrient concentration could reduce the effect of nutrient interaction, dilution or accumulation in plant tissues. The compositional nutrient diagnosis (CND) which has been recently proposed for nutritional diagnosis includes not only physiological concepts, such as nutrient interactions, but also a mathematical constraint to a closed system known as the bounded-sum constraint (Parent *et al.,* 1994). Therefore, the CND nutrient imbalance in plants as developed by Parent and Dafir (1992), uses log transformed multi - nutrient ratios (row centered log ratios) which is fully compatible with principal component analysis (PCA). The present investigation was undertaken based on hypothesis of identification of nutrient imbalances which would help the Pomegranate growers (farmers) of Northern Dry Zone of Karnataka to prioritize investments in nutrient inputs.

- To investigate the nutritional status of plants in Pomegranate orchards
- To develop nutrient diagnostic norms and identification of most yield limiting nutrients using CND indices.
- To study nutrient interaction using machine learning tool –PCA.

Methodology

A survey was carried out during 2019-20 in Vijayapura district where pomegranate is being extensively cultivated. Leaf samples (n=80) for selecting 8th pair of leaves (counting from the growing tip) from the new growth in the month of August are collected (Bhargava and Dhandar, 1987) and analyzed for macro and micronutrient status. The entire population was divided into two *i.e*low- and high-yielding population based on cutoff yield of 150 fruits tree^{-1}.The dataset comprised 48 orchards in the high-yielding population and 32 orchards in the low-yielding population.

Compositional Nutrient Diagnosis (CND):

The CND norms were developed by adopting the procedure followed by Parent *et al*., (1994). The full composition array for D nutrient proportions in plant tissues can be described by the following simplex S^D contained to 100%.

S^D= [(N, P, K....R): N>0, P>0, K>0.....R>0; N+P+K.....+R] =100 %.....(1)

Where, 100% was dry matter content; N, P, K were the nutrient concentrations and R was filling value between 100% and sum of the nutrients concentrations. Nutrient concentration was corrected by geometric mean, G of all components including R.

$G= (N \times P \times K \times .....\times R)^{1/D}$ .....(2)

The row centered log ratios were generated as follows:

V_N=In (N/G) .....V_B=In (B/G) ..... (3)

Expressions such as N/G. ……. B/G are multi-nutrient ratios, since each nutrient is divided by geometric means of all the components (the determined nutrients and the filling value). The row-centered log-ratios are linearized (undistorted) estimates of the original components that are fully compatible with PCA (Parent *et al*., 1994).

Principal Component Analysis (PCA) and CND indices :

The PCA was performed on log transformed data of the original nutrient concentration prior to statistical computation that followed normal distribution. The correlation matrix in PCA generates a linear combination of standardized row centered log-ratios as follows:

$PC_j=a_{ij}(V_N-V^*_N)/SD^*_N+..... + a_{(D-1)\,j}\,(V_B-V^*_B)/SD^*_B$ .....(4)

Where PC_j is the j^{th} principal component, and a_{ij} to a $_{(D-1)}$ [(D-1) components excluding R as specified above] are PC score coefficients of standardized row centered log-ratios. V^*_N to V^*_{Mo} and SD^*_N to SD^*_B were CND norms (indicated by asterisks) i.e. mean and standard deviation of each row centered log ratio in the high yielding orchards. Standardized variables $(V_N-V^*_N)/SD^*_N$ to $(V_B-V^*_B)/SD^*_B$ were CND nutrient indices. The indices (I) for N to Mo are calculated in low yielding orchard by using the formula

$I_N= (V_N-V^*_N)/SD^*_N$,.....,$I_B\,(V_{Mo}-V^*_B)/SD^*_B$ ..... (5)

Independent values of V_N to V_B were introduced in the equation (5) for diagnostic purpose.
The PC loading in eigen vector having values greater than the selection criterion (SC) only were considered significant. For a selection criterion to be declared as significant, PCs must have eigen values >100/P, where P is the total number of varieties under diagnosis. Alternatively, PCs showing eigen values <1 were considered to be not significant. Selection criterion would be computed as follows (Ovalles and Collins, 1988):

SC = 0.50 / (PC eigen values) $^{0.5}$ …….... (5)

Statistical analysis

The selection of high and low yielding orchard was carried out using Microsoft Office Excel-2010. The calculation of norms, indices and PC analyses were carried out using GenStat 64-bit release

14.1 (VSN International Ltd. International Crop Research Institute for Semi -Arid Tropics -ICRISAT, Hyderabad, India).

Results

The CND norms in pomegranate:

The CND nutrient element norms (mean and standard deviation) used to solve equations 3 and 4 are presented in Table 1. Results revealed that, CND norms for Nitrogen (V_N), Phosphorus (V_P) and Potassium (V_K) were 4.27, 2.69 and 3.39 respectively whereas CND norms for Calcium (V_{Ca}), Magnesium (V_{Mg}) and Sulphur (V_S) were 4.72, 3.54 and 1.38 respectively. The V_{Ca} norm was higher than that of V_{Mg}norm. Similarly, the CND norms for Iron (V_{Fe}), Manganese (V_{Mn}), Zinc (V_{Zn}), Copper (V_{Cu}) and Boron (V_B) were -0.32, -1.39, -2.02, -1.89 and 0.04 respectively. Among micronutrients, B and Fe norms had higher norm values indicating higher B and Fe requirement as compared to other micronutrients.

Table 1: Compositional nutrient diagnosis norms (mean and standard deviation), row centered log-ratios of pomegranate for the high yielding population.

Row Centered Log-Ratios	Mean	Standard deviation
V_N	4.27	0.16
V_P	2.69	0.31
V_K	3.39	0.28
V_{Ca}	4.72	0.33
V_{Mg}	3.54	0.28
V_S	1.38	0.25
V_{Fe}	-0.32	0.33
V_{Mn}	-1.39	0.27
V_{Zn}	-2.02	0.30
V_{Cu}	-1.89	0.32
V_B	0.04	0.26

The CND indices in pomegranate

In CND analysis, an index value of zero indicates that the nutrient is at an "optimum" level relative to others. Negative values suggest a deficiency, while positive values suggest an excess or luxury consumption (Table 2). Diagnostic norms developed were used for identification of yield-limiting nutrients in low-yielding orchards.The CND indices identified Ca, S followed by B and Zn as most common yield limiting nutrients in pomegranate.Similarly reported by Anjaneyulu and Raghupathi (2010) that Zn and B were the common deficient nutrient in sapota and similarly reported by Savita *et al.,* 2020 in litchi crop.

Table 2. CND indices of selected low yielding orchards of Pomegranate

Orchard no.	N	P	K	Ca	Mg	S	Fe	Mn	Zn	Cu	B
1	1.01	0.79	0.37	-0.18	1.33	0.67	1.59	1.01	2.81	0.38	-0.54
2	0.89	-0.07	-0.11	0.76	1.73	1.10	2.50	1.73	-2.36	-1.07	1.04
6	0.46	0.28	0.77	-1.01	1.25	-0.57	2.38	2.00	-2.01	0.69	0.52
7	0.66	-0.12	0.49	-0.28	1.69	-1.35	2.29	2.24	2.56	-0.46	1.03
9	1.15	1.79	1.16	-0.27	1.65	-1.75	3.55	0.75	2.23	-1.06	0.96
10	1.55	0.62	1.41	-0.50	1.37	0.72	2.55	1.65	0.38	-1.01	1.39
11	-0.23	0.84	-0.09	-0.01	0.47	0.22	1.46	0.54	2.38	0.46	-0.52
12	-0.31	0.14	-0.46	0.23	0.47	-0.26	0.47	0.33	2.59	1.20	1.30
13	0.33	1.23	0.86	-1.67	1.50	0.80	0.62	0.47	1.30	2.71	-0.16
14	1.00	0.46	-0.46	-2.07	1.20	-0.01	1.15	1.83	-2.84	2.55	0.47
15	-0.64	0.11	-0.37	-0.04	0.43	0.17	1.35	1.68	0.86	1.48	0.37
16	-0.58	0.58	0.04	0.29	-0.31	-0.48	1.68	2.40	-1.03	0.66	-0.75
17	0.86	2.15	0.58	-1.54	-0.08	-0.65	1.38	1.06	0.57	2.75	1.48
18	-0.54	1.81	-0.77	0.54	0.00	-0.15	0.01	1.55	0.15	1.83	1.54
19	-0.84	2.04	-0.87	-1.37	0.81	-0.96	1.91	1.62	-0.74	2.67	0.40
20	-0.53	1.85	0.21	-0.99	0.84	-1.55	0.93	1.31	0.50	2.37	-0.08
21	0.50	0.96	-0.58	1.23	0.16	1.23	1.19	2.07	0.19	1.98	0.28
24	0.05	0.29	-0.50	0.67	1.00	-0.83	3.23	1.56	-0.61	0.79	1.88
25	-1.15	0.05	0.75	0.52	-0.52	1.53	0.05	1.60	-0.92	2.18	-0.04
26	1.60	-0.70	1.68	1.56	1.56	2.19	2.18	1.35	-0.55	-1.62	1.75
27	1.87	-0.14	1.59	1.96	-0.89	2.45	1.21	0.46	-0.64	0.07	1.50
28	-0.57	-1.60	0.31	1.62	1.40	1.64	0.07	1.06	0.90	2.16	2.31
31	0.56	-0.29	-0.46	0.12	0.34	1.84	-0.18	0.34	-1.61	5.04	-0.08
32	2.15	2.23	1.14	0.76	1.41	2.70	-0.47	0.99	-0.68	-0.02	0.49

PCA performed on log-transformed nutrient data of pomegranate

Principal Component Analysis (PCA) performed on log-transformed nutrient data of pomegranate extracted five principal components (PCs) with eigenvalues greater than one, cumulatively explaining 71.85% of the total variation**.** Among these**,** PC1 contributed the highest variance (24.28%)**,** followed by PC2 (14.59%)**,** PC3 (12.39%)**,** PC4 (10.97%)**,** andPC5 (9.63%) (Table 3). Macronutrients (Ca, S, N, P, K) are major contributors to variability in pomegranate nutrition. Micronutrients (Fe, Zn, Mn, Cu, B) play a significant role in specific components, reflecting their importance in nutrient balance.Nutrient interactions were investigated using PCA loading performed on log transformed data of pomegranate for N, Ca and S showed positive correlation whereas, Mg and Zn have shown negative correlation. Altogether, PCA indicated the existence of multi-nutrient interaction in pomegranate.The presence of both positive and negative loadings across components suggests complex interactions, including synergistic and antagonistic relationships among nutrients.

Table 3: Principal component analysis (PCA) loading performed on log-transformed data of Pomegranate

Nutrients	PC1	PC2	PC3	PC4	PC5
N	0.541*	0.439*	0.425	-0.257	0.008
P	-0.115	0.718*	-0.253	-0.347	0.153
K	0.285	0.195	0.726*	0.153	0.340
Ca	0.764*	-0.162	-0.002	0.227	-0.116
Mg	-0.677*	0.317	0.023	-0.242	0.017
S	0.767*	0.306	-0.150	0.105	0.004
Fe	-0.643*	0.191	0.311	0.195	0.333
Mn	-0.060	0.398*	-0.078	0.771*	0.178
Zn	-0.475*	0.036	0.180	0.439	-0.533*
Cu	0.097	0.447*	-0.606	0.208	0.045
B	-0.027	-0.493	-0.258	0.081	0.691
Eigen Value	2.671	1.605	1.363	1.206	1.059
%Variation	24.281	14.589	12.392	10.965	9.626
Selection criteria*	0.306	0.395	0.428	0.455	0.486

* Significant over selection criteria

Conclusion

The CND indices identified Ca, S followed by B and Zn as most yield limiting nutrients in low yielding Pomegranate orchards. CND is recognized high order interaction between nutrients and this methodology has been used successfully to interpret results of foliar analysis in pomegranate.Thus, diagnostic norms and nutrient interactions help evolve nutrient management strategies for pomegranate to realize higher yields and better quality.

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PP-26: Geospatial modeling and soil health dynamicsunder long-term sugar factory effluent application in Northern Karnataka with AI tools.

PATIL C. R., NOOLI S.S., HUNDEKAR S. T. AND SOURABH MUNNOLLI

[1] Professor and Head (Agril. Microbiology), College of Agriculture, Dharwad,
[2]Scientist (Agronomy), AICRP-Sugarcane, ARS, Sankeshwar
[3]Scientist (Soil Science) and Head, AICRP-Agroforestry, UAS, Dharwad
[4]Assistant Professor (Agronomy), KLE College of Agricultural Sciences, Tenikolla
E-mail: crpatiluasd@gmail.com
Mobile: 9448013373

Impact assessment of long-term application of treated sugar factory effluentfrom factory premises of Ugar Sugar Works Limited, Ugar Khurd in Belgaum district of Karnataka state over 1200 acres of land was undertaken during the period from 2023 to 2025. The study involved extensive survey and mapping of the study area depicting its geospatial features. Grids of 60 m were overlaid in the study area to mark sampling sites. A total of 23 profiles were dug to collect representative samples from each profile at regular intervals up to 150 cm depth each sample collected at an interval of 30 cm. In all 105 profile samples at different depths were collected for analyzing the chemical properties and biological activity.

Soil properties *viz.,* Soil pH, Electrical Conductivity (dS/m), Soil Organic Carbon content (%), Free Lime Content, Exchangeable Cations (Cmol(P+)/kg), Exchangeable Na and K, Exchangeable Sodium Percentage (ESP), Water Soluble Cations, Water Soluble Na, Water Soluble K, water soluble anions, available nitrogen (kg/ha), available P_2O_5 (kg/ha), available K_2O(kg/ha) and micronutrient status (DTPA extractable Micro Nutrients concentration) in all 105 profile samples were estimated. Similarly soil biological activity (Dehydrogenase activity (µg TPF/g/soil/day, urease activity (µg NH_4-N formed/g/soil/day), Acidic and alkaline phosphatase (µg PNP released/g/soil/h), Soil respiration (Mg of CO_2/ h/ 100 g soil) and microbial biomass carbon (µg/g) were also determined for each sample. The collected data were first organized in a structured tabular format (Excel) and AI tools were applied to develop thematic maps, ensuring that each record contained both spatial (coordinates) and attribute (soil properties) information. This dataset was then imported into ArcGIS Pro, where the geographic coordinates were used to generate point features representing the sampling locations through the “Display XY Data” function. The point layer thus created served as the base for further spatial analysis. Subsequently, the attribute data were linked to the spatial layer, allowing visualization of individual soil parameters in the digital maps developed.Thematic maps were developed by applying appropriate symbology techniques such as graduated colors and classified ranges to represent variations in soil properties. This helped in distinguishing simultaneously different levels of 26 parameters studied across the study area. To enhance spatial understanding, interpolation techniques such as Inverse Distance Weighting (IDW) were used to convert discrete point data into continuous surface maps.

These interpolated maps provided a clear representation of spatial distribution patterns and helped in identifying zones of variation within the study region. Map layouts were designed using ArcGIS layout tools by incorporating essential cartographic elements including title, legend, scale bar, north arrow and coordinate grid. The final maps were exported in suitable formats for reporting and interpretation, ensuring clarity, accuracy and effective presentation of spatial data which can be used as field data book by the ground staff. The mapped information will serve as one sheet data sheet data set on all these parameters for future studies.

Key words: Thematic maps, Inverse Distance Weighting, ArcGIS.

Theme II

Climate Modeling and Resource Management

PP-27: Climate risk forecasting of major diseases in cardamom using meteorological data: a dynamic advisory approach for Uttara Kannada district, Karnataka

GUNA M, SHESHAKUMAR GOROSHI, RAJAVEL MANICKAM, PILLI SANDEEP, PRASAD A, AND RAJU V ROKHADE

[1,4&6] North Karnataka Agrometeorological Forecasting and Research Centre (NKAFC), India Meteorological Department, Dharwad, Karnataka, India
[2]Agromet Advisory Services Division, India Meteorological Department, New Delhi, India
[3&5]Meteorological Centre, India Meteorological Department, Bengaluru, Karnataka, India
E-mail: hawkgunams@gmail.com

Introduction

Cardamom (*Elettaria cardamomum*), a high-value spice crop, is widely cultivated in the humid tropical ecosystems of the Western Ghats, including Uttara Kannada District. The region is characterized by complex terrain, dense vegetation, and annual rainfall ranging from 2500 to over 4000 mm, creating a favourable microclimate for cardamom cultivation under shaded conditions. However, these same environmental conditions, particularly intense monsoonal rainfall, prolonged leaf wetness, and high relative humidity also promote the incidence and spread of major diseases such as capsule rot (Azhukal), rhizome/clump rot, and leaf blotch/spot. Conventional crop calendars and advisory systems are largely static and based on generalized seasonal patterns. Such approaches often fail to capture intra-seasonal variability in weather, leading to delayed or sub-optimal disease management interventions. In recent years, the availability of high-resolution geospatial datasets and cloud-based analytical platforms has enabled the development of climate-informed decision support systems for agriculture. The present study was undertaken with the following objectives: (i) to analyze the influence of rainfall variability on major cardamom diseases; (ii) to develop climate-based disease risk indices using threshold-based approaches; (iii) to generate a spatio-temporal assessment of disease risk using historical datasets; and (iv) to validate the derived risk patterns with agrometeorological advisory bulletins (AAB) to assess their operational relevance. The study emphasizes a retrospective and near real-time climate risk assessment framework, rather than purely forecast-based systems, for improving disease management in cardamom plantations.

Keywords: Cardamom, Climate Risk Forecasting, Capsule Rot, Azhukal, Google Earth Engine, Disease Advisory, Western Ghats

Materials and Methodology

The study was conducted in NKAFC Dharwad for Uttara Kannada District, which experiences a humid tropical climate with strong monsoonal influence. The analysis covered the period 1996–2025, ensuring consistency and completeness of meteorological records.

Daily rainfall data were obtained from IMD gridded datasets (Pai *et al.,* 2014), while temperature data were sourced from ERA5-Land reanalysis (Muñoz-Sabater *et al.,* 2021). Administrative boundaries at district level were used for spatial aggregation. All dataprocessing and analysis were carried out using the R programming language. Time-series analysis tecphniques were used to derive weather indices relevant to disease development.

A 5-day moving cumulative rainfall (R_5) approach was adopted to capture short-term moisture conditions influencing disease incidence. Based on established epidemiological relationships, disease risk indices were defined as follows:

- Capsule rot (Azhukal): Triggered when $R_5 > 100$ mm, indicating prolonged wetness favourable for *Phytophthora* infection.
- Rhizome/clump rot: Associated with continuous rainfall events leading to soil saturation and poor drainage conditions.
- Leaf spot/blotch: Linked to moderate rainfall (20–70 mm) and humid atmospheric conditions.

These thresholds were used to classify disease risk into low, moderate, and high categories for each time step. A time series of disease risk was generated for the study period. From the derived dataset, the following analyses were performed:

- Temporal analysis of disease risk using moving window techniques
- Seasonal characterization of disease occurrence
- Frequency analysis of high-risk events
- District-level aggregation of disease risk

Validation Using Agrometeorological Advisories

To assess the operational relevance of the developed risk indices, model outputs were validated against agrometeorological advisories issued under the Gramin Krishi Mausam Sewa (GKMS) through Agrometeorological Field Units (AMFUs).

Historical advisories were reviewed to identify disease-related recommendations, particularly for capsule rot, rhizome rot, and leaf spot. The dates of advisories were compared with model- derived disease risk levels.

Validation was carried out by

- Matching high-risk periods with advisories recommending plant protection measures
- Assessing agreement between observed advisories and modeled risk levels
- Estimating qualitative and percentage-based accuracy

This approach provided a practical evaluation of the model's effectiveness in replicating real- world advisory conditions.

Results and Discussion

The analysis revealed clear seasonal patterns in disease risk across the study period. High-risk conditions for capsule rot were predominantly observed during the peak monsoon months (July–August), corresponding with heavy rainfall events and prolonged wetness conditions. These findings are consistent with the known epidemiology of *Phytophthora* spp. (Nair, 2011; Thomas *et al*., 2015). Rhizome rot risk was closely associated with continuous rainfall and soil saturation, highlighting the importance of drainage management in plantation systems. Leaf spot diseases were observed during transitional periods characterized by moderate rainfall and humid conditions. The temporal patterns derived from the analysis showed strong agreement with advisories issued under GKMS, particularly during high rainfall events when fungicide application and drainage management were recommended. This demonstrates the capability of the developed framework to capture disease-conducive conditions effectively.Compared to

conventional crop calendars, the climate-driven approach provides a more responsive and data-based mechanism for disease risk assessment. It enables improved timing of interventions, reduces unnecessary chemical applications, and enhances the efficiency of advisory services.

Conclusion

The study demonstrates the effectiveness of a climate-driven disease risk assessment framework for cardamom plantations using historical meteorological data and R-based analysis. The use of short-term rainfall indices provides a simple yet robust method for identifying disease-prone periods. Validation with GKMS advisories highlights the operational applicability of the approach for agrometeorological services. The framework can be readily integrated into advisory systems and extended to other plantation crops in humid tropical regions. This work contributes to the development of climate-smart, data-driven decision support systems for sustainable crop management under changing climatic conditions.

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PP-28: Development of crop weather calendar for groundnut and its role in climate-smart agriculture

ROHINI S., KUMAR NAIK A. H., S. SRIDHARA AND AMITH G.

[1]M.Sc. Scholar, Department of Agronomy,KeladiShivappa Nayaka University of Agricultural and Horticultural Sciences, Shivamogga, Karnataka
[2]Assistant Professor & Nodal Officer (GKMS), AMFU, Hiriyur
[3]Professor & Principal Nodal Officer (GKMS), AMFU
[4]Technical Officer (GKMS), AMFU

Introduction

Groundnut (*Arachis hypogaea L.*) is one of the most important oilseed crops cultivated under rainfed conditions in semi-arid regions of India. Its productivity is highly sensitive to weather variability, particularly rainfall distribution, temperature fluctuations and humidity levels. Climate variability and increasing frequency of extreme weather events have intensified risks in groundnut cultivation, making traditional farming practices less reliable.

In this context, weather-based decision support tools are gaining importance in next-generation farming. Among these, Crop Weather Calendar (CWC) serves as an effective tool for aligning crop phenology with prevailing and expected weather conditions. When integrated with Agrometeorological Advisory Services (AAS), digital platforms and emerging technologies such as Artificial Intelligence (AI), CWCs can significantly enhance farm-level decision-making. The present study was undertaken to develop a scientifically robust Crop Weather Calendar for groundnut under semi-arid conditions of Karnataka and to analyze the relationship between weather parameters, crop phenophases and pest-disease dynamics.

Objectives

- To develop a Crop Weather Calendar for groundnut using long-term climatic data
- To identify optimal weather conditions for different phenological stages
- To assess the influence of weather parameters on pest and disease incidence
- To explore the potential of integrating CWC with agromet advisory services.

Materials and Methods

The study was conducted during 2025 in the *kharif* season at ZAHRS, Agro-Meteorological Field Unit (AMFU), Hiriyur, which is situated in the Central Dry Zone (Zone-4) of Chitradurga, Karnataka at 13^0 57' 32" North latitude and 70^0 37' 38" East longitude with altitude of 606.1 m above the mean sea level (MSL).

Long-term weather data were collected and analysed, including weekly rainfall, maximum temperature, minimum temperature, relative humidity and wind speed.

The data were arranged according to Standard Meteorological Weeks (SMW) and correlated with different phenological stages of the groundnut crop. Based on this analysis, favourable weather conditions for each growth stage were identified and structured into a Crop Weather Calendar. Additionally, weather conditions conducive for major pests and diseases were analyzed to incorporate plant protection advisories into the calendar.

Results and Discussion

4.1 Crop Weather Calendar Development

The developed Crop Weather Calendar clearly defines stage-wise weather requirements for groundnut. The sowing and seedling emergence stage (8-10 days) required optimal conditions with weekly rainfall ranging from 12.4-28.1 mm, maximum temperature of 29.0-30.7°C and minimum temperature of 19.9-21.1°C. These conditions ensured better germination and uniform crop establishment.

- During the vegetative stage (11-27 days), crop growth was found to be favourable under higher temperature ranges of 32-35°C with average rainfall around 68 mm, supporting vigorous vegetative development.
- The flowering to pegging stage (28-45 days) was highly sensitive to moisture stress. Moderate rainfall of about 23.1 mm and relative humidity between 75-83 per cent were critical for successful pegging and flower retention.
- The pegging to pod development stage (40-50 days) required higher rainfall of about 83.1 mm and a temperature range of 32-33°C, which supported pod initiation and development.
- The pod development to maturity stage (60-110 days) required relatively lower temperatures (31-33°C maximum and 20-23°C minimum) and higher cummulative rainfall of about 153.6 mm for proper pod filling and maturation.

Similar findings were reported by Sharma (2021). These findings demonstrate that synchronization of crop stages with favorable weather conditions is crucial for maximizing yield.

4.2 Weather-Pest and Disease Relationships

Weather parameters played a significant role in pest and disease occurrence. Leaf miner and thrips were favoured by prolonged dry spells and temperature rise of 3-5°C. Red hairy caterpillar emerged after rainfall events of 20 mm or more. *Spodoptera spp*. incidence was associated with moderate rainfall of 10-20 mm, temperature of 30-32°C and high relative humidity above 80 per cent. Late leaf spot and rust were promoted by continuous leaf wetness, high humidity above 90 per cent and reduced sunshine hours.

Conclusion

The study successfully developed a Crop Weather Calendar for groundnut under semi-arid conditions, highlighting the critical role of weather parameters in influencing crop growth, yield and pest-disease dynamics. The findings emphasize that proper alignment of crop stages with favourable weather conditions can significantly enhance productivity, while weather-based advisories can minimize risks associated with climate variability. Integration of CWC with AI, automation and digital technologies can further improve farm-level decision-making. The developed CWC can be used as a reliable decision-support tool for farmers, extension workers and policymakers to promote sustainable and climate-resilient groundnut production.

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PP-29: Development of a taluk-level rainfall analytics dashboard integrating SPI and crop weather calendar for irrigation scheduling over North Interior Karnataka (1996–2025)

PILLI SANDEEP, DR. GUNA M, SHESHAKUMAR GOROSHI, RAJAVEL MANICKAM, AND PUVIARASAN N

[1]North Karnataka Agrometeorological Forecasting and Research Centre (NKAFC), India Meteorological Department, Dharwad, Karnataka, India
[2]Agromet Advisory Services Division, India Meteorological Department, New Delhi, India
[3]Meteorological Centre, India Meteorological Department, Bengaluru, Karnataka, India
E-mail: hawkgunams@gmail.com

Introduction

Rainfall variability is a key determinant of agricultural productivity in monsoon- dependent regions such as North Interior Karnataka, where crop planning, irrigation scheduling, and risk management are strongly influenced by the temporal and spatial distribution of rainfall. At the taluk level, variability in rainfall is often more pronounced due to local topography and microclimatic conditions, making it essential to analyze rainfall at finer spatial scales. Traditional methods of rainfall analysis are largely static and do not provide dynamic, user-driven insights required for real-time decision-making. With advancements in geospatial data availability and analytical tools, there is increasing scope to develop integrated platforms that convert long-term climate data into actionable information. In this context, the present study focuses on developing a taluk-level rainfall analytics dashboard for North Interior Karnataka covering the period 1996–2025, integrating multiple analytical components such as annual and seasonal rainfall patterns, Standard Meteorological Week (SMW) analysis, Standardized Precipitation Index (SPI), and crop weather calendar-based irrigation scheduling. The study aims to enhance agrometeorological advisory services by providing a scientific and interactive decision support system.

Keywords Rainfall variability, SPI, Crop Weather Calendar, Irrigation Scheduling, Agrometeorology, North Interior Karnataka

Materials and Methodology

The study was carried out at the North Karnataka Agrometeorological Forecasting Centre (NKAFC), Dharwad, using long-term daily rainfall data for the period 1996–2025. The rainfall dataset was obtained from high-resolution gridded products developed by the India Meteorological Department (IMD), ensuring spatial consistency and temporal completeness. Taluk boundary shapefiles were used for spatial aggregation and mapping of rainfall data. All data processing, analysis, and visualization were performed using the R programming environment, incorporating packages for statistical analysis, geospatial processing, and web- based visualization. Daily rainfall data were aggregated to derive annual averages, monthly climatology, and SMW-based rainfall patterns to capture both seasonal and intra-seasonal variability. The Standardized Precipitation Index (SPI) was computed using long-term rainfall distributions to quantify drought conditions at different time scales.

The SPI values were categorized into drought classes such as mild, moderate, and severe drought, providing insights into rainfall anomalies and water stress conditions. In addition, a crop weather calendar framework was developed by aligning rainfall patterns with crop growth stages and water requirements. Periods of rainfall deficit identified through SPI were used to determine irrigation scheduling windows, thereby supporting efficient water management. An interactive dashboard was developed using the Shiny framework, integrating time-series visualization, statistical summaries, and GIS-based mapping, along with data download capabilities.

Results and Discussion

The analysis revealed significant spatial and temporal variability in rainfall across taluks during the study period. Annual average rainfall showed considerable differences between regions, reflecting variations in monsoon intensity and distribution. Monthly climatological analysis indicated that a major proportion of rainfall is concentrated during the southwest monsoon season, particularly between June and September, with peak rainfall occurring in July and August. The SMW-based analysis provided detailed insights into intra- seasonal rainfall variability, clearly identifying the onset, peak, and withdrawal phases of the monsoon. The computation of SPI highlighted the occurrence of multiple drought years with varying intensity, indicating periods of significant rainfall deficit that could adversely affect crop growth and productivity. Moderate to severe drought conditions were observed in several years, emphasizing the importance of continuous monitoring and early warning systems. The integration of SPI with rainfall analysis improved the understanding of drought dynamics at the taluk level. Furthermore, the crop weather calendar-based irrigation scheduling approach demonstrated its utility in identifying critical periods for supplemental irrigation. By aligning rainfall probability with crop water requirements, the framework enables better water resource management and reduces the risk of crop stress. The interactive dashboard developed in this study provides a user-friendly platform for visualizing and analyzing rainfall data, offering real-time insights for researchers, planners, and farmers. Compared to conventional static reports, the dashboard significantly enhances data accessibility and supports informed decision-making.

Conclusion

The study successfully demonstrates the development of a comprehensive rainfall analytics dashboard that integrates climatological analysis, drought assessment using SPI, and crop weather calendar-based irrigation scheduling. The system provides a robust and scalable framework for transforming long-term meteorological data into actionable insights for agricultural planning and management. The inclusion of SPI enhances drought monitoring capabilities, while the crop weather calendar approach supports efficient irrigation scheduling under variable climatic conditions. The interactive nature of the dashboard makes it a valuable decision support tool for agrometeorological services under GKMS project, particularly within the framework of operational advisory systems.

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PP-30: Post-harvest loss prediction in onion (*Allium cepa*)

BANGAREMMA WADEYAR, KUSHAL AND KALAVATI K.

[1]Department of Genetics and Plant Breeding
[2]Department of Horticulture
[3]Department of Agricultural Entomomolgy
University of Agricultural Sciences, Dharwad, India
E-mail: wadeyarbs13558@uasd.in

Onion is one of the most widely cultivated and consumed vegetable crops globally, playing a crucial role in both household consumption and agricultural economies. Despite its importance, onions are highly prone to significant post-harvest losses, which can range from 20% to 40% depending on handling, storage conditions, and environmental factors. These losses not only affect farmer income but also contribute to market instability and food insecurity. Therefore, predicting post-harvest losses in onion has become an essential area of research to ensure better storage management, reduce waste, and enhance supply chain efficiency.

Post-harvest losses in onion occur due to a combination of physiological, pathological, and mechanical factors. Physiological losses include moisture loss, sprouting, and respiration, which lead to weight reduction and quality deterioration. Pathological losses are mainly caused by fungal and bacterial infections such as neck rot, black mold, and basal rot. Mechanical damage during harvesting, transportation, and handling further accelerates deterioration by creating entry points for pathogens. These complex interactions make loss prediction a challenging but necessary task.

Traditionally, post-harvest loss estimation relied on manual inspection and empirical observations, which are often subjective and inaccurate. However, with advancements in technology, predictive modeling approaches have gained prominence. These approaches use historical data, environmental parameters, and crop characteristics to forecast potential losses during storage and distribution. Factors such as temperature, relative humidity, storage duration, bulb size, curing efficiency, and varietal differences are critical inputs for developing reliable prediction models.

Statistical models, including regression analysis, have been widely used to identify relationships between storage conditions and loss parameters. For instance, linear and nonlinear regression models can estimate weight loss or decay percentage based on temperature and humidity variations. However, these models may have limitations when dealing with complex, non-linear interactions among multiple variables.

To overcome these limitations, machine learning (ML) techniques are increasingly being applied in post-harvest loss prediction. Algorithms such as decision trees, random forests, support vector machines, and artificial neural networks have shown promising results. These models can handle large datasets and capture complex relationships between variables, leading to more accurate predictions. For example, an artificial neural network can integrate multiple inputs like storage temperature, humidity, and duration to predict spoilage rates with high precision.

In recent years, the integration of Internet of Things (IoT) devices has further enhanced prediction capabilities. Sensors installed in storage facilities can continuously monitor environmental conditions such as temperature and humidity. This real-time data can be fed into predictive models to provide early warnings about unfavorable conditions that may lead to increased losses. Such systems enable farmers and storage managers to take timely corrective actions, such as adjusting ventilation or temperature, thereby minimizing damage.

Another emerging approach involves the use of image processing and computer vision techniques. These technologies can assess onion quality by analyzing visual attributes such as color, size, and surface defects. Combined with machine learning algorithms, image-based systems can detect early signs of spoilage or disease, allowing for better sorting and grading before storage. This reduces the risk of contamination and improves overall storage efficiency.

Accurate prediction of post-harvest losses also has significant economic implications. By anticipating losses, farmers can make informed decisions regarding storage duration, market timing, and pricing strategies. It also helps policymakers and supply chain stakeholders in planning logistics, reducing wastage, and stabilizing market supply. Moreover, minimizing post-harvest losses contributes to sustainable agriculture by reducing resource wastage and improving food availability.

However, challenges still exist in implementing predictive systems at a large scale. Limited access to technology, lack of standardized data, and high initial costs can hinder adoption, especially among smallholder farmers. Additionally, variability in climatic conditions and regional practices requires location-specific models, which may not always be readily available.

In conclusion, post-harvest loss prediction in onion is a critical component of modern agricultural management. Advances in statistical modeling, machine learning, IoT, and image analysis have significantly improved prediction accuracy and reliability. By integrating these technologies into storage and supply chain systems, it is possible to reduce losses, enhance profitability, and ensure a more stable onion market. Future research should focus on developing cost-effective, user-friendly models and promoting their adoption among farmers to achieve sustainable post-harvest management.

PP-31: AI-driven weather forecasting and crop disease detection system

RAJESHWARI V PATIL, SUMAN YALIGAR, BIRADAR S R AND LEENA I SAKRI, KRUTHIKA S M, BHAKTI U GADKAR

[1&2]Assistant Professor, Dept.of AIML, SDMCET, [3]Professor,Dept.of AIML,SDMCET

[4]Assistant Professor, Dept.of AIML, SDMCET

Abstract: The economy depends heavily on agriculture, and farmer income and productivity are strongly impacted by crop health. Late diagnosis of plant diseases, which results in substantial crop loss, is one of the biggest problems farmers confront. Conventional illness identification techniques rely on manual inspection, which is laborious, prone to mistakes, and frequently necessitates specialized knowledge. The goal of this research is to employ machine learning and image processing to create a leaf disease detection system. Using visual signs including discolouration, spots, and texture changes, the system examines photos of plant leaves taken using a camera or mobile device to identify illnesses. To accurately diagnose diseases, the suggested method makes use of feature extraction, classification algorithms, and image preprocessing. Several crops, including cotton, paddy, tomatoes, and potatoes, can be supported by the method. The system helps farmers take prompt action, use fewer pesticides, and increase crop output by offering early detection and diagnosis.Farmers can simply access and utilize this software module because it is made to be integrated into a mobile application. All things considered, the system serves as a sophisticated decision-support tool in contemporary agriculture.

Introduction

Plant health and environmental circumstances have a major impact on agriculture. Plant diseases are one of the major problems influencing agricultural output; if they are not identified early, they can spread quickly. Particularly in rural locations, farmers frequently lack access to professional advice, which can result in delayed or inaccurate diagnosis.

Images may now be used to automatically detect diseases because to developments in computer vision and artificial intelligence (AI). Since most plant illnesses show obvious signs on leaves, leaf-based disease detection is especially successful. These symptoms include:

• Discoloration or yellowing

• Black or brown patches

• Curling or deforming leaves

• Patterns of fungal development

As a component of the "Krishi Drishti" project, the suggested system seeks to offer an automated method for identifying plant diseases through image-based analysis.

The system enables users to:

• Take a picture of a plant leaf and upload it.

• Use machine learning models that have been trained to analyze the image.

• Receive instant results about the disease type

• Obtain recommendations for preventative actions

This method assists farmers in making data-driven decisions and lessens reliance on manual inspection. Accessibility, usability, and scalability are guaranteed when this solution is incorporated into a mobile application.

The approach for detecting leaf disease uses a structured pipeline with several steps:

Capturing Images

• Pictures are gathered using:

• Portable cameras

• Publicly available datasets, such as the PlantVillage dataset

• Both healthy and sick leaves are included in the dataset.

Methodology

1. **Preprocessing of Images**

Preprocessing eliminates noise and enhances image quality.

Among the steps are:

- Resizing pictures to a set size
- Filter-based noise reduction (Gaussian blur)
- Color conversion (from RGB to HSV or grayscale)
- Using segmentation to separate the leaf from the surroundings

This stage guarantees that the model receives only pertinent features.

2. **Extraction of Features**

The processed photos are used to extract significant features:

- Color characteristics → Identify patterns of discoloration
- Texture characteristics ⇒ Determine fungal growth or roughness
- Shape characteristics ⇒ Id Methods employed:
- Analysis of histograms
- Gray Level Co-occurrence Matrix, or GLCM
- The detection of edges

3. **Training and Classifying Models**

To categorize illnesses, machine learning models are trained.

Potential models:

- Convolutional neural networks (CNNs) are favored because to their superior accuracy.
- SVM stands for Support Vector Machine.
- The Random Forest

Workflow:

i. Divide the dataset into sets for testing and training.

ii. Use annotated images to train the model

iii. Assess performance and accuracy

iv. Use hyperparameter tuning to optimize

The model that has been trained forecasts:

• A healthy leaf

• A particular kind of disease (such as bacterial spot or leaf blight

Conclusion

Early disease detection is one of the main problems in agriculture, and the leaf disease detection system offers a clever and practical answer. The technology uses machine learning and image processing to automate the detection process and lessen the need for human review.

Overall, by lowering needless pesticide use, decreasing crop losses, and increasing productivity, the system supports sustainable agricultural methods. This system has the potential to develop into a full decision-support tool that empowers farmers and fortifies the agricultural ecosystem with additional enhancements including bigger datasets, real-time weather integration, and multilingual support.

PP-32: Rainfall variability and climate risks in northern dry agro-climatic zones of Karnataka

YADAHALLI G. S. *, JAGADISH HIREMATH, LAVANYA P., PATIL S. B., POTDAR M. P. VIDYAVATHI G. Y. AND VASANTAKUMARI J.

Department of Agronomy,
University of Agricultural Sciences, Dharwad 580 005, Karnataka, India
E-mail: guruyadahalli@uasd.in

Abstract: Indian agriculture is predominantly dependent on monsoon, which is experiencing changes over space and time with increased variance, mainly due to anthropogenic global warming and climate change. The Northern Dry Zone of Karnataka is one of the driest regions among the 10 agroclimatic zones of Karnataka. Most of the agricultural lands in the Northern Dry Zone are under rainfed. Rainfall trend analysis studies lead to better understanding of rainfall patterns and planning of agricultural practices. This paper aims to analyze the rainfall trend in the Northern Dry Zone of Karnataka, which includes 9 districts of Karnataka. 30 years (1991-2020) of daily rainfall data have been analyzed for different seasons, i.e., winter (Jan-Feb), pre-monsoon (Mar-May), southwest monsoon (Jun-Sep), and northeast monsoon (Oct-Dec) using the Man-Kendal test, Sen's slope estimator, and linear regression equation methods. The results showed that there is an increasing trend in winter (Jan-Feb) and pre-monsoon (Mar-May) rainfall among all the districts of NDZ, except Bagalkote, which showed a decreasing trend in the winter season. Whereas during the Southwest monsoon (Jun-Sep), an increasing trend was observed in Bagalkote, Bellary, Dharwad, and Vijayanagara, Belagavi, Gadag, Koppal, Raichur, and Vijayapura Districts showed a decreasing trend. During the northeast monsoon all the districts showed a decreasing trend. For annual rainfall trends, most districts showed a decreasing trend, except Dharwad and Vijayanagara Districts, which showed an increasing trend.

Key words: Rainfall trend, Mann–Kendall test, Sen’s slope, Northern Dry Zone, Karnataka, climate variability

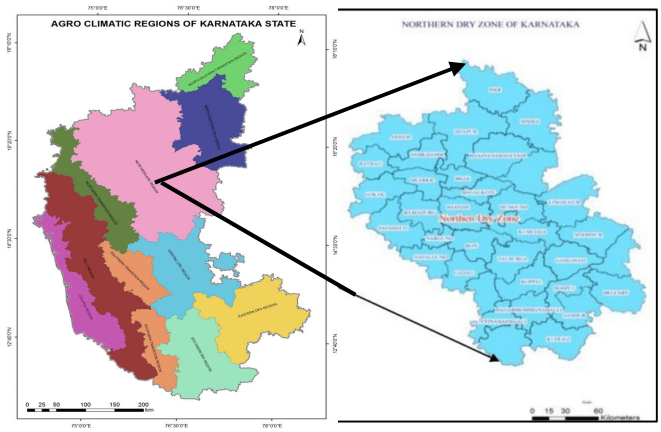
Introduction

Climate change over the past century has significantly altered rainfall and temperature patterns, with changing precipitation being a major impact (Anie John &Brema, 2018). Rainfall, a vital factor for all life, varies widely in time, space, intensity, and volume, and in India, it is primarily driven by the monsoon (Mahadev prasad *et al.*, 2022). Understanding climate variability is essential for adapting cropping patterns and management techniques to achieve sustainable agriculture. Rainfall variability profoundly affects a country’s economy by influencing agriculture, power, and industry, with seasonal rainfall being a key determinant of India’s GDP (Gadgil & Gadgil, 2006). The IPCC (2007) highlights that climate change increases risks of hunger, water scarcity, and hydro-meteorological disasters like floods and droughts, emphasizing the need for research on rainfall variability.

Karnataka’s rainfall is unevenly distributed: Malnad and Coastal regions receive heavy rainfall, while much of the state is semi-arid. The climate has four main seasons: southwest monsoon (June–September), northeast monsoon (October–December), winter (January–February), and summer (March–May), with the southwest monsoon contributing ~80% of annual rainfall (Venkatesh *et al.,* 2016). Karnataka is divided into 10 agro-climatic zones based on topography, soil, crops, vegetation, and rainfall patterns. The Northern Dry Zone (NDZ) spans 4.78 Mha, with annual rainfall of 464.5–785.7 mm, ~52% received during the Rabi season. Elevation ranges from 450–900 m, soils are mostly black clay, and key crops include jowar, maize, bajra, groundnut, cotton, wheat, sugarcane, and tobacco. NDZ covers 35 talukas across Bagalkot, Ballari, Gadag, Koppal, Raichur, Vijayanagara, Vijayapura, and parts of Belagavi and Dharwad. This paper examines rainfall variability in Karnataka’s Northern Dry Zone.

Materials and Methods

The Northern Dry Zone (NDZ) of Karnataka covers 4.78 Mha, with annual rainfall ranging from 464.5–785.7 mm, about 52% of which occurs during the *Rabi* season (Fig1). Elevation varies between 450–900 m, and soils are predominantly shallow to deep black clay. Historical daily rainfall data (1991–2020) were obtained from the Karnataka State Natural Disaster Monitoring Centre (KSNDMC). Descriptive statistics, including mean, standard deviation (SD), and coefficient of variation (CV), were computed to assess rainfall variability over time (Fig-1).



*Trend Analysis:*The analysis was carried out using a non –parametric test, to detect changes in the time-series data especially rainfall. The trend detection gained attention, especially in the connection with the anticipated changes in the global climate. Mann-Kendall test (Mann, 1945), a non-parametric method is used to detect the trend in rainfall data series trend (Sanjeevaiah *et al.,* 2021). Sen's slope estimator has been widely used for determining the magnitude of trend in hydro-meteorological time series. Linear regression analysis is a parametric model, most commonly used methods to detect a trend in a data series. This develops a relationship between the two variables for the districts of Northern Dry Zone.

The CV was considered for the variability classification i.e., < 20 % as less variability, 20 % to 30 % as moderate variability, > 40 % as high variability and if it is >70 % then was classified under rather heavy variability. Further, monthly, annual and seasonal rainfall and rainy days data were used for mapping by Arc GIS software and thereby maps for spatial variations of rainfall and rainy days were prepared.

Results and discussion

Characteristics of annual rainfall and rainy days: Daily rainfall data (1991–2020) for districts in Karnataka's Northern Dry Zone were analyzed by season wise *viz.,*Winter (Jan–Feb), Pre-monsoon (Mar–May), Southwest monsoon (Jun–Sep), and Northeast monsoon (Oct–Dec). During winter season the rainfall varies from 2–6 mm and higher was recorded in Raichur (6 mm) followed by Bellary and Vijayapura (5 mm). Similarly, coefficient of variation (CV) ranges from 5–51%. During pre-monsoon season rainfall noticed from 64–119 mm. The highest was recorded in Dharwad (119 mm) and followed by Gadag (113 mm) and varies from 22–29% of CV. Average rainfall during Southwest monsoon (Jun-Sep) season ranging between 321 to 388 mm. Maximum rainfall observed in Vijayapura (388 mm) followed by Koppal, Bellary, Dharwad, Gadag, Bagalkote and Vijayanagara districts. mean rainfall during North East monsoon (Oct-Dec) season ranging between 124 mm to 145 mm. maximum rainfall observed in Raichur (152 mm), followed by Koppal, Gadag,Dharwad, Bagalkote and Vijayanagara districts. The percent Co-efficient of variance CV(%) during Winter (Jan- Feb) season ranging between 5 to 51, CV(%) during pre- monsoon (Mar-May)season ranging between 22 to 29. similarly during Southwest monsoon (Jun-Sep) season ranging between 5 to 8 during North East monsoon (Oct-Dec) season ranging between 34 to 45. During Winter (Jan-Feb) and Southwest monsoon (Jun-Sep) season it is observed least variations as compared with other season. It indicates highly dependent (Table -1 and Fig. 2).

Table 1. Seasonal rainfall variability in the districts of Northern Dry Zone of Karnataka

SEASON	Rainfall (mm)	% of Annual	No. of Rainy days	% of Annual
Winter (Jan to Feb)	3.8	0.6	0	0.8
Pre-monsoon (Mar to May)	85.1	14.3	7	15.3
SWMS (Jun-Sept)	362.7	61.0	27	64.3
NEMS (Oct to Dec)	143.1	24.1	8	19.6
KHARIF (Jun-Aug)	239.5	40.3	20	46.4
RABI (Sept to Nov)	261.0	43.9	16	36.7

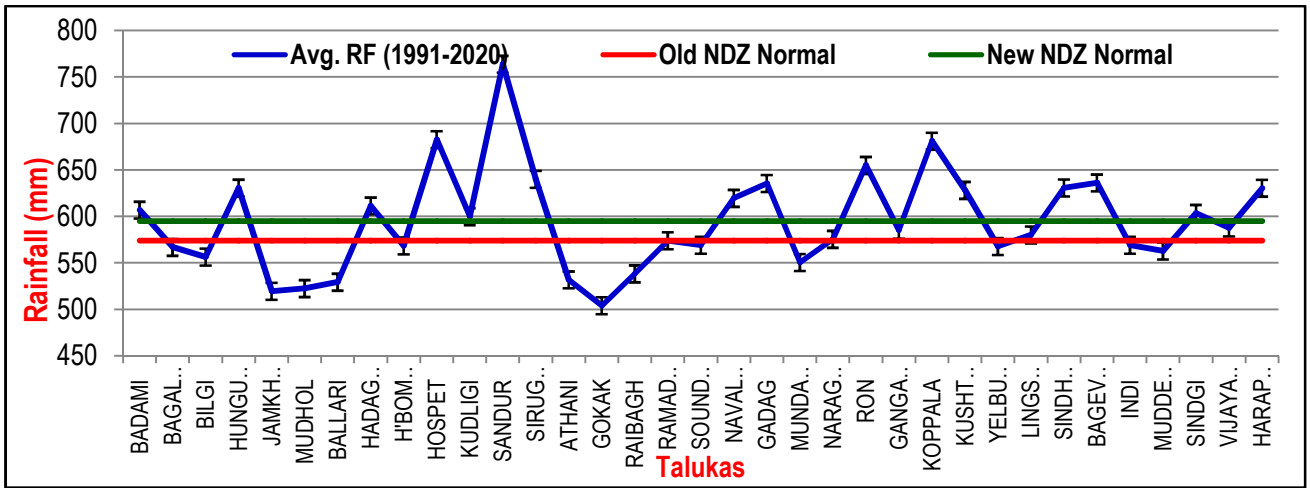


Fig. 2Talukawise average rainfall compared with old and new normals.

Annual and monthly rainfall and rainy days variability in the district of NDZ: The annual rainfall trends and corresponding linear regression equations for the districts of the Northern Dry Zone (NDZ) are presented in Table 2. Most districts exhibit an increasing rainfall trend, while Koppal, Raichur, and Vijayapura show a decreasing trend. The mean annual rainfall of the Northern Dry Zone during 1991–2020 ranged from 537.0 mm in Belagavi to 630.0 mm in Dharwad (Table 2).

Table 2 Annual rainfall trend and linear equation for the districts of NDZ

Districts	Trend	R^2
Increasing trend		
Belagavi	y = 0.410x + 530.4	0.000
Dharwad	y = 5.172x + 529.5	0.062
Vijayanagara	y = 3.09x + 538.70	0.05
Decreasing trend		
Bagalkote	y = -1.257x + 579.9	0.005
Bellary	y = -0.049x + 630.6	9.00E-06
Gadag	y = -0.983x + 618.2	0.003
Koppal	y = -2.381x + 652.6	0.014
Raichur	y = -3.892x + 669.2	0.037
Vijayapura	y = -4.489x + 662.7	0.068

Trend Analysis: Mann-Kendall (MK) test and Sen's slope estimator

Estimation of sense slop and Kendall's test statistics (Zc) values from 1991 to 2020.30 years (1991-2020) daily and monthly rainfall data has been analysed for different seasons i.e., winter (Jan-Feb), Pre-Monsoon (Mar-May), Southwest monsoon (Jun-Sep) and North-East monsoon (Oct-Dec) using Man-Kendal test, Sens' slop estimator and linear regression equation methods.(Table 5). The results showed that there is an increasing trend in winter (Jan-Feb), and Pre-Monsoon (Mar-May) among all the districts except Baglkote showed Decreasing trend in winter season. whreas during Southwest monsoon (Jun-Sep) observed increasing trend in Baglkote, Bellary, Dharwad,andVijayanagara whereas Belagavi, Gadag, Koppal, Raichur and Vijayapura Districts showed decreasing trend. During North-east monsoon all the districts showed decreasing trend. For annual rainfall trend most of districts showed decreasing trend except Dharwad and Vijayanagara Districts showed increasing trend (Table - 3).

Table 3. Kendall's test statistics (Zc) and Sen's slop estimate for Seasonal and Annual rainfall (mm) for the for districts of NDZ (1991-2020)

District	Winter (Jan-Feb)		Pre-monsoon (Mar-May)		SWM (Jun-Sep)			NEM (Oct-Dec)	Annual	
	MK test (Z_c)	Sen's slop	MK test (Z_c)	Sen's slop	MK test (Z_c)	Sen's slop	MK test (Z_c)	Sen's slop	MK test (Z_c)	Sen's slop
Bagalkot	-0.16	0.000	0.45	0.442	0.40	0.785	-1.63	-5.116	-1.01	-4.368
Bellary	0.79	0.080	1.76	2.377	0.14	0.490	-2.68	-4.806	-0.57	-1.349
Belagavi	0.94	0.000	0.14	0.146	-0.30	-0.632	-1.92	-3.443	-1.09	-3.656
Dharwad	2.46	0.000	2.03	2.867	0.10	0.307	-1.68	-3.547	0.10	0.132
Gadag	0.87	0.000	1.52	1.611	-0.81	-2.270	-2.46	-5.619	-1.64	-6.569
Koppal	1.26	0.013	1.28	1.015	-0.18	-0.600	-2.54	-6.382	-1.24	-5.441
Raichur	2.03	0.021	1.23	0.904	-0.41	-0.941	-2.71	-6.557	-1.40	-7.175
Vijayanagara	1.55	0.000	2.33	3.118	0.06	0.263	-1.56	-2.685	0.28	0.734
Vijayapura	0.41	0.000	0.14	0.139	-0.65	-1.945	-3.02	-4.704	-2.00	-6.863

Climate risk assessment

1. Drought: The India Meteorological Department (IMD) classifies meteorological drought as slight (11–25% below normal rainfall), moderate (26–50% below normal), and severe (more than 50% below normal). Using 30 years of rainfall data (1991–2020), the Northern Dry Zone (NDZ) experienced 7 years of deficit rainfall (1997, 2002, 2003, 2012, 2015, 2016, 2018), 17 years of normal rainfall, 4 years of excess rainfall (1996, 1998, 2010, 2020), and 1 year of large excess rainfall (2009) (Fig.3).

2. ***Standardized Precipitation Index:*** The Standardized Precipitation Index (SPI) is a widely used, simple index that identifies meteorological drought by calculating the rarity of precipitation over different timescales. Athani, Badmi, Baglkot, Bellary, Bilagi , Gangavathi, Gokak, Hagai bommanahalli, Indi, Jamakhandi, Lingasugur, Muddebihal, Mudhol, Mundaragi Naragund, Ramadurg, Rayabaga, Savadatti, Vijayapura and Yelburga blocks were categorized under drought prone area (Fig - 4).

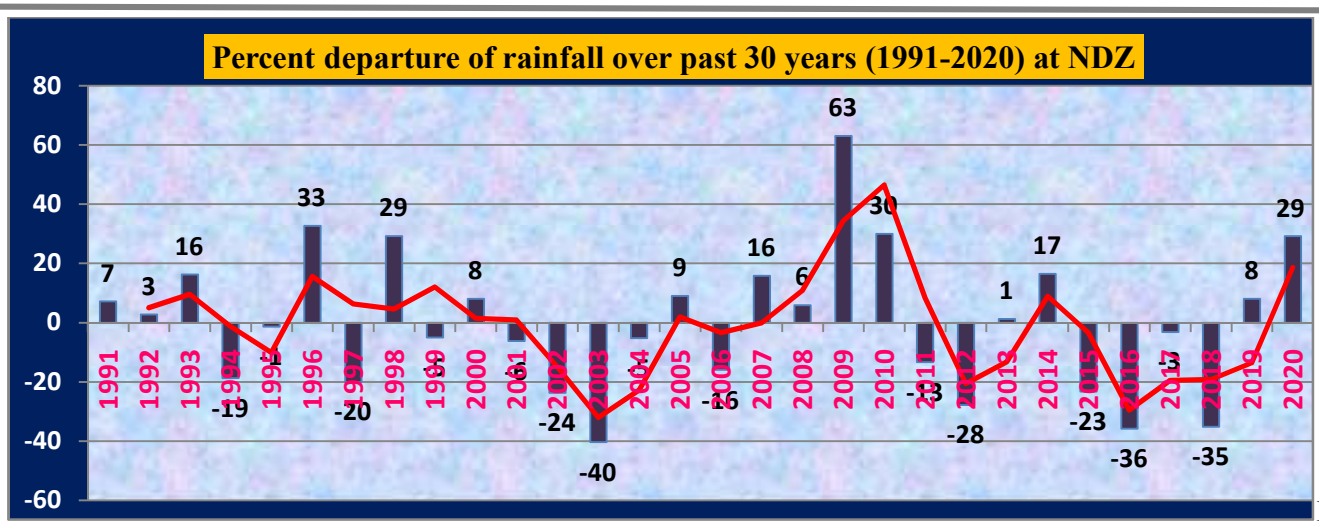


Fig. 3 Drought characterization of rainfall over past 30 years (1991-2020) at NDZ

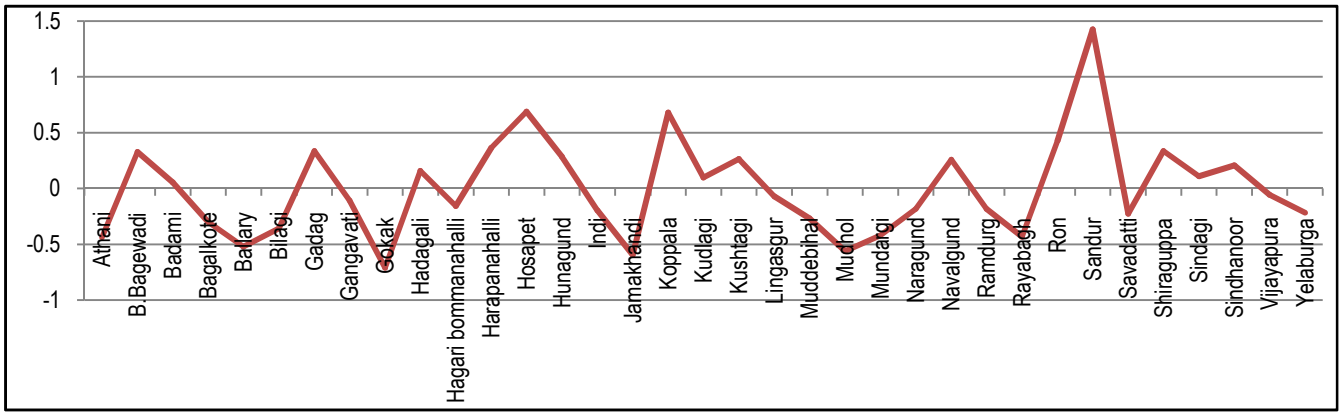


Fig 4 SPI values all blocks in Northern dry zone of Karnataka

Conclusion: Trend analysis using the Mann-Kendall test, Sen's slope, and linear regression revealed increasing rainfall trends in winter (Jan–Feb) and pre-monsoon (Mar–May) across most districts of the Northern Dry Zone, except Bagalkote in winter. During the southwest monsoon (Jun–Sep), increasing trends were observed in Bagalkote, Bellary, Dharwad, and Vijayanagara, while other districts showed declines. All districts exhibited decreasing trends during the northeast monsoon (Oct–Dec). Annually, most districts showed decreasing rainfall, except Dharwad and Vijayanagara, which recorded increasing trends. These findings are important for crop planning, and further drought severity studies could enhance the analysis.

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.PP-33: Land resources inventory for assessment of crop suitability and land capability of Karekal-1 micro watershed

VIDYAVATHI, G. Y[1]., RAJESH, N. L., YADAHALLI, G. S. AND BHEEMARAYA

University of Agricultural Sciences, Dharwad

Abstract: The detailed land resource inventory of Karekal-1 micro watershed (781.82 ha) was carried out at 1:8000 scale, under World Bank funded Sujala-III project at Shorapur taluk Yadgir district, Karnataka state, India. Traversing was done using cadastral map, SOI toposheet and IRS Cartosat-I imagery (2.5 m) merged with LISS IV (5.8 m). Physiographic units were identified and initial legend was prepared by studying soils in representative places. Total four series such as Dhoni, Karekal, Nagarabavi, and Teerth (8 mapping units *viz.,* NGBhB2, NGBhB3, TERhB3, TERhB3S1, TERcC3g2S2, KARmB2go and KARmB2g1), LCC were derived *viz*., IIIewf, IIIewsf, IVef and IVesf. The crop suitability for field crops *viz*., Cotton, Pigeon pea, Ground nut, Sorghum, Pearl millet, Green gram and Chick pea and horticultural crops *viz*., Mango, Guava and Sapota were derived based on the soil fertility, climatic regime and land quality. The cadastral map was over laid on LCC and crop suitability to deliver parcel based information.

Key words: Remote sensing, Micro watershed, LCC, Crop suitability, Land resource inventory

Introduction

Natural resources like soil and land should be managed scientifically and sustainably to meet development needs without compromising future potential. Land suitability assessment is essential for rational cropping systems and optimal land use (Sys, 1985). Land capability classification groups soils based on inherent characteristics, external features, and environmental limitations, providing information on physiography, parent material, texture, structure, clay type, consistency, permeability, depth, and soil reaction, all of which influence soil behavior and management. Geographic Information System (GIS) has emerged as an effective tool for watershed planning and development (Srivastava *et al.,* 2010). Sustainable crop production relies on land use planning that considers soil quality and constraints. Thus, soil characterization, classification, and evaluation are crucial for developing eco-friendly land use systems. In this context, the present study was conducted in Karekal-I micro watershed, Shorapur taluk, Yadgir district, Karnataka, India (1:8000 scale), under the World Bank-funded Sujala-III project, aiming to characterize soils physically and chemically, classify them, and assess their suitability for various crops using GIS.

Materials and methods

Karekal-I microwatershed located in Shorapur taluk of Yadgir district, Karnataka. The microwatershed with a total area of 781.82 ha lies between 16° 40’ to 16° 40’ E longitudes and 77° 10’ to 77° 11’ N latitudes. The microwatershed is surrounded by Koyalur and Pogalpur village on the north, Koluru village on the south, Jinkera village on the east and Mustur village on the west. The location map of the study area is depicted in Fig. 1.

Fig. 1: Location of the Karekal-1 MWS

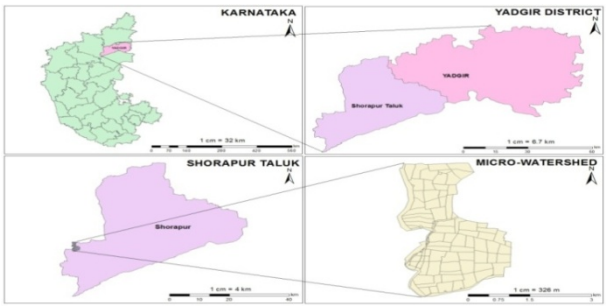
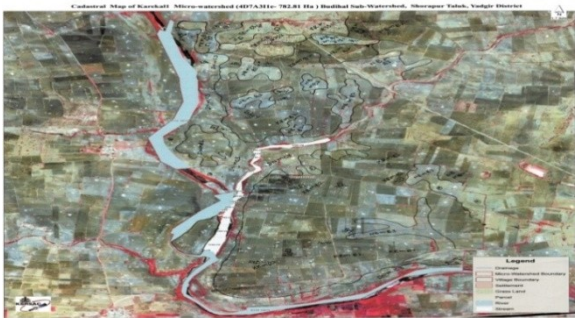


Fig. 2: Cadastral map



The study area is represented by semi arid climate belongs to North eastern dry Zone of Karnataka with annual rainfall of 750.90 mm. The mean maximum and minimum temperature are 34.29 and 21.24 respectively. The land use includes redgram, jowar, sugarcane, ginger, paddy, maize and mango.

A detailed village survey was conducted using cadastral maps (Fig. 2) and IRS imagery, with rapid traverses covering soils across varying physiographic positions. Landforms and physiographic units were identified based on geology, drainage, surface features, slope, and land use. Pedons were examined for morphological properties following standard procedures (Anon. 1999), and surface samples were collected from fields to assess fertility (macro- and micronutrients) and horizon-wise physicochemical properties. Four soil series were identified and mapped into eight units (Fig. 3). Soils were non-gravelly, coarse to fine textured, medium subangular blocky, well-drained, non-calcareous, moisture-retentive, and moderately to severely erosion-prone (Table 1). Weighted mean properties (Table 2) were used to determine land capability and crop suitability based on FAO (1976) criteria.

Results and discussion

Land capability classification

The land capability classes of the study area were grouped in to two classes III and IV based on the limitations of Based on the limitations of climate, drainage conditions, erosion and soil factors as shown in the Fig 4 and Table 3. Considering the extent and type of limitations, the soil mapping units DNIfC3 was grouped under IIIewf subclasses having limitations of erosion, drainage and organic carbon, KARMB2g0 and KARmB2g1 were classified underIIIewsfsubclasses having moderate limitation of erosion, drainage, texture and organic carbon, NGBhB2 and NGBhB3 were classified underIVsf with limitations of texture(s), soil depth (s) and organic carbon, TERhB3 and TERhB3S1 were groupedunder IVesfsub class with limitations of erosion, texture and organic carbon. Due to higher coarse fragments, low basesaturation and texture limitations the area of Bhanapurmicro watershed were grouped under III, IV and V classes (Patil*et al*., 2011). The area of Sarvar village were classified under II, III, V, VI and VIII classes based on the limitations like drainage, soil erosion, soil slope, soil depth, soil pH and coarse fragments (Das and Shinde, 2014). Mary Silpa and Nowshaja (2016) classified the soils of Ollukarablock panchayat usingGIS into five classes namely II, III, IV, VI and VII respectively based on slope percentage, erosion, soil depth and texture limitations.

Crop suitability classification

Based on degree of limitations of soil fertility, climatic regime and land quality the soil site suitability criteria of Karikal-I microwatershed classified for field crops and horticultural crops. The optimum requirements of a crop are always region specific. Climate and soil-site parameters play significant role in maximizing the crop yields.Crop suitability in Karekal micro watershed was influenced by key soil and climatic factors such as depth, texture, $CaCO_3$, organic carbon, pH, base saturation, erosion, slope, and rainfall. Cotton performed best on soils with 100–200 cm depth, 10–15% $CaCO_3$, 220 mm moisture storage, and >80% base saturation; mapping units NGBhB2 and NGBhB3 were marginally suitable, TERhB3/TERhB3S1/TERcC3g2S2 marginally suitable due to erosion and OC, while DNIfC3, KARmB2g0, and KARmB2g1 were moderately suitable.

Pearl millet favored >75 cm depth, clay texture, and 10% $CaCO_3$; suitability followed similar patterns with moderate to severe limitations in erosion, temperature, slope, and drainage.Sorghum yield depended on rainfall, temperature, slope, base saturation, $CaCO_3$, CEC, and texture; most units were marginally to moderately suitable due to limitations in temperature, erosion, depth, soil reaction, and organic carbon.Pigeonpea, requiring deep soils, was marginally suitable on NGBhB2/NGBhB3 and TERhB3 units due to depth, erosion, and ESP; DNIfC3 and KARmB2 units were moderately suitable.Green gram suitability was constrained by soil reaction, depth, texture, and ESP; NGBhB2/NGBhB3 were marginally suitable, TERhB3/TERhB3S1/TERcC3g2S2 and DNIfC3/KARmB2 units were moderately suitable.Groundnut, requiring less depth and rainfall, was moderately suitable on NGBhB2/ NGBhB3 (erosion, depth, texture limitations) and marginally suitable on TERhB3/ TERhB3S1/TERcC3g2S2 and DNIfC3/KARmB2 units due to severe erosion, depth, texture, drainage, and pH constraints.These findings align with observations from Bhanapurmicrowatershed (Patil *et al.,* 2011).

The soil depth and soil reactions influence on growth and development of horticultural crops (Whiley 1984). The mapping units DNIfC3, KARmB2g0 and KARmB2g1were marginally suitable with the severe limitations of $CaCO_3$, texture and organic carbon whereas the mapping units NGBhB2, NGBhB3, TERhB3,TERhB3S1 and TERcC3g2S2 were unsuitable for mango (Fig. 11) cultivation having sever limitations of soil depth. The mapping units TERhB3, TERhB3S1 and TERcC3g2S2 were marginally suitable for guava cultivation with severe limitations of soil depth. However, the mapping units NGBhB2, NGBhB3, DNIfC3, KARmB2g0 and KARmB2g1 unsuitable for Guava (Fig. 12) with sever limitation of depth and soil reaction. The mapping unitsTERhB3, TERhB3S1, TERcC3g2S2, DNIfC3, KARmB2g0 and KARmB2g1were marginally suitable for sapota with severe limitations of soil depth and pH whereas, mapping units NGBhB2 and NGBhB3 were unsuitable for sapota (Fig. 13) cultivation with severe limitation of soil depth. Similarly, Kassa Teka and Mulu Haftu (2012) reported that the midlands of Tigray, Ethiopia were marginally suitable (91.54 %) and permanently unsuitable (8.5 %) for cultivation of *Cicer arietinium*, *Psidium guajava* and *Mangifera indica*.Sonali *et al.* (2013) reported that the physiographic units P12, P22 and H12 of watershed Dehradun district, Uttarakhand state, India were moderately suitable for mango cultivation with a limitations of steep slopes and piedmont plains. Remote sensing and GIS based cadastral level detailed LRI help to derive land suitability and land capability at parcel level for improved agricultural planning and management (Rajesh *et al.,* 2016).

Conclusion

The GIS tool was effectively utilized at the study area for land capability and crop suitability classifications. The land capability classification of the study area placed under class III (72.48 %) and IV (18.22 %). The land suitability for different agriculture and horticulture crops were matched with the land characteristics, the mapping units DNIfC3, KARmB2go and KARmB2g1 were moderately suitable for most of the crops (cotton, pigeonpea, sorghum, bajra, sapota, mango, guava *etc.*) and rest were marginally suitable. The mapping units restricted for different crops can be managed by adapting the suitable soil and water conservation practices. Hence, it can be concluded that the cadastral level detailed LRI based crop suitability and land capability classification assessment at micro watershed level will help in improved planning at parcel level.

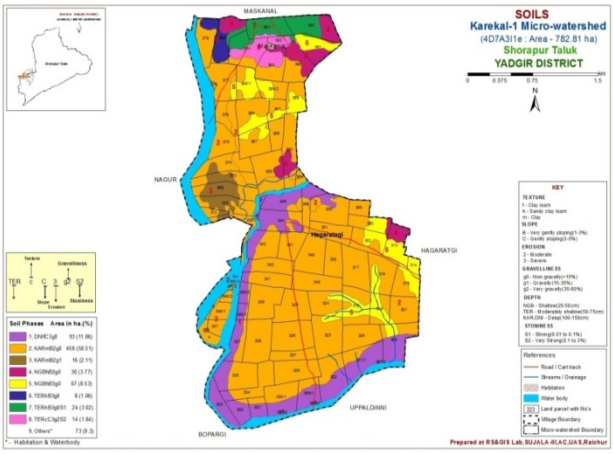


Fig. 3: Soil mapping units of Karekal-1 MWSFig.

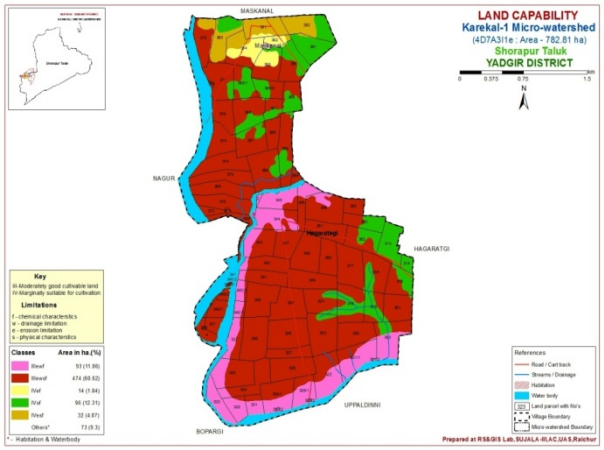


Fig. 4: LCC of soils in Karekal-1 MWS

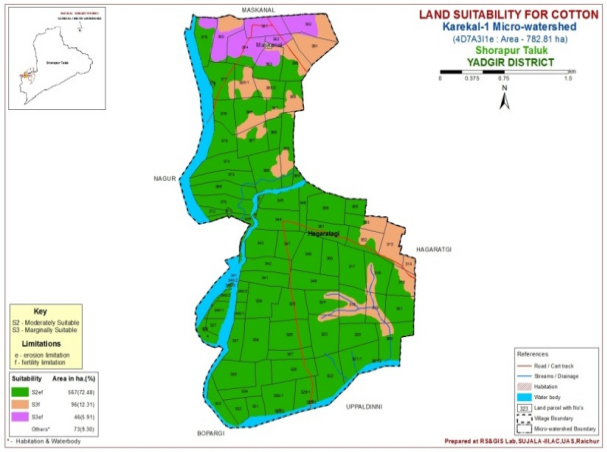


Fig. 5: Crop suitability for Cotton

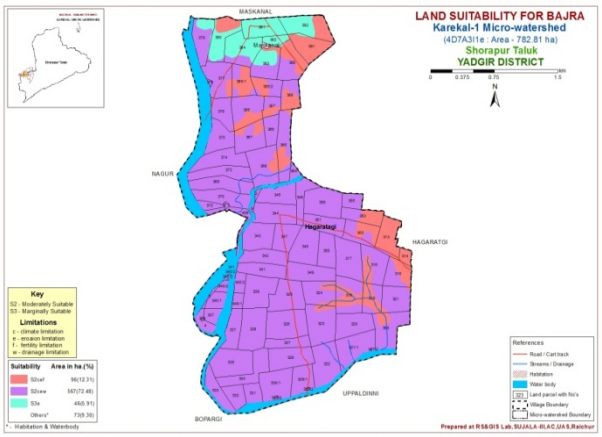


Fig. 6: Crop suitability for Bajra

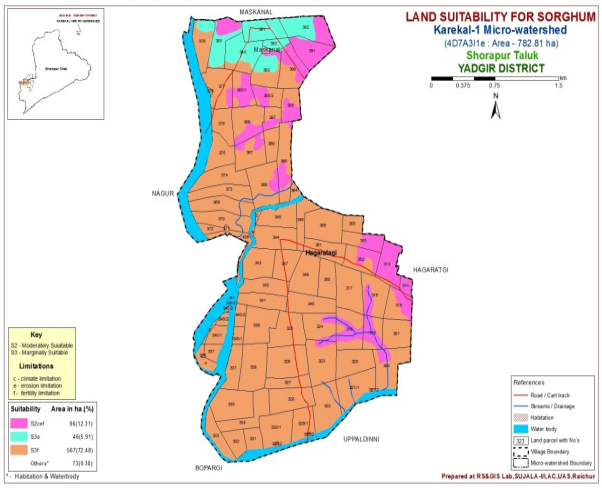


Fig. 7: Crop suitability for Sorghum

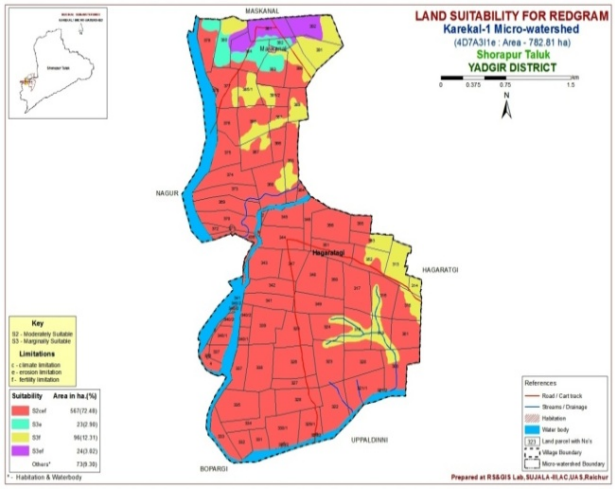


Fig. 8: Crop suitability for Pigeonpea

Fig. 9: Crop suitability for Greengram

Fig. 10: Crop suitability for Groundnut

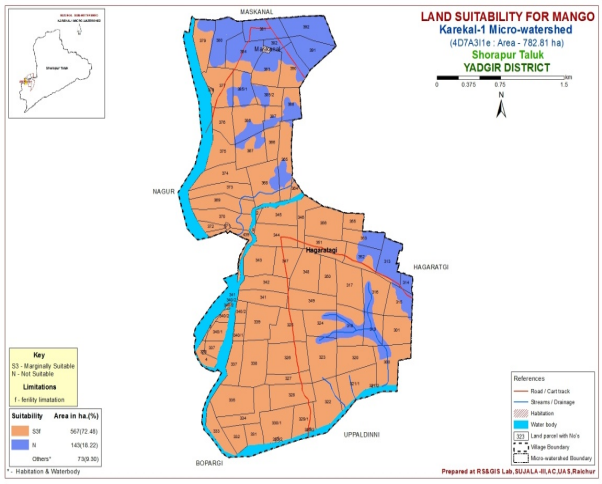


Fig. 11: Crop suitability for Mango

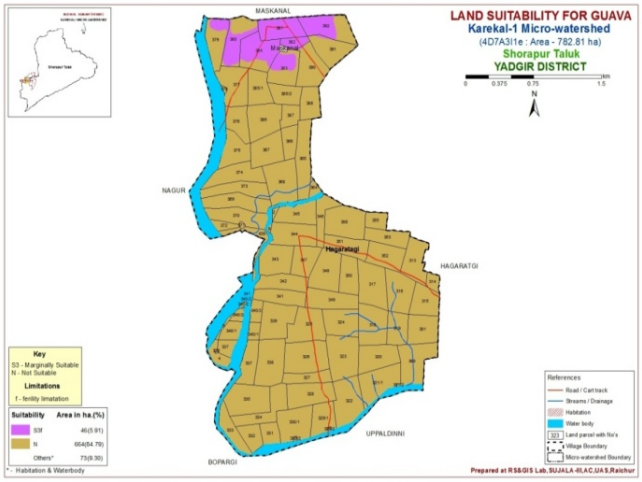


Fig. 12: Crop suitability for Guava

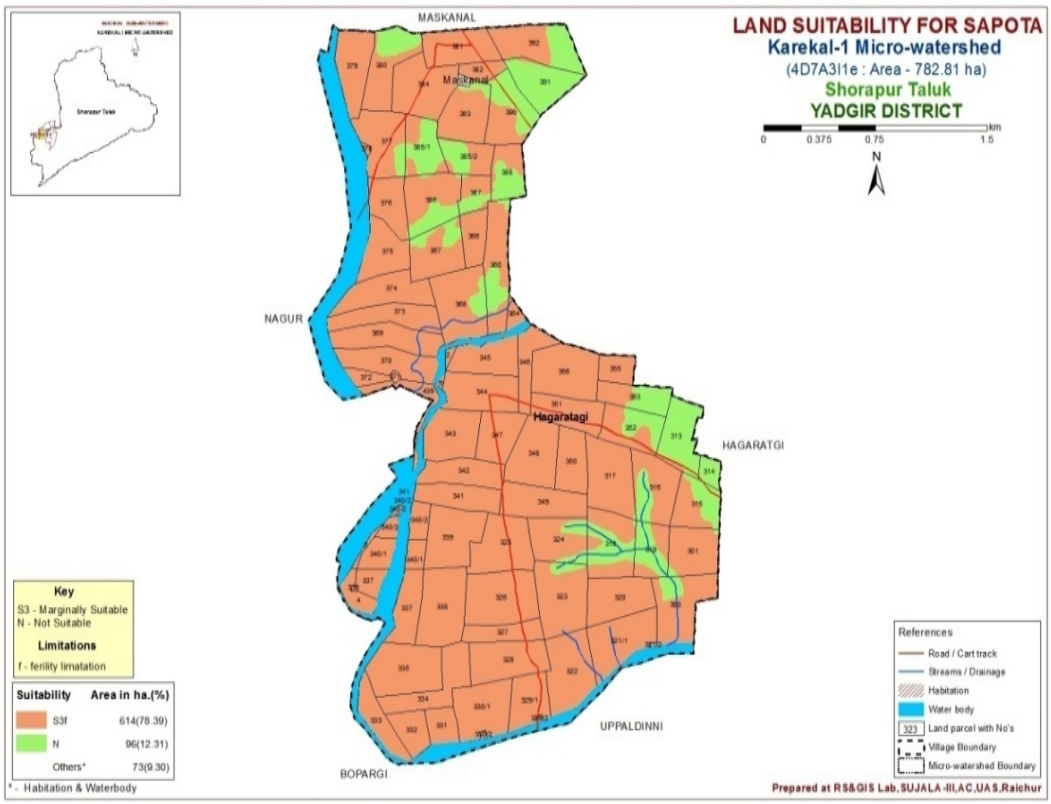


Fig. 13: Crop suitability for Sapota in Karekal-1 MWS

Table 1. Morphological features of mapping units of Karekal -1 MWS

Name of Soil series	Mapping unit	Texture	Structure		Consistency		Effervescence	Gravelliness		Erosion	Rooting size		Stoniness	Drainage
			Surface	Sub-surface	Surface	Sub-surface		Surface	Sub-surface		Surface	Sub-surface		
Nagarabavi	NGBhB2	scl	2 msbk	2 msbk	Sh, fr, ss, sp	sh, fi, ss, sp	Slight	Nil	Nil	Moderate	vf	f	Nil	Well drainage
	NGBhB3	scl	2 msbk	2 msbk	sh, fr, ss, sp	sh, fi ss, sp,	Slight	Nil	Nil	Severe	vf	f	Nil	Well drainage
Teerth	TERhB3	scl	2 msbk	3 msbk	Sh, fr, ss,sp	Sh, fi, vs, sp	Slight	Nil	Nil	Severe	vf	f	Nil	Well drainage
	TERhB3S1	scl	2 msbk	3 msbk	sh,fr,ss,sp	sh,fi,ss,sp	Slight	Nil	Nil	Severe	vf	f	0.01-0.1%	Well drainage
	TERcC3g2S2	sl	2 msbk	3 msbk	sh, fr, ss, sp	sh, fi, vs, sp	Slight	20-25%	Nil	Severe	vf	f	0.1-3.0%	Well drainage
Dhoni	DNIfC3	cl	2 msbk	3 csbk	sh, fr, s, sp	h, fi ,s, p	Slight	Nil	Nil	Severe	vf	f	Nil	Moderately well drainage
Karekal	KARmB2g0	c	2 msbk	3 csbk	sh, fr, s, p	h, vfi, vs,vp	Slight	Nil	Nil	Moderate	vf	f	Nil	Moderately well drainage
	KARmB2g1	c	2 msbk	3 csbk	sh, fr, s, p	h,vfi, vs, vp	Slight	10-20%	Nil	Moderate	vf	f	Nil	Moderately well drainage

Note: sh – slighly hard, fr – friable, ss – slightly sticky, sp – slightly plastic, fi-firm,vs – very sticky, s – sticky, p – plastic,h – hard,vfi – very firm, m – medium, sbk – subangular blocky, c – coarse, vf – very fine roots,f – fine roots

Table 2. Crop suitability characteristics of Karekak-1 MWS for land evaluation

Mapping units	Climate (c)				Land form characteristics			Physico - chemical characteristics (f)							
	RF	Max. Temp	Min. Temp	RH	Slope (t)	Erosion (e)	Drainage (w)	Depth	pH	EC (dS m^{-1})	OC (%)	$CaCO_3$ (%)	CEC (meq $100g^{-1}$)	BS (%)	ESP
NGBhB2	750.9	34.29	22.68	65.32	1-3%	Moderate	Well drained	25-50	7.21	0.18	3.30	5.77	31.00	79.97	8.04
NGBhB3	750.9	34.29	22.68	65.32	1-3%	Moderate	Well drained	25-50	7.39	0.15	3.50	6.97	30.55	80.33	5.70
TERhB3	750.9	34.29	22.68	65.32	1-3%	Severe	Well drained	50-75	7.77	0.12	3.70	7.45	27.33	78.94	6.94
TERhB3S1	750.9	34.29	22.68	65.32	1-3%	Severe	Well drained	50-75	7.72	0.16	3.90	7.02	35.20	78.07	10.19
TERcC3g2 S2	750.9	34.29	22.68	65.32	3-5%	Severe	Well drained	50-75	8.04	0.18	3.70	7.17	34.30	77.94	5.49
DNIfC3	750.9	34.29	22.68	65.32	3-5%	Moderate	Moderate	100-150	8.46	0.25	5.00	10.05	45.05	91.67	7.84
KARmB2g 0	750.9	34.29	22.68	65.32	1-3%	Moderate	Moderate	100-150	8.52	0.23	5.20	10.43	51.80	92.25	5.41
KARmB2g 1	750.9	34.29	22.68	65.32	1-3%	Moderate	Moderate	100-150	8.58	0.47	5.30	10.23	51.70	91.59	6.93

Table 3. Land capability classification of Karekal-1 MWS

Mapping units	Land form characteristics			Physical characteristics (s)			Chemical characteristics (f)			LCC
	Slope (t)	Erosion (e)	Drainage (w)	Texture	Soil depth	Pedon Development	CEC	OC	BS	
Nagarabavi series										
NGBhB2	II	III	I	IV	IV	III	I	IV	III	IVsf
NGBhB3	II	III	I	IV	IV	III	I	IV	II	IVsf
Teerth series										
TERhB3	II	IV	I	IV	III	III	I	IV	III	IVesf
TERhB3S1	II	IV	I	IV	III	III	I	IV	III	IVesf
TERcC3g2S2	III	IV	I	III	III	III	I	IV	III	IVef
Dhoni series										
DNIfC3	III	III	III	II	II	II	I	III	I	IIIewf
Karekal series										
KARmB2g0	II	III	III	III	II	II	I	III	I	IIIewsf
KARmB2g1	II	III	III	III	II	II	I	III	I	IIIewsf

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Theme III
AI driven Genomic selection and Predictive breeding

PP-34: AI tools and challenges: analysis of 3k panel of rice genotypes

THRUPTHI A.P.SHIVASHANKARGOUDA PATIL, SADANAND INAMDAR, PREMSAGAR N. S. AND JAYATEERTHA R DIWAN

Abstract: Large and complicated genomic datasets are produced by Next-Generation Sequencing (NGS), which is difficult for conventional computational techniques to effectively analyze. One way to increase scalability, accuracy, and automation in genomic analysis is toincorporate artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL). All phases of NGS are enhanced by AI, including wet-lab automation, bioinformatics, data interpretation, and experimental design. AI systems (e.g., CNNs, RNNs) are preferred for OMICS analysis such as gene expression (transcriptomics) and single-cell sequencing as CNNs and RNNs perform better than conventional techniques. Conventional rice breeding has achieved substantial genetic gains through hybridization and phenotypic selection; however, its reliance on visual traits limits resolution and slows improvement of complex characteristics such as Root System Architecture (RSA) and shoot morphology, particularly under Direct-Seeded Rice (DSR) systems. Molecular breeding approaches, including marker-assisted selection and genome-wide association studies, have enhanced selection efficiency by associating DNA markers with phenotypic traits, yet they often inadequately capture epistatic interactions, non-coding regulatory variation and the complex genotype-phenotype relationships underlying polygenic traits across diverse field environments. The availability of large-scale genomic resources such as the 3k Rice Genome Project provides unprecedented opportunities to dissect the molecular basis of complex agronomic traits at high resolution, although extracting biologically meaningful insights from such high-dimensional datasets remains challenging. Integrative analytical frameworks that combine sequence-level variant analysis, statistical genomics and genomic prediction models offer a more comprehensive strategy to address these limitations. In this context, the tools such as PlantBreedAI, AlphaGenome andDeepVariant can be used for various plant breeding and genome analysis research activities. The tools helps in acceleration of crop improvement efforts to derive genotypes with specific requirements like identification of loci associated with RSA and shoot-related traits and prioritization of putative causal variants relevant to DSR adaptability. By modeling long-range genomic dependencies and multi-environment phenotypic data, this systems-level framework facilitates reconstruction of gene regulatory networks governing key adaptive traits and strengthens the translation of genomic information into breeding decisions, thereby accelerating the development of climate-resilient, direct-seeded rice cultivars through precision breeding. AI is being used more and more in third-generation sequencing, which facilitates faster base calling and epigenetic detection while addressing long-read sequencing issues like high error rates and complicated signal interpretation.Significant obstacles include data-related problems that lower model reliability, such as high volume, noise, batch effects, and variability. The model limitations associated with poor interpretability (also known as the "black-box" problem); and limited cross-platform generalization. High computational requirements (GPU, storage), as well as difficulties with reproducibility and validation, are some practical limitations.

PP-35: Green genome twin: predicting plant dna hybridization outcomes in seconds using ai-powered digital twins

LEENA I. SAKRI, DANESHWARI KORI, ABHAY G, RAJESHWARI V PATIL, SUMAN YALIGAR

Department of Artificial Intelligence and Machine Learning,
SDM College of Engineering and Technology, Dharwad, Karnataka, India
E-mail: [1]leenaignatiusakri@gmail.com, [2]danukori@gmail.com, [3]abhaygargi1234@gmail.com, 4rajeshwarivpatil0320@gmail.com, [5]sumansumeet24@gmail.com

Abstract: Plant genomics research demands faster, cheaper alternatives to months-long laboratory crossing trials. We present GreenGenome Twin: a framework coupling deep learning with digital twin technology to predict intraspecific DNA hybridization outcomes within seconds. A 1D-CNN–BiLSTM model extracts hybridization features from encoded genomic sequences; a three-layer digital twin simulates offspring genotype distributions and maps them to trait scores for growth rate, stress tolerance, and adaptability. Evaluated on a model grass species, the system achieves a mean absolute error of 0.08 normalised trait units and simulates each crossing scenario in ~4.7 seconds, versus weeks for wet-lab methods. All 20 invalid genotype inputs were correctly rejected, confirming robust validation.

Key Words: DNA hybridization, digital twin, intraspecific genomics, deep learning, plant genomics, precision agriculture, bioinformatics.

Introduction

High-throughput sequencing has transformed plant genomics, yet intraspecific hybridization trials still demand months of controlled field work and substantial cost before any phenotypic data emerge. Deep learning over raw genomic sequences now offers predictive modelling of hybridization outcomes without physical experimentation, while digital twins—continuously updated virtual replicas of physical systems—have begun migrating from industrial engineering into the biological sciences.

We focus exclusively on intraspecific hybridization within a single species, ensuring dataset homogeneity and maximising model precision. The result is GreenGenome Twin: a unified pipeline covering genomic data acquisition, AI-based feature extraction, and digital twin simulation that predicts key breeding traits without a single greenhouse cross.

Related Work

Machine learning for genomic selection dates to regularised linear models (ridge regression, LASSO) predicting quantitative traits from genome-wide markers [1], later surpassed by CNNs on raw nucleotide sequences for complex polygenic traits [2]. Digital twins were formalised by Grieves and Vickers [3] in product lifecycle management and have since appeared in precision medicine [4] and plant phenotyping [5]. Bioinformatics tools such as BLAST and Bowtie perform sequence alignment [6] but lack generative trait-prediction capacity. The present work is the first to couple a single-species-constrained deep learning model with a live digital twin for full phenotypic trait prediction.

Methodology

A. Three-Phase Pipeline

Phase 1 – Genomic Data Acquisition: Reference assemblies and raw reads for the target species are drawn from NCBI GenBank and Ensembl Plants, quality-filtered, aligned with BWA, and variant-called (SNPs, InDels) with GATK. Sequences are encoded via one-hot encoding and k-mer frequency vectors.

Phase 2 – AI Hybridization Modelling: A hybrid 1D-CNN–BiLSTM architecture detects local sequence motifs and captures long-range dependencies. The model is trained on labelled intraspecific crossing outcomes using Mean Absolute Error (MAE) loss for continuous trait regression.

Phase 3 – Digital Twin Simulation: Given two parent genotype vectors, the twin performs Monte Carlo forward simulation weighted by the learned model, producing offspring genotype distributions. A secondary regression head maps distributions to trait scores (growth rate, stress tolerance, adaptability).

Digital Twin Architecture

The twin comprises three layers. The Genome Layer stores the reference assembly and variant data as a queryable graph (nodes = genomic loci; edges = linkage disequilibrium). The Simulation Layer runs AI inference and Monte Carlo sampling. The Trait Layer applies phenotype–genotype association models to yield agronomic scores. A stateless REST API connects layers, enabling modular upgrades without system downtime, concurrent scenario evaluation, and full logging for experimental traceability.

AI Integration

Model development uses PyTorch on NVIDIA CUDA-compatible GPUs, reducing genome-scale training from days to hours. Explainability is provided through 1D Grad-CAM attribution maps that highlight genomic regions driving each trait prediction—critical for biological interpretability and wet-lab hypothesis generation. The AI pipeline is encapsulated as a microservice communicating with the digital twin over HTTPS REST.

Results And Discussion

Evaluated on a model grass species using publicly available genomic data, the framework simulated 50 intraspecific crossing scenarios at a mean wall-clock time of 4.7 seconds per scenario on a standard GPU workstation—orders of magnitude faster than physical trials. Growth-rate prediction reached MAE = 0.08 normalised units on the held-out validation set. All 20 intentionally invalid genotype inputs (e.g., allelic frequency violations) were correctly rejected before simulation. Grad-CAM maps highlighted known regulatory regions, confirming biological credibility. Full quantitative validation against replicated field trial data is ongoing.

TABLE I – Performance Summary

Metric	Proposed Framework	Conventional Method
Prediction time / scenario	~4.7 seconds	Weeks to months
Trait prediction MAE	0.08 (normalised)	N/A (empirical)
Invalid scenario rejection	100% (20/20)	Manual inspection
Species scope	Single species	Variable

KEY APPLICATIONS

The framework serves six primary use cases: (i) Accelerated crop improvement—screening thousands of crosses computationally before committing to field trials, especially valuable for species with long generation times; (ii) Stress-tolerance breeding—simulating allelic introgressions to identify climate-resilient genotypes without physical experimentation; (iii) Disease resistance screening—flagging candidates likely to carry effective R-gene alleles prior to inoculation assays; (iv) Bioinformatics pipeline

integration—modular REST APIs connect directly to BWA and GATK outputs for end-to-end automation; (v) Genomic education—providing an interactive simulation environment for researchers and students without requiring laboratory infrastructure; and (vi) Genomic selection—augmenting GEBV pipelines with AI-derived trait scores to improve selection accuracy for complex polygenic traits.

Conclusion

GreenGenome Twin demonstrates that coupling a single-species-constrained deep learning model with a continuously updated digital twin can deliver rapid, biologically interpretable hybridization trait predictions at a tiny fraction of conventional experimental cost. With a trait MAE of 0.08 and per-scenario simulation time of ~4.7 seconds, the framework is ready for integration into breeding pipelines. Future work targets large-scale field-trial validation, environmental sensor fusion for phenotype–environment interaction modelling, natural-language query interfaces, and extension to multi-user collaborative research environments.

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Theme IV
Automation and Robotics in Agriculture

PP-36: Drone is an armament in groundnut production to combat man power scarcity

B. S. YENAGI, LAXMI C. PATIL, S. V. HUGAR, GURUPAD BALOL, REKHA VADDATTI AND RAJASHEKAR ANAGOUDAR

[1]Senior Scientist (Agronomy), UAS, Dharwad, Karnataka
[2]Scientist (Plant Breeding), UAS, Dharwad, Karnataka
[3]Scientist (Entomology), UAS, Dharwad, Karnataka
[3]Scientist (Plant Pathology), UAS, Dharwad, Karnataka
[4 & 5]Officers of Karnataka State Department of Agriculture, Dharwad, Karnataka
E-mail: yenagibs@uasd.in

Groundnut is vital edible oil seed crop grown predominately under rainfed condition in India particularly in Gujarat, Andhra Pradesh, Karnataka, Telangana, Tamil Nadu and Rajsthan during *Kharif* season. It provides both edible pod containing cooking oil(45 to 52 %) for human consumption and palatable fodder(Haulm) rich in protein for livestock. The acreage under groundnut reduced in recent years but livestock stake holders definitely grow groundnut as a part of their cropping system. In Karnataka, among then groundnut growing districts, Dharwad is having an area of 0.5 lakh acres during *Kharif* season. The major twin challenges in this crop during *Kharif* season is yellowing of top leaves due to nitrogen deficiency under excess moisture condition and defoliator damage. To address nitrogen deficiency existing recommendation is 2.0 % conventional urea at 30 and 60 days after sowing (DAS) and spraying of 0.5 ml of 5 EC lambda cyhalothrin per liter of water to manage defoliator. Before under taking demonstration through drone in Amminbhavihobli of Dharwad taluka of Dharwad district, Karnataka state, the observation was taken on 10 farmer's field. The average SPAD (relative greenness indication) value of the crop was 38.9 (moderate yellow foliage) and percent foliar damage was of 15.9% (*Spdopetra*) during *Kharif* 2025. Demonstration was conducted on five farmer's field who were growing groundnut variety G2-52 of UAS, Dharwad under the banner of RSK, Amminbhavi. The drone spraying was undertaken with 10 liter capacity covering 0.5 acre with 250 ml of nano urea and 50 ml of 5 EC lambda cyhalothrin. The spray was taken as indicated. The crop was observed after 15 days after spray (DAS) and 30 DAS. The SPAD value increased to 40.8 and 42.1 indicating absorption of nitrogen and its further involvement in photosynthesis which leads to greenness of the foliage. Nano-formulations deliver nutrients at the molecular level, improving nutrient use efficiency and reducing environmental impact. Similarly, percent foliar damage was of 15.9% (*Spdopetra*) reduced to 14.2% and 10.9% at 15 and 30 DAS. The demonstration perforated message to the groundnut farmers that nitrogen use efficiency through nano urea. After the harvest of the crop, the results showed that application of basal dose of 12:32:16 @ 40 kg per acre + foliar spray of 500 ml nano urea per acre at pegging to pod formation stage increased the average dry pod yield to the extent of 140 kg per acre per farmer (4 bags of 35 kg each in farmers language) which amounts to increase in gross returns of Rs.9520/- per acre (MSP of Groundnut is Rs.68.00 per kg) when compared to the neighboring farmers yield where the demonstration was not undertaken(foliar application of nitrogen and insecticide). Many studies reported that marginal increase in yield of legume crops with supplemental foliar application of nitrogen or nano urea along with recommended dose of fertilizer rather than substitution. Finally, precision spraying with drone combined with nano-fertilizer technology offers a sustainable path to enhance groundnut yield as the country at present is importing substantial quantity of edible oil particularly palm oil.

PP-37: Assessment of plant protection constraints and the emergence of drone technology in maize and soybean cultivation: a case study of Haveri District, Karnataka

PRIYA P., BABU P. AND NOOR NAWAZ A. S.

[1]Department of Agronomy, College of Agriculture, Hanumanamatti – 581 115
[2]Department of Horticulture, College of Agriculture, Hanumanamatti – 581 115
[3]Department of Microbiology, College of Agriculture, Hanumanamatti – 581 115
University of Agricultural Sciences, Dharwad
Email : priyap@uasd.in

The introduction of drone technology for chemical spraying in field crops marks a transition from labor-intensive manual methods to precision agriculture. Unlike traditional knapsack sprayers, drones can cover an acre in just 15–20 minutes, significantly reducing water usage and chemical wastage through specialized atomizing nozzles. By operating above the canopy, they eliminate direct human exposure to hazardous chemicals and bypass the physical challenges of spraying tall or waterlogged crops. This modern approach not only ensures uniform coverage but also provides a timely and efficient solution for managing large-scale pest outbreaks and nutrient deficiencies. Hence, a survey was conducted in the Haveri district of Northern Karnataka to study the growing interest of farmers in agricultural drones, particularly for the precision application of nutrients and pesticides in field crops. Major crops grown in Haveri district are: Maize, Soybean, Cotton, Jowar, chilli, Sugarcane, Groundnut, Greengram, Cowpea, Safflower etc. But farmers using drone for spraying chemicals to major field crops *viz*., maize and soybean.

Materials and methods

The survey was conducted during 2025 in major maize and soybean growing areas of Haveri district. The objective of the study was to document the plant protection constraints experienced by farmers in maize and soybean cultivation in Haveri district. Totally 8 villages *viz.*, Karjagi, Yelagach, Konantambagi, Ramapur, Devagiri, Naganur, Aladakatti and Varadahalli were identified for the study. From each of the selected villages, 30 (Progressive, big, medium, small and marginal) farmers were selected by random sampling. Thus totally 240 farmers were selected. The data was collected with the help of structured interview schedule which was prepared based on the objective of the study. The data was subjected to statistical analysis such as frequencies and percentages.

Results and Discussion

The survey of documentation of plant protection constraints experienced by maize and soybean growing farmers of Haveri district of Northern Karnataka revealed that, there was 100 percent infestation of *Spodoptera litura*andfall armyworm in Soybean and maize, respectively. However, disease infestation is less in both the crops (17.58 and 48.28 % in maize and soybean, respectively). Almost 88.33 percent of farmers uses knapsack sprayer (hand operated/battery operated) for spraying plant protection chemicals. Only progressive and big farmers' (11.67 %) uses drone (hired from private company or custom hiring centre) for spraying chemicals. In Haveri district nearly 95 per cent of farmers are aware of drone technology through social media and local demonstrations, actual adoption remains concentrated among progressive and large-scale farmers (approx. 11.67%) (Table 1). This is in confirmation with Sanketh *et al.* (2025) who Conducted a study in Karnataka and found that while 40 per cent of farmers were highly

aware of drone capabilities, factors like landholding size, education, and high initial costs (Rs. 1.5 to 5 lakhs) significantly limited actual adoption to large-scale/progressive farmers.Farmers have expressed both advantages and disadvantages of spraying using drone. The advantages are: less/no labour is required while spraying, less time consumption (20-30 minutes/ac), good control of pest, less wastage of chemicals, less human exposure to the chemical, very effective in uniform spray, helping in proper distribution of pesticides across the field and good accessibility of drone (Table 2). Disadvantages are: requires skill/experience/training for operating drone, less battery life, not suitable for spraying of post emergent herbicide, field should locate in an open area (Tree/electricity line etc. should not be there in the field) and not suitable for all the crops. Satish *et al.* (2025) also Identified that the limited battery life (flight time of 15–20 mins) and the lack of skilled operators are the two most critical technical hurdles preventing full-scale deployment in Indian fields.

The survey concludes that maize and soybean crops in Haveri district face 100 per cent pest infestation levels, necessitating efficient plant protection measures. Although manual spraying remains the dominant practice, drone technology is emerging as a superior alternative for reducing labor and chemical wastage. Despite its current limitations regarding battery life and operational complexity, the advantages of drone usage—particularly in terms of human safety and time efficiency—outweigh the drawbacks. Addressing the identified technical and skill-based constraints will be essential for the successful transition from traditional spraying methods to modernized, drone-assisted crop protection.

Table 1: Plant protection constraints experienced by maize and soybean growing farmers in Haveri district of Northern Karnataka

Production constraint	Frequency	%
1. Infestation of *Spodoptera litura* in Soybean	182	100
2. Rust disease in Soybean	32	17.58
3. Infestation of Fall armyworm in maize	203	100
4. *Turcicum l*eaf blight disease in maize	98	48.28
5. Traditional method of spraying (Knap sack sprayer)	212	88.33
6. Spray using drone	28	11.67
7. Spray using Knapsack sprayer and drone	22	9.17

Table 2: Comparison between Traditional method of spraying and drone spraying

Particulars	Traditional method of spraying	Drone spraying
1. Cost of spray	Rs. 450/ac	Rs. 1000/hr.
2. Time taken to spray	One ac/day	20-30 min./ac
3. Source of sprayer	Own	Hiring from private company and custom hiring centre
4. Years of adoption	20-25 years	1-2 years
5. Efficiency of spray	Low	Very high

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PP-38: Effectiveness of paclobutrazol application on groundnut yield improvement through drone spray technology

G. SOMANAGOUDA, SHALINI N. HUILGOL, G.K. NAIDU, HARSHIYA BANU AND ROOPA U

[1]AICRP on Soybean, MARS, University of Agricultural Sciences, Dharwad
[2]AICRP on Potato, MARS, University of Agricultural Sciences, Dharwad
***E-mail:** sgouda111@gmail.com

Groundnut (*Arachis hypogaea* L.) is most important oilseed crop in India and elevated a significant place in the Indian Agricultural economy. Despite being a tropical crop, it can be grown in all seasons. But the main problem during *kharif* season is the growth of vegetative parts become rapid which induce the disturbance in reproductive growth as well as incidence of pest and diseases. Since its vegetative stage continues along with reproductive stage, the partition of assimilates is severely affected with excessive dry matter distribution to stems and results in low pod yield. For the same reason, yield during kharif is also lesser than other seasons. Considering the above facts application of growth retardant Paclobutrazol which helps to control excess vegetative growth, promoting healthier pod formation and boosting productivity.Paclobutrazol 23% w/w SC, a member of the triazole family encourages different morphological changes such as shoot inhibition by the inhibition of gibberellin biosynthesis, increase in the chlorophyll content and also altered carbohydrate status. So, PBZ can be used in order to maintain the balance between vegetative and reproductive growth by reducing the competition for assimilate help in increment of yield. Hence, the objective of present study was to study the effects of different concentrations of foliar spray of paclobutrazol applied through drone spray on growth and yield of groundnut during *kharif* 2022 to monitor signs of phytotoxicity at the Main Agricultural Research Station, University of Agricultural Sciences in Dharwad. Groundnut variety GPBD-4 was sown with a spacing of 10 x 15 cm. All the recommended agronomical package of practices was followed to raise a good crop. Results revealed that using 70 µm to 250 µm droplet size and 30-50 droplet/sq.cm distribution at 1.5 m to 2.5 m above crop canopy, doses of 125 and 250 ml per hectare showcased no leaf tip injuries, no wilting, no vein clearing, no necrosis, or any other signs of stress. The plants maintained their natural growth patterns without any hint of epinasty or hyponasty. Therefore, application of Paclobutrazol 23% w/w SC can be a sound option for *kharif* groundnut production.

Keywords: Yield improvement, Drone technology, Phytotoxicity, Soybean

PP-39: Use of drone UAV technology to study the impact of quantis on soybean phytotoxicity

G.SOMANAGOUDA, SHALINI N. HUILGOL, R. CHANNAKESHAVA, HARSHIYA BANU AND ROOPA U

[1]AICRP on Soybean, MARS, University of Agricultural Sciences, Dharwad
[2]Agricultural Research Station, Bailhongal, University of Agricultural Sciences, Dharwad
3AICRP on Potato, MARS, University of Agricultural Sciences, Dharwad

***E-mail:** sgouda111@gmail.com

Soybean (*Glycine max* L.) is a major oilseed and pulse crop cultivated worldwide for its high nutritional value, providing an important source of plant protein and edible oil. Despite its worldwide importance, Soybean production is constrained by several factors, including abiotic stresses. These stresses can severely reduce productivity contributing to 50–70% yield losses in global crop production. To mitigate these effects and enhance plant resilience, biostimulants and stress-alleviating formulations like Quantis have been increasingly utilized in modern crop management systems. Quantis enhances plant performance and reduces yield loss caused by abiotic stress conditions. Recently drone Unmanned Aerial Vehicle (UAV) technology has revolutioned and efficient approach for precise and uniform application of agricultural inputs.The present investigation was undertaken during *kharif*-2022 at Main Agricultural Research Station, University of Agricultural Sciences, Dharwad. Soybean ruling variety JS 335 was sown at 30 x 10 cm spacing with a plot size of 30 m x 35 m. Recommended agronomical package of practices was followed to raise a good cropto study the phytotoxic effects of Quantis on soybean under drone-based application**,** tackling on visual injury symptoms such as leaf spotting, chlorosis, necrosis, stunting and growth inhibition.The study intended to provide that Quantis, when delivered through UAV technology is safe crop-compatible and suitable for integration into precision agriculture practices for eco-friendly soybean cultivation. The studies on phytotoxicity effect of Quantis @ 2000ml and 4000 ml/ha by using drone application indicated that, there was no phytotoxic effect *viz*., leaf injury on tips and leaf surface, wilting, vein clearing, necrosis, epinasty and hyponasty on soybean crop assessed in the experiment through drone application. Overall, the study demonstrates that the use of drone application enhances precision, reduces pest-disease induced crop loss and ensures environmental safety. The newer molecules, particularly when applied through UAVs, provide an efficient, eco-friendly and sustainable solution for Soybean production.

Keywords: Crop safety, UAV technology, Phytotoxicity, Soybean

Theme V

Data Analytics, IoT and Digital Agricultural Platforms

PP-40: Groundnut AI chatbot: an AI-driven weather-based advisory system

KUMAR NAIK, A. H, SRIDHARA S AND AMITH G

Associate Professor of Agronomy, Principal Investigator, AICRP on Groundnut & Nodal Officer, GKMS project, ZAHRS, Hiriyur, KSNUAHS, Shivamogga, Karnataka
Director of Research & Sr. Professor of Agronomy & Co-ordinator, Center for Climate Resilient Agriculture, KSNUAHS, Shivamogga, Karnataka
Technical Officer, GKMS project, ZAHRS, Hiriyur, KSNUAHS, Shivamogga, Karnataka
E-mail: kumarnaikah@uahs.edu.in,sridharas2017@gmail.com and amithnaik055@gmail.com, kumarnaikah@uahs.edu.in

Abstract: The rapid advancement of Artificial Intelligence (AI), automation, and digital technologies is transforming modern Agriculture into a data-driven and precision-oriented system. However, delivering real-time, location-specific, and scientifically validated advisories to farmers in an accessible manner remains a major challenge. To address this gap, the present work introduces the Groundnut AI Chatbot, a web-based intelligent advisory platform designed to support decision- making in Groundnut cultivation. The system integrates multiple knowledge sources, including the Package of Practices (PoP) developed by Agricultural Universities, real-time weather data, and advanced AI language models such as Gemini and other AI agents. By combining these components, the platform provides dynamic, context-aware, and crop-stage-specific recommendations through a simple conversational interface. The chatbot architecture consists of three major components: a knowledge integration layer that consolidates validated agronomic practices including nutrient management, pest and disease control, and irrigation scheduling; an AI-driven interaction engine capable of understanding farmer queries in natural language and generating precise responses; and a weather intelligence module that retrieves live and forecasted weather parameters to deliver climate-responsive advisories. A key strength of the system is its ability to merge static scientific recommendations with dynamic environmental data, enabling personalized advisories tailored to current field conditions. For instance, irrigation schedules, pest incidence warnings, and disease management strategies are automatically adjusted based on prevailing and forecasted weather scenarios. Designed as a lightweight, web-based platform, the chatbot ensures accessibility even in low-bandwidth rural settings and supports multilingual interaction, enhancing its usability among diverse farming communities. Preliminary observations indicate that the system improves timely access to reliable information, reduces dependence on conventional extension mechanisms, and enhances the accuracy of farm-level decision-making. By effectively bridging the gap between research institutions and farmers, the Groundnut AI Chatbot demonstrates the potential of AI-enabled digital tools in strengthening Agricultural Extension services. This innovation aligns with the vision of next-generation farming by Integrating Artificial Intelligence, automation, and digital transformation to promote sustainable, climate-resilient, and farmer-centric agriculture.

Key words: *AI, Digital Agriculture, Groundnut Chatbot, Weather-based Advisory*

Introduction

Agriculture remains the backbone frural livelihood sin India, particularly in states like Karnataka where rainfed farming dominates. Groundnut (Arachis hypogaea L.) is one of the most important oil seed crops cultivated under diverse agro-climatic conditions. However, its productivity is highly influenced by weather parameters such as rainfall distribution, temperature, humidity, and solar radiation.

Climate variability has increased the frequency of droughts, dry spells, and unseasonal rainfall, significantly impacting groundnut yield. Traditional extension services under programs like GKMS have improved advisory dissemination, but challenges remain:

- Limited last-mile connectivity
- Delayinadvisorydelivery
- Lackofpersonalization
- Dependencyonhumanintermediaries

With the advent of Artificial Intelligence and digital agriculture, there is an opportunity to revolutionize advisory systems. AI-powered chatbots can provide:

- Instantresponses
- Scalableadvisory delivery
- Personalized recommendations
- 24/7 availability

This study introduces an AI-basedchatbot specifically designed for groundnut farmers, integrating weather intelligence with agronomic expertise.

1. Objectives

Thestudy aimsto:

1. Develop an AI-based conversational system for groundnut advisory
2. Integratereal-time and forecast weather data into advisory generation
3. Providestage-wise,weather-responsive crop management recommendations
4. Improve accessibility of scientific knowledge to farmers
5. Enhance decision-making efficiency under climate variability
6. Strengthen digital Agromet advisory services under GKMS

2. Systemarchitecture (Detailed)

The system is designed using a multi-layered modular architecture that integrates AI, agronomic knowledge, and weather data (Figure1). Each layer performs a specificfunction to ensure accurate and real-time advisory delivery.

User Interface Layer

This layer provides a web-based chat botinter face that allows farmers to interacteasily with the system. It is mobile-responsive and designed to be simple, intuitive, and farmer-friendly for better accessibility.

AI Processing Layer

This layer uses Natural Language Processing (NLP) to understand farmer queries in conversational language. It identifies user intent and generates context-aware responses using AI models.

Knowledge Integration Layer

This layer contains validated agronomic information including Package of Practices (PoP), pest and disease management, and crop-specific recommendations. It ensures that all advisories are scientifically accurate and reliable.

WeatherIntelligence Layer

This layer integrates real-time and forecast weather datatomakead visories climate-responsive. It applies weather-based rules to adjust recommendations based on current and expected conditions.

Output Layer

This layer delivers the final advisory in a clear and actionable format. It provides stage-specific recommendations that farmers can directly implement in their fields.

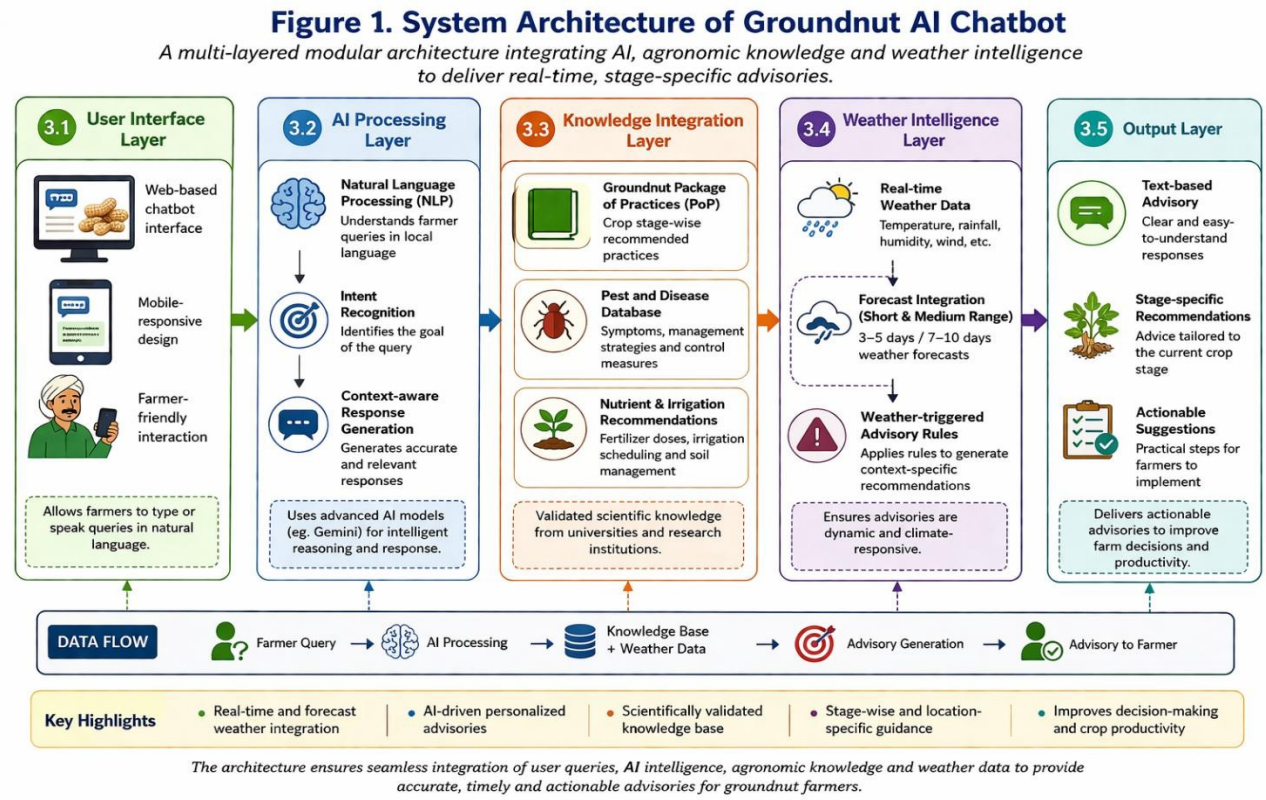


Figure1: Multi-layered Architecture of AI-Driven Weather-Based Advisory System for Groundnut

Methodology

Data Collection

The development of the Groundnut AI Chatbot is based on multiple reliable data sources. Agronomic information was collected from validated Package of Practices (PoP) developed by agricultural universities, which include crop stage – wise recommendations for nutrient management, irrigation scheduling, and pest and disease control. Inaddition, historical and real-time weather data such as rainfall, temperature, humidity, and wind parameters were incorporated. Pest and disease thre shold values were also integrated to enable condition-based advisory generation.

System Design

The system is designed using a hybrid framework that combines artificial intelligence with rule-based decision support mechanisms. A modular architecture was adopted to ensure flexibility, scalability, and ease of integration with external data sources. The chatbot is deployed as a web-based platform, making it accessible across devices, including smartphones, tablets, and desktops. The design emphasizes simplicity, responsiveness, and usability for farmers in low-bandwidth environments**.**

1.1 AIModel Functioning

The chat bot operates using Natural Language Processing (NLP) techniques to interpretuser queries expressed in conversational language. When a farmer submits a query, the system processes it to identify the intent and context. The query is then matched with relevant information stored in the knowledge base.AdvancedAI models are used to generate context-aware responses, ensuring that the output is accurate, relevant, and easy to understand.

1.2 Weather-Based Advisory Logic

A key component of the system is its ability to integrate weather data into advisory generation. The chatbot retrieves real-time and forecast weather information and applies predefined rules to adjust recommendations.Forexample, rainfall forecasts influence irrigation advisories, while temperature and humidity conditions are used to predictpest and disease incidence. This ensures that advisories are dynamic, location-specific, and responsive to changing climatic conditions.

1.3 Validation and Testing

The generated advisories are validated against standard agronomic recommendations to ensure scientific accuracy and reliability. The system was tested under pilot conditions to evaluate its performance in real-world scenarios. Feedback from experts and users was used to refine the advisory logic and improve the overall effectiveness of the chatbot.

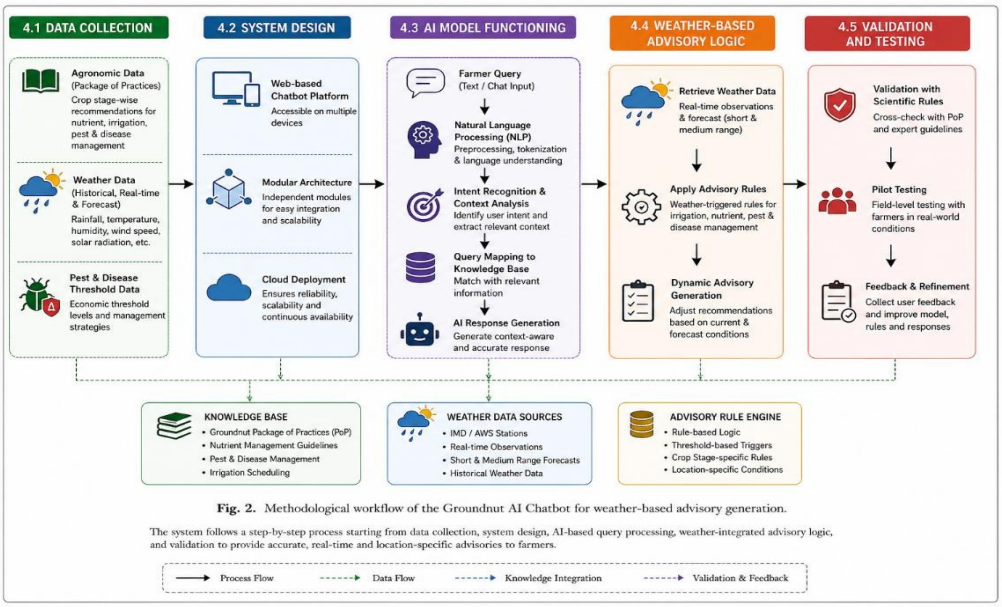


Fig. 2. Methodological workflow of the Groundnut AI Chatbot for weather-based advisory generation.

The system follows a step-by-step process starting from data collection, system design, AI-based query processing, weather-integrated advisory logic, and validation to provide accurate, real-time and location-specific advisories to farmers.

Figure2: Step wise methodology Systemfor Groundnut

Features of the System

The Groundnut AI Chatbot is designedto provide **real-time, weather-based advisories** to farmers through an interactive and user-friendly interface. It enables instant access to scientifically validated recommendations, helping farmers make timely decisions for crop management.

The system integrates **weatherdata with agronomic knowledge** to deliver dynamic and climate-responsive advisories. Recommendations are tailored based on crop stage, prevailing weather conditions, and forecast information, ensuringlocation-specificguidance.Additionally,thechatbot offers a **conversational AI interface**, allowing farmers to interact using simple language. The platform is lightweight, mobile-friendly, and optimized for use in low-bandwidth environments, making it accessible to awiderangeofusers. Overall, the system enhances the **efficiency, accuracy, and accessibility** of Agromet advisory services, supporting better farm-level decision-making and improved crop productivity.

Results and Discussion

Comparative Analysis

Parameter	Traditional Advisory System	AIChatbot System
AdvisoryDeliveryTime	Delayed(hourstodays)	Instant(seconds)
Accessibility	Limited(through extension)	High(24/7 access)
Personalization	Generalrecommendations	Location-specific
Scalability	Limited	Highly scalable
Decision Support	Reactive	Proactive
WeatherIntegration	Limited	Real-time+forecast
FarmerEngagement	Moderate	High

Results

The implementation of the Groundnut AI Chatbot significantly improved the efficiency of advisory delivery compared to traditional extension systems. The system provides instant responses, reducing delays from hours or days to a matter of seconds. This ensures that farmers receive timely recommendations, especially during critical crop growth stages.

The chatbot also enhances accessibility by providing 24/7 support through a web-based interface. Farmers can access advisory services at any time without depending on field visits or extension personnel. This improves the reach of Agromet services, particularly in remote and underserved regions.

Discussion

The integration of real-time and forecast weather data enables the system to deliver dynamic and climate-responsive advisories. Unlike conventional systems that provide generalized recommendations, the chatbot generates location-specific and crop-stage-specific guidance. This improves the accuracy and relevance of advisories.

Further more, the AI-based conversational interface increases farmer engagement by allowing natural language interaction. The system reduces the knowledge gap between scientific research and field-level

implementation by translating complex information into simple, actionable recommendations, as illustrated in Figure. 3.

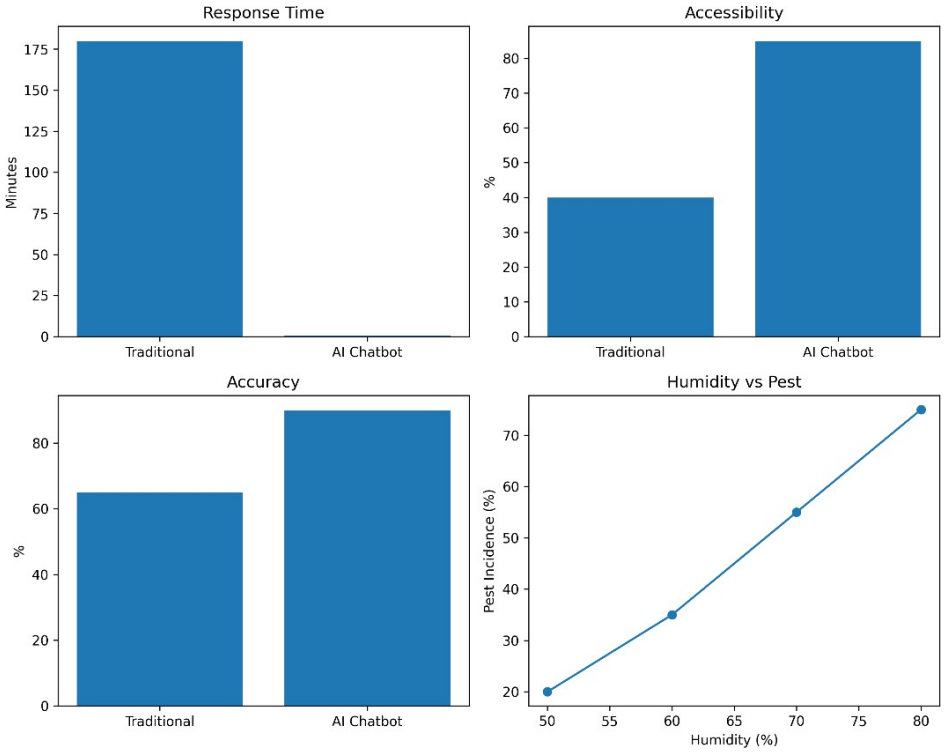


Figure 3: Multi-Panel Analysis of AI-Based Weather Advisory System for Groundnut
(a) Response time comparison, (b) Accessibility improvement, (c)Accuracy enhancement, and (d) Weather–pest relationship.

Advantages

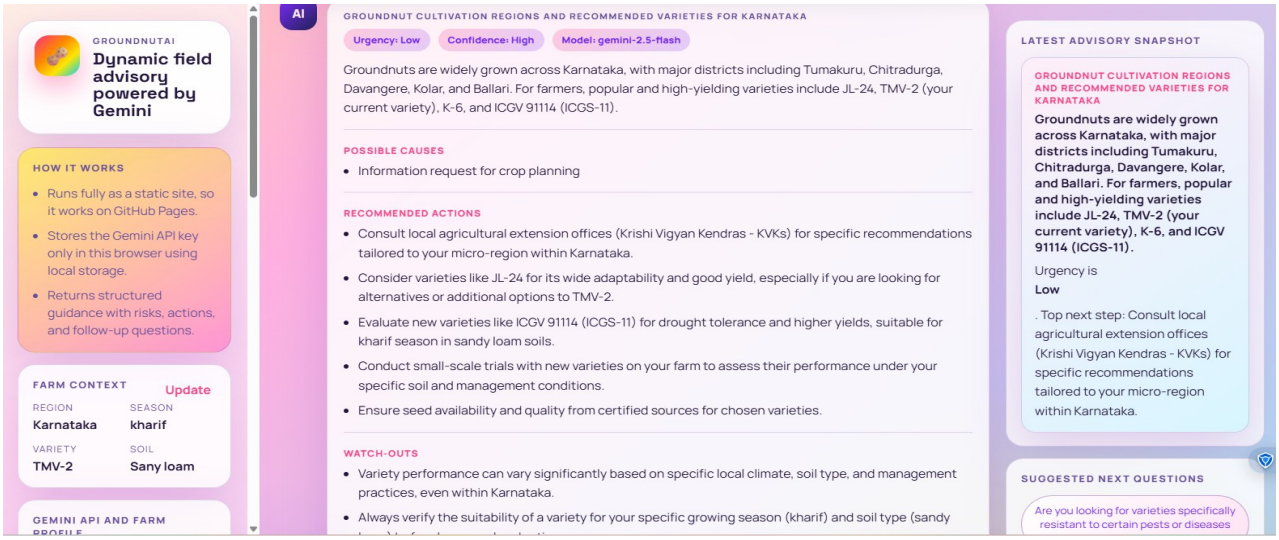
The Groundnut AI Chatbot offers significant advantages in improving agricultural advisory services. It enables rapid dissemination of information, ensuring that farmers receive timely recommendations during critical crop stages. The integration of AI and weather data enhances decision accuracy by providing precise, location-specific advisories.

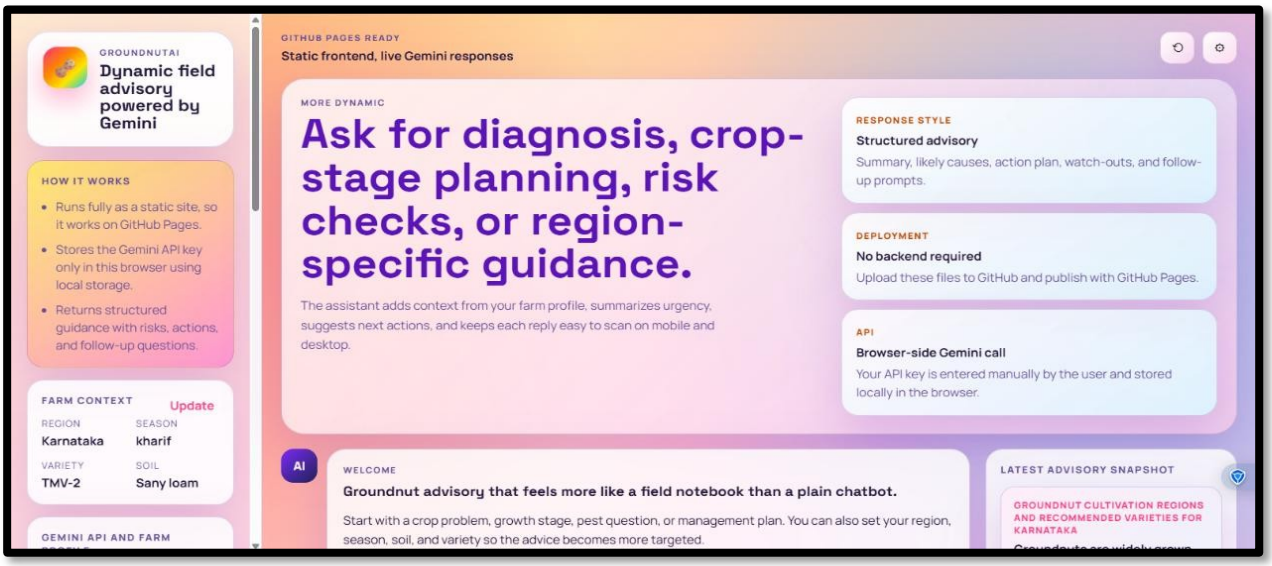
The system also reduces dependency on traditional extension services by delivering instant guidance directly to farmers. Its scalable design allows expansion to multiple crops and regions, making it aversatile tool for digital agriculture. Additionally, the chatbot supports precision farming practices and contributes to climate resilience by offering weather-responsive recommendations.

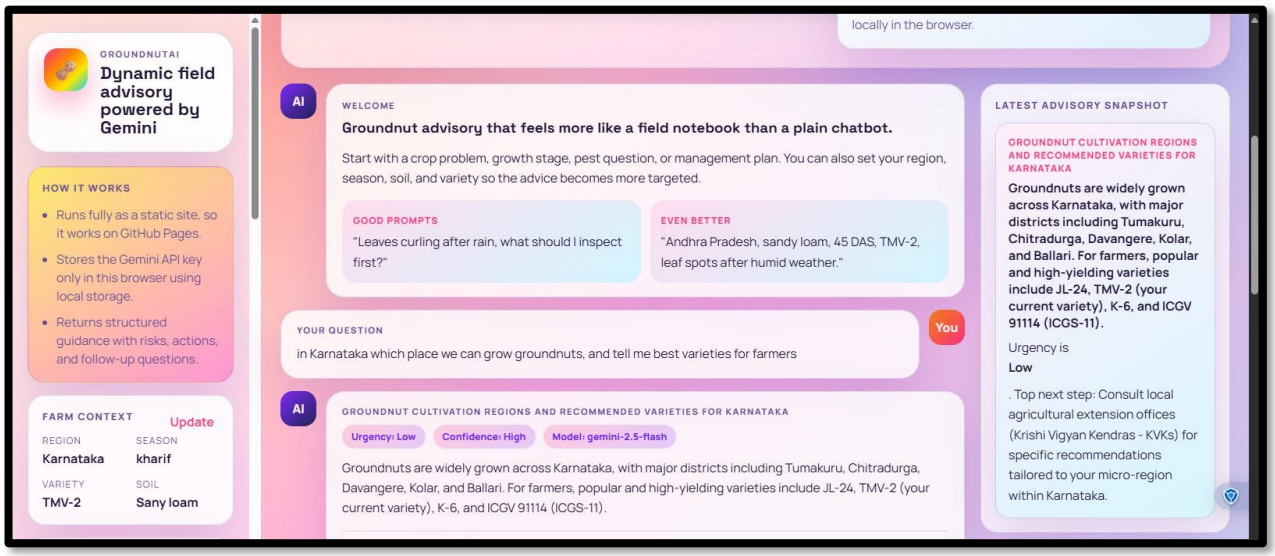
Limitations

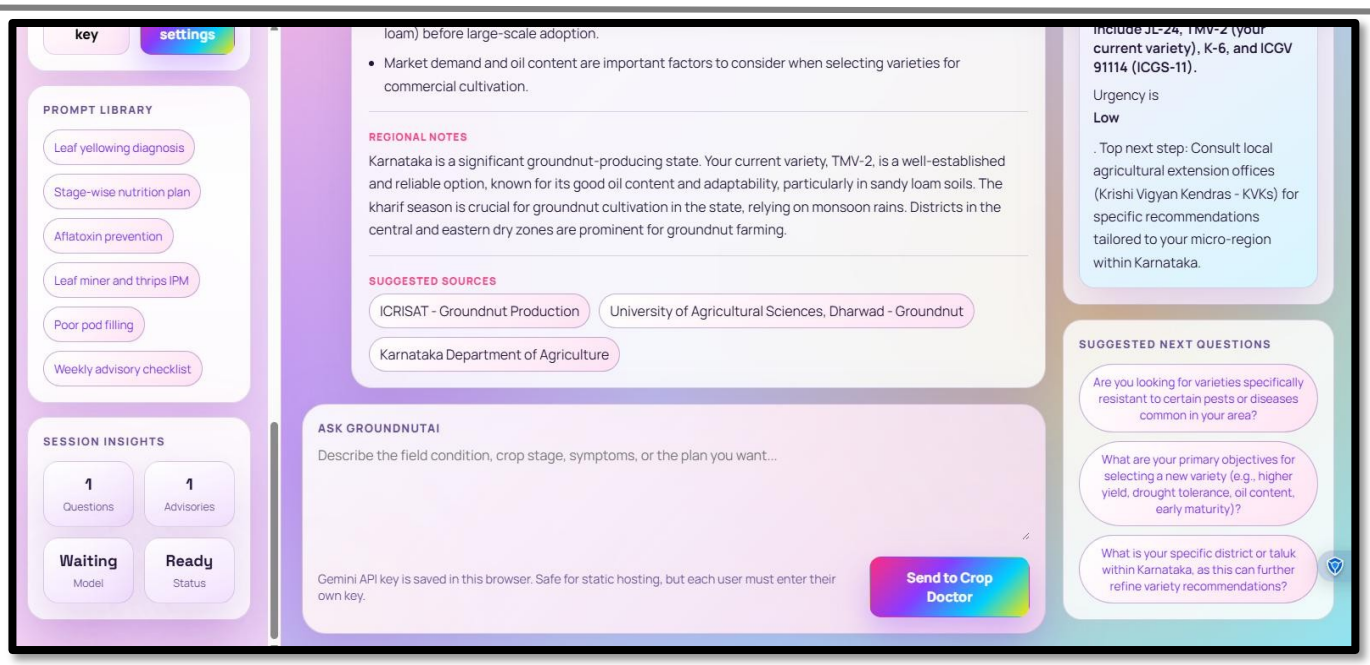
Despite its advantages, the system has certain limitations that need to be addressed. The effectiveness of the chatbot depends on internet connectivity, which can be a constraint in rural areas with limited network access. Additionally, the system requires continuous updating of agronomic and weather data to maintain accuracy and relevance. Language barriers also pose a challenge, as regional dialects and local languages may not be fully supported. Furthermore, the accuracy of advisories is influenced by the reliability of weather forecasts, which may vary depending on data sources and prediction models.

Chatbot Interface Showing User Query Processing and Advisory Output









Futurescope

The system has strong potential for further development and enhancement. Integration with IoT-based sensors, such as soil moisture and temperature sensors, can improve real-time field monitoring and advisory precision. The development of voice-based interaction will make the system more accessible to illiterate and semi-literate farmers. Future improvements also include the deployment of adedicated mobile application and expansion of the system to cover multiple crops. Incorporating satellite data and advanced machine learning models can further enhance predictive capabilities, including yield forecasting and early warning systems for pest and disease outbreaks.

Conclusion

The Groundnut AI Chatbot represents a significant advancement in the field of digital agriculture by effectively integrating artificial intelligence, agronomic knowledge, and real-time weather data into aunified advisorysystem. The study demonstrates that AI-driven conversational platforms can overcome the limitations of traditional extension services by providing instant, reliable, and location-specific recommendations to farmers.

The system has provenits capability to enhance decision-making efficiency by delivering weather-responsive and crop-stage-specific advisories. A shighlighted in Figure.3, the chatbot significantly improves response time, accessibility, and advisory accuracy compared to conventional systems. This ensures that farmers receive timely and actionable guidance, reducing risks associated with climate variability and improving overall crop management practices. Moreover, the chatbot bridges the critical gap between scientific research and field-level implementation by translating complex agronomic information into simple, understandable recommendations. Its user-friendly interface and scalability make it suitable for large-scale deployment, particularly in regions with limited access to extension services.

The Groundnut AI Chatbot has strong potential to transform agrometeorological advisory systems and contribute to sustainable and climate-resilient agriculture. With further enhancements such as IoT integration, multilingual support, and expansion too there crops, the system canplay avitalrole in strengthening farmer-centricdigital ecosystems and improving agricultural productivity at scale.

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PP-40: Next-Gen soil monitoring: the power of IoT and smart sensors

VALA Y. B., SOLANKI D. M., GHETIYA K. P., PATEL V. Y., VAGHELA S. J. AND PATEL K. M.

[1,3,4,5,6] Department of Agronomy, C. P. College of Agriculture,
Sardarkrushinagar Dantiwada Agricultural University, Sardarkrushinagar-385 506, Gujarat
[2]Department of Agricultureal Chemistry and Soil Science, C. P. College of Agriculture,
Sardarkrushinagar Dantiwada Agricultural University, Sardarkrushinagar-385 506, Gujarat
E-mail: ybvala@sdau.edu.in

Abstract: Soil health is a fundamental driver of agricultural productivity, environmental sustainability and food security. Traditional soil assessment methods are often labor-intensive, time-consuming and limited in their ability to provide real-time insights. This paper explores the integration of Internet of Things (IoT) technologies and advanced sensor systems to enable intelligent soil monitoring and management. By deploying networks of sensors that continuously capture critical parameters such as moisture content, temperature, pH levels and nutrient composition, farmers and land managers can gain accurate, real-time data to support informed decision-making. The collected data is transmitted through IoT platforms and analyzed using data analytics techniques to generate actionable insights for optimizing irrigation, fertilization and crop selection. This approach not only enhances resource efficiency but also minimizes environmental impact by reducing overuse of water and chemicals. Furthermore, the adoption of IoT-based soil intelligence systems contributes to precision agriculture, improving crop yield and long-term soil sustainability. The study highlights the potential of smart soil monitoring as a transformative solution for modern agriculture, bridging the gap between traditional practices and digital innovation for resilient and sustainable farming systems.

Key words: *IoT, Soil Monitoring, Precision Agriculture, Smart Sensors, Sustainable Farming*

Introduction

Agriculture plays a vital role in the economy of India, supporting a large portion of its population and contributing significantly to national development. However, with increasing population pressure and limited natural resources, traditional farming methods are no longer sufficient to meet rising food demands. This has created an urgent need for advanced, technology-driven agricultural practices that enhance productivity while ensuring sustainability.

Next-generation soil monitoring, powered by the Internet of Things (IoT) and smart sensors, is transforming the way farmers manage their fields. These technologies enable real-time monitoring of crucial soil parameters such as moisture, temperature, nutrient levels, and pH. By continuously collecting and transmitting data, IoT-based systems provide actionable insights that help farmers make precise and timely decisions.The integration of smart sensors with data analytics supports efficient resource utilization, reducing the excessive use of water, fertilizers, and pesticides. This not only lowers operational costs but also minimizes environmental impact. Furthermore, next-gen soil monitoring enhances crop health assessment, irrigation planning, and yield prediction, making farming more efficient and resilient.

Although still emerging in India, the adoption of IoT-driven soil intelligence is steadily growing, offering a powerful solution to modern agricultural challenges and paving the way for smarter, data-driven farming practices.

Soil management is the application of operations, practices and treatments to protect soil and enhance its performance (such as soil fertility or soil mechanics). It includes soil conservation, soil amendment and optimal soil health. In agriculture, some amount of soil management is needed both in nonorganic and organic types to prevent agricultural land from becoming poorly productive over decades. **Soil monitoring** allow farmers to collect data about rainfall, temperature and other metrics over time to track trends and predict needs.

What is IoTs and Sensors?

The Internet of Things (IoT) describes the network of physical objects "things" hat are embedded with sensors, software and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. Over the past few years, IoT has become one of the most important technologies of the 21st century. Now that we can connect everyday objects. i. e. kitchen appliances, cars, thermostats, baby monitors to the internet via embedded devices, seamless communication is possible between people, processes and things. By means of low-cost computing, the cloud, big data, analytics and mobile technologies, physical things can share and collect data with minimal human intervention. In this hyperconnected world, digital systems can record, monitor and adjust each interaction between connected things.

The physical world meets the digital world and they cooperate.

Importance of IoTs in agriculture:

The world population is expected to increase from the current level of just over seven billion people to nine or ten billion by 2050. That's a lot more mouths to feed and there simply won't be enough resources left if we don't start smart agriculture now. To meet this demand, farmers and agricultural companies are turning to the Internet of Things for analytics and greater production capabilities. IoT sensors can help farmers monitor their crops in real-time so that they know exactly how much water and nutrients each plant needs at any given time not too little and not too much.This means less waste for the environment while maximizing food production with sustainable methods that are good for both humans and animals.

IoTs and Predictive Analysis

Predictive analytics are the key to understanding how our food is grown and IoT can help in this regard. Farmers use predictive analytics to track crop growth patterns over time so that they know when it's time for a new planting cycle or if there will be enough rain for their current crops.

Predictive analytics also helps farmers understand which seeds work best with certain soils, weather conditions and growing locations all of which play major roles in agriculture.We could say that smart sensors will save us from starving while ensuring sustainability at every turn.

SOIL & WATER MANAGEMENT USING IoTs SENSORS

1. Optical Sensors

Optical sensors are used in agriculture to understand the properties of the soil and crop by the analysis of the amount of reflected light on the growing parts of the crop and soil in real-time.

Optical sensors tell the analysis tools to increase the dosage of nitrogen for weaker and unhealthy plants and regulate the dosage of nitrogen for the healthy ones.

Optical sensors are also used to study the crop vigour by including the biomass of the soil and Nitrogen to other gases ratio in the soil as variables.This helps farmers regulate the moisture levels in the air and soil and prevent damp conditions. (Damp conditions accelerate the rate of growth for bacteria and moss).

2. Electro-Chemical Sensors

Monitoring the pH level of the soil is essential for sustainable and eco-friendly farming while maximising revenue. Electrochemical sensors are used to monitor and analyse the soil quality and take measures to alter the pH level or continue practices to maintain the current level for the next phases in the lifecycle of a crop.

3. Mechanical Sensors

Mechanical sensors are used to measure the resistance offered by the soil by applying resistive forces. This is mainly carried out with load cells or strain gauges. Mechanical sensors are used to determine the amount of force that roots are exerting to absorb water and this data is used to optimise the tilling methodologies and optimizing the inflow of water. This data is also used in the early stages of the life cycle of the crop to determine the right amount of pressure that is exerted by the tractor to offer maximum yield on a long duration.

4. Soil Moisture Sensors

Dielectric soil moisture sensors are used to monitor the moisture levels of the soil to help optimize methods of irrigation management.This helps the farmer better understand the nature of the soil, its capacity to hold moisture, understand the median and mean of the evaporation rate and also get a detailed insight on the root zone of the crop.Water potential sensors and tensiometer sensors are the two prominently used di-electric soil moisture sensors used in precision farming.

5. Air Flow Sensors

Airflow sensors are used to record the number of gaseous substances present in the soil at a particular landscape after irrigation or to get an overview of the land that is to be cultivated before the seeding process. It determines the optimum pressure required to pump air to aerate the soil. It is also used to determine the properties of the soil, its compaction, moisture-holding capacity, etc.

Conclusion

Next-generation soil monitoring powered by the Internet of Things and smart sensors represents a decisive shift from reactive to data-driven agriculture. By enabling real-time insights into soil health and field variability, these technologies support precision input use reducing water consumption by up to 30% and fertilizer use by nearly 20%, while improving crop yields by 10–25% as observed in precision agriculture practices. In a country like India, where resource efficiency and food chain management are critical, such advancements can significantly enhance farmer incomes and sustainability. Although adoption is still growing, the proven benefits of IoT-enabled soil intelligence make it a transformative solution for building resilient, efficient and future-ready agricultural systems.

PP-42: Plant OS: an IoT-enabled smart greenhouse monitoring system with integrated machine learning for greengram cultivation

MINAL P. SHINDE, SUJAL S PATIL, ISHA P PANDIT, ABHISHEK KARAD

Research Scholar, III Year B.Tech, Electronics & Communication Engineering (AI & ML)
Department of EEE, Dr. Vishwanath Karad MIT World Peace University, Pune

Introduction

Global food security faces mounting pressure from population growth and climate variability, with the world population projected to reach 9.7 billion by 2050. Precision agriculture offers a viable response, yet existing commercial greenhouse monitoring systems remain expensive, narrowly scoped, and technically inaccessible to small-scale growers - each addressing only a single aspect such as germination detection, soil nutrient sensing, or irrigation control.

Mung bean (Vigna radiata) is particularly sensitive to soil composition, moisture levels, and germination conditions, making it an ideal candidate for precision monitoring. The three macronutrients - nitrogen (N), phosphorus (P), and potassium (K), collectively referred to as NPK - are critical for healthy vegetative development, and their deficiencies manifest as measurable changes in plant optical properties. These spectral signatures form the basis of the PlantOS sensing strategy.

System Architecture

PlantOS is organised into four hierarchical layers. The Sensing Layer acquires multi-parameter environmental and spectral data at two-second intervals. The Processing and Actuation Layer runs three machine learning models on incoming data and issues irrigation commands. The Communication Layer manages Wi-Fi HTTP data exchange using JSON payloads between the ESP32 microcontroller and a FastAPI backend. The Application Layer presents data through a Streamlit dashboard and provides agronomic advice via an integrated LLM assistant.

The primary sensing node is built on an ESP32 microcontroller (dual-core Xtensa LX6, 240 MHz) integrating four sensors: an AS7341 eleven-channel spectral sensor covering 415–590 nm; a DS18B20 digital soil temperature sensor (±0.5 °C); a BMP280 barometric pressure sensor; and a resistive hygrometer for volumetric soil moisture. A separate ESP8266 microcontroller manages actuation, driving a relay-controlled submersible pump and tracking water volume via a YF-S201 hall-effect flow sensor.

Machine Learning Pipeline

Three Random Forest classifiers form the intelligence core of PlantOS. Random Forest was selected for its resistance to overfitting, scale invariance, and proven accuracy on small, irregular datasets. All models were trained using scikit-learn v1.3 in Python 3.10.

Germination Classification: Accepts eleven inputs including six AS7341 spectral channel readings and soil/air temperature. Trained on controlled mung bean germination trials over seven days. Achieved 91.60% accuracy (F1: 91.6%), with the 555 nm and 590 nm channels most discriminative for chlorophyll onset.

NPK Nutrient Inference: Derives spectral proxy indicators from AS7341 channel ratios F2–F6, classifying each nutrient as Low, Medium, or High and computing a composite Soil Fertility Index. Achieved 92.05% overall accuracy; nitrogen performed best (94.2%) due to its strong spectral signal, while potassium was weakest (89.8%). NPK estimates correlated with lab reference measurements at R^2 = 0.87.

Irrigation Decision: Combines threshold logic with ensemble classification. Moisture below 30% unconditionally triggers PUMP_ON; above 70% triggers PUMP_OFF. In the 30–70% range, barometric pressure and spectral channels resolve edge cases. Achieved 92.50% decision accuracy (F1: 92.7%), maintaining soil moisture within ±4.8% of configured thresholds.

Table 1. Machine Learning Model Performance Summary

Model	Output Classes	Key Input Features	Accuracy	F1
Germination	Unlikely / In-Progress / Likely	AS7341 ch0–ch5, soil temp, air temp, moisture	91.60%	91.6%
NPK Inference	Low / Medium / High (per nutrient)	Spectral ratios F2–F6	92.05%	92.0%
Irrigation Decision	PUMP_ON / HOLD / PUMP_OFF	Soil moisture, pressure, spectral channels	92.50%	92.7%

Software Stack & Dashboard

The backend is implemented in FastAPI (Python), providing asynchronous ASGI request handling, automatic OpenAPI documentation, and Pydantic-based validation. The Streamlit frontend dashboard auto-refreshes every 30 seconds and displays real-time metrics for temperature, moisture, pressure, and irrigation history. NPK progress bars, an AS7341 spectral bar chart, germination status, fertility index, and a moisture trend line are all surfaced. A GroqLLaMA-based AI assistant is embedded in the dashboard, pre-loaded with five agronomic prompt buttons for rapid user queries, while manual pump override buttons send direct HTTP commands to the ESP8266 actuation module.

Results & Validation

Validation trials ran over three weeks in an indoor rooftop greenhouse at MIT-WPU, Pune, using mung bean variety K-851. System latency profiling showed an average end-to-end sensor-to-dashboard round-trip of 312 ms (95th percentile: 780 ms). The ESP32-to-FastAPI HTTP POST median latency was 85 ms, ML inference time 12 ms, and HTTP response time 8 ms. Water volume measurement accuracy was ±3%, confirming near-real-time monitoring capability without dedicated edge computing hardware.

Compared to competing approaches, PlantOS offers a compelling balance of capability and cost. Its total hardware cost of under ₹2,500 is approximately 166× lower than terahertz imaging systems and 7–17× lower than electrochemical NPK sensor arrays (₹16,000–₹41,000). PlantOS is the only evaluated system that simultaneously provides germination prediction, NPK nutrient classification, intelligent irrigation control, real-time data visualisation, and LLM-based natural language advisory - all within a low-cost, reproducible open hardware platform.

Conclusion & Future Directions

PlantOS demonstrates that affordable visible-light spectroscopy, dual-microcontroller IoT actuation, ensemble machine learning, and modern web frameworks can deliver agricultural intelligence at a fraction of the cost of conventional precision farming systems. All three Random Forest models collectively achieve accuracy above 91% across germination, nutrient, and irrigation tasks, validating spectral proxies as a viable substitute for expensive electrochemical or terahertz sensing modalities.

Future development includes persistent time-series storage (SQLite/PostgreSQL) for longitudinal analysis; containerised cloud deployment for multi-site use; extended AS7341 configuration with 610–860 nm channels for improved NPK generalisability; and integration of a plant disease recognition network (MobileNetV3 fine-tuned on PlantVillage) to enable foliar disease detection correlated with soil nutrient profiles.

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PP-43: Internet of Things (IoT): A New Era in Plant Protection

MANISH J. JOSHI, RABARI P. H., HADIYA G. D., BARAD B. D. AND PATEL P. S.

Department of Entomology, C. P. College of Agriculture,
S. D. Agricultural University, Sardarkrushinagar-385 506
E-mail: drmanishjoshi.ento@gmail.com

Abstract: The Internet of Things (IoT) is revolutionizing modern agriculture by enabling smart and precise plant protection practices. IoT refers to a network of interconnected devices, sensors, cameras, drones and automated systems that collect and exchange real-time information through the internet. In plant protection, IoT technologies help monitor pest populations, detect plant diseases, analyse environmental conditions and support precision pesticide application. The integration of IoT with artificial intelligence (AI), cloud computing and remote sensing enhances decision-making and improves the efficiency of crop protection strategies. IoT-based systems contribute to sustainable agriculture by reducing pesticide misuse, minimizing environmental pollution and improving crop productivity. Although challenges such as high installation costs, limited internet access, and lack of technical awareness still exist, IoT has immense potential to transform plant protection and promote climate-resilient agriculture.

Key words: IoT, Plant Protection, Pest Management, Precision farming

Introduction

Agriculture is facing increasing challenges due to climate change, pest outbreaks, disease epidemics and the excessive use of pesticides. Traditional plant protection methods often rely on manual monitoring and blanket pesticide applications, which may lead to higher production costs, environmental contamination and pest resistance. In this context, the Internet of Things (IoT) has emerged as an innovative solution for modern crop protection.

IoT is a technology that connects physical devices through sensors and communication networks to collect, process, and share data in real time. In agriculture, IoT systems include smart sensors, weather stations, automated irrigation systems, drones, GPS-enabled devicesand cloud-based platforms. These technologies help farmers monitor field conditions continuously and make timely decisions regarding crop protection.

Role of IoT in Plant Protection

1. Real-Time Pest Monitoring

IoT-enabled smart insect traps and sensor-based monitoring systems help detect pest populations in the field. Cameras and image-processing systems can identify insect species and provide instant alerts to farmers through mobile applications or cloud platforms. This helps in taking preventive measures before pests reach economic threshold levels.

2. Disease Prediction and Early Warning Systems

Plant diseases are highly influenced by environmental conditions such as temperature, humidity, rainfall and leaf wetness. IoT sensors continuously monitor these parameters and analyse disease risk. Early warning systems can predict disease outbreaks and recommend timely control measures, thereby reducing crop losses.

3. **Precision Pesticide Application**

IoT-based smart sprayers and drones allow precise application of pesticides only in affected areas. GPS-guided systems reduce overuse of chemicals and ensure uniform spraying. Precision application not only lowers input costs but also minimizes environmental pollution and pesticide residues in agricultural produce.

4. **Integration with Artificial Intelligence and Data Analytics**

IoT devices generate a large amount of agricultural data. When integrated with AI and machine learning, these data can be analyzed for pest forecasting, disease diagnosis and crop health assessment. Farmers receive data-driven recommendations that improve decision-making and enhance integrated pest management (IPM) practices.

5. **Remote Field Monitoring**

Farmers can monitor crop health, soil moisture, weather conditions, and pest activity remotely using smartphones or computers. This reduces the need for frequent field visits and allows efficient management of large agricultural areas.

Advantages of IoT in Plant Protection

1. Early detection of pests and diseases
2. Reduction in unnecessary pesticide applications
3. Improved crop productivity and quality
4. Lower labor and input costs
5. Better environmental sustainability
6. Conservation of beneficial organisms
7. Efficient use of water and agrochemicals
8. Support for climate-smart agriculture

Challenges in Adoption of IoT

1. High initial investment costs
2. Lack of internet connectivity in rural areas
3. Limited technical knowledge among farmers
4. Maintenance and data management issues
5. Concerns related to data privacy and cybersecurity
6. Governments, research institutions, and private industries are working to develop affordable and user-friendly IoT solutions to overcome these challenges.

Conclusion

The Internet of Things (IoT) is opening new possibilities in plant protection by enabling real-time monitoring, precision farming, and intelligent decision-making. IoT technologies help farmers detect pests and diseases early, optimize pesticide use and improve the overall efficiency of crop protection practices. The integration of IoT with AI, drones, remote sensing and cloud computing is transforming conventional agriculture into smart agriculture. Although challenges related to cost, infrastructure, and technical awareness remain, the future of IoT in plant protection is highly promising. Wider adoption of IoT-based technologies can contribute significantly to sustainable agriculture, environmental conservation, food security and increased agricultural productivity.

PP-44: Soil management and monitoring with iots / sensors

DHARMESH M. SOLANKI, VALA Y. B., KULDIP. A. SOLANKI, CHAUHAN K. J. AND CHOVATIYA N. C.

[1,4,5] Department of Agricultural Chemistry and Soil Science, C. P. College of Agriculture, Sardarkrushinagar Dantiwada Agricultural University, Sardarkrushinagar-385 506, Gujarat
[2,3]Department of Agronomy, C. P. College of Agriculture, Sardarkrushinagar Dantiwada Agricultural University, Sardarkrushinagar-385 506, Gujarat
E-mail: dmsolanki@sdau.edu.in

Abstract: Agriculture remains the backbone of the Indian economy, supporting a large proportion of the population while facing increasing pressure from resource limitations and climate variability. The integration of Internet of Things (IoT) technologies with precision agriculture offers a transformative approach to address these challenges. This review highlights the role of IoT-based sensors and data-driven systems in enhancing soil and water management practices. Key sensor technologies, including optical, electrochemical, mechanical, soil moisture and airflow sensors, enable real-time monitoring of critical soil and crop parameters such as moisture content, nutrient status, pH and environmental conditions. These technologies facilitate site-specific management, optimizing the use of inputs like fertilizers, irrigation and pesticides, thereby improving resource-use efficiency and crop productivity. Despite these advantages, challenges such as high initial costs, lack of standardization, data security concerns and the need for skilled workforce hinder widespread adoption. Overall, IoT-enabled precision agriculture presents a sustainable pathway for increasing agricultural productivity while minimizing environmental impact, making it a critical tool for future food security.

Key words: Precision Agriculture; Internet of Things (IoT); Soil Monitoring; Soil Moisture Sensors; Smart Farming; Sensor-Based Irrigation; Soil Health Management; Remote Sensing (RS); Geographic Information System (GIS); Nitrogen Use Efficiency (NUE); Site-Specific Crop Management (SSCM); Predictive Analytics in Agriculture; Sustainable Agriculture

Introduction

Agriculture is the backbone of India's economy, which accounts for 20.19% of India's Gross Domestic Product (GDP) and hires about half of the countries workforce. More than 70% of rural families depend on agriculture for their livelihood. Housing about 17% of the total world population, India faces the challenge of fulfilling the demands of agricultural commodities for this ever-growing population. It's imperative to upgrade traditional farming practices and prepare for a tech-revolution to develop eco-friendly systems for enhancing crop productivity. Smart farming concepts like precision agriculture or sensor-based farming can be suitable to achieve this goal. Precision farming is an integrated crop management system which uses remote sensing (RS), GPS and geographical information system (GIS) to monitor the crop field at ground level. The disparities in crop or soil properties within a field are recorded and mapped. Then management decisions are taken as a result of continuous assessment of the spatial variability within that field.In the Indian agricultural scenario, it can be described as the precise utilization of agricultural inputs depending upon the crop, soil and weather requirement to optimize the use of fertilizers, pesticide and irrigation requirements for maximum productivity.

Precision Agriculture Technology

Precision agriculture (PA) or satellite farming or site-specific crop management (SSCM) is a farming management concept based on observing, measuring and responding to inter and intra-field variability in crops.

Application of Precision Agriculture Technology

- Soil and Field Analytics
- Planting
- Crop Spraying
- Crop Monitoring
- Irrigation
- Assessing Crop Health

IoTs and Sensors

The Internet of Things (IoT) describes the network of physical objects "things" that are embedded with sensors, software and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. Over the past few years, IoT has become one of the most important technologies of the 21st century. Now that we can connect everyday objects. *i.e.* kitchen appliances, cars, thermostats, baby monitors to the internet via embedded devices, seamless communication is possible between people, processes and things. By means of low-cost computing, the cloud, big data, analytics and mobile technologies, physical things can share and collect data with minimal human intervention. In this hyperconnected world, digital systems can record, monitor and adjust each interaction between connected things. The physical world meets the digital world and they cooperate.

Importance of IoTs in agriculture

The world population is expected to increase from the current level of just over seven billion people to nine or ten billion by 2050. That's a lot more mouths to feed and there simply won't be enough resources left if we don't start smart agriculture now. To meet this demand, farmers and agricultural companies are turning to the Internet of Things for analytics and greater production capabilities. IoT sensors can help farmers monitor their crops in real-time so that they know exactly how much water and nutrients each plant needs at any given time not too little and not too much.

This means less waste for the environment while maximizing food production with sustainable methods that are good for both humans and animals alike

- The IoT technology is more efficient due to following reasons:
- Global connectivity through any devices.
- Minimum human efforts
- Faster access
- Time efficiency
- Efficient communication

There are two ways that IoT can be used in agriculture include providing real time data about your crops and helping farmers make better decisions on how to harvest their plants. Instead of relying on estimations and guesswork, farmers can now use this system to monitor their crops. They can then make predictions about when they will ripen and optimize the amount of water used for irrigation in order to grow high quality product. The technology behind IoT sensors is also helpful outside of agriculture because you can track temperature, humidity levels, plant diseases and more without having people spend all day monitoring readings manually.

Soil & Water Management Using Iots Sensors

Optical Sensors

Optical sensors are used in agriculture to understand the properties of the soil and crop by the analysis of the amount of reflected light on the growing parts of the crop and soil in real-time. it tells the analysis tools to increase the dosage of nitrogen for weaker and unhealthy plants and regulate the dosage of nitrogen for the healthy ones. They are also used to study the crop vigour by including the biomass of the soil and nitrogen to other gases ratio in the soil as variables. This helps farmers regulate the moisture levels in the air and soil and prevent damp conditions. (Damp conditions accelerate the rate of growth for bacteria and moss).

Electro-Chemical Sensors

Monitoring the pH level of the soil is essential for sustainable and eco-friendly farming while maximising revenue. Electrochemical sensors are used to monitor and analyse the soil quality and take measures to alter the pH level or continue practices to maintain the current level for the next phases in the lifecycle of a crop. These sensors are used in both outdoor farms and greenhouse-based farming establishments.

Mechanical Sensors

Mechanical sensors are used to measure the resistance offered by the soil by applying resistive forces. This is mainly carried out with load cells or strain gauges. These are used to determine the amount of force that roots are exerting to absorb water and this data is used to optimise the tilling methodologies and optimizing the inflow of water. This data is also used in the early stages of the life cycle of the crop to determine the right amount of pressure that is exerted by the tractor to offer maximum yield on a long duration.

Air Flow Sensors

Airflow sensors are used to record the number of gaseous substances present in the soil at a particular landscape after irrigation or to get an overview of the land that is to be cultivated before the seeding process. It determines the optimum pressure required to pump air to aerate the soil. It is also used to determine the properties of the soil, its compaction, moisture-holding capacity, *etc*.

Benefits or Advantages Of Soil Iots / Sensors

Excelled efficiency:

Today's agriculture is in a race. Farmers have to grow more products in deteriorating soil, declining land availability and increasing weather fluctuation. IoT-enabled agriculture allows farmers to monitor their product and conditions in real-time. They get insights fast, can predict issues before they happen and make informed decisions on how to avoid them.

Expansion:

By the time we have 9 billion people on the planet, 70% of them will live in urban areas. IoT-based greenhouses and hydroponic systems enable short food supply chains and should be able to feed the people.

Optimizing the use resources:

Plenty of agricultural IoT solutions are focused on optimizing the use of resources water, energy, land. Precision farming using IoT relies on the data collected from diverse sensors in the field which helps farmers accurately allocate just enough resources to within one plant.

Cleaner process

Not only do IoT-based systems for precision farming help producers save water and energy but, also make farming greener, thus, significantly scale down on the use of pesticides and fertilizer.

Agility

One of the benefits of using IoT in agriculture is the increased agility of the processes. Thanks to real-time monitoring and prediction systems, farmers can quickly respond to any significant change in weather, humidity, air quality as well as the health of each crop or soil in the field. In the conditions of extreme weather changes, new capabilities help agriculture professionals save the crops.

Improved product quality

Data-driven agriculture helps both grow more and better products. Using soil and crop sensors, aerial drone monitoring and farm mapping, farmers better understand detailed dependencies between the conditions and the quality of the crops. Using connected systems, they can recreate the best conditions and increase the nutritional value of the products.

Drawbacks or Disadvantages of Soil Iots / Sensors

Privacy & Security

Security is an essential pillar of the Internet while the major challenge for the IoT. As the time goes the trend of IoT inflates from millions of devices to tens of billions. As increasing the number of connected devices, the chance to exploit safety vulnerabilities is also increase, like in cheap or low standard designed devices, due to incomplete data streams the chances of data theft is increased.

Standards

Absence of standards and documents can assist senseless activities by IoT devices. Low standard or cheap designed and configured devices have undesirable consequences for the networking resources. Without standards to guide developers and manufacturers, sometimes design products that operate in disruptive ways on the Internet.

Complexity in Operations

IoT may seem to be managing tasks with ease, a lot of complex operations are done behind it. If by mistake the software makes a wrong calculation, this will affect the rest of the process. The above-mentioned can be very critical sometimes. *i.e.* error code in water dam software could cause a disastrous flood. That is the reason, many times a mistake in IoT is not always easy to manage.

Trained workforce

Implementation of every technology requires team of skilled persons those have ample knowledge of network, hardware, software and about that technology. And India is backward in this point where agricultural manpower still using traditional technologies.

Conclusion

Soil monitoring through sensors allows for better soil conservation which can be installed along irrigation systems where they then monitor temperature, humidity levels, crop health and so much more helping farmers proactively take care of their crops as opposed to continually reacting when things go wrong. The use of sensor-based technologies has the potential to produce maximum yields and increase NUE without a detrimental reduction in crop yield. The use of a wireless sensor network for real-time sensing of substrate water status is an effective tool for precision irrigation management in greenhouse soilless conditions.

Theme VI

AI for Supply Chain, Post Harvest and Agri-business

PP-45: Leveraging AI for consumer segmentation and adoption patterns of vegetable powder products

MELITA SIMOES, ALOK GADDI, PRATIKSHA KULKARNI, SAGAR KORI

[1,2,3&4] School of Management Studies and Research (SMSR), KLE Technological University, Hubli

E-mail: melita.simoes@kletech.ac.in ; alok.gaddi@kletech.ac.in; 01fm24mba026@kletech.ac.in; 01fm24mba048@kletech.ac.in

Abstract: Vegetable powder products constitute a growing convenience food category in urban households in India. Understanding household-level adoption patterns is critical for designing AI-enabled strategies for digital agriculture platforms, supply chain optimization, and precision marketing. This study applies artificial intelligence, specifically hierarchical cluster analysis using Ward's method, to segment 51 urban household grocery decision-makers based on demographic, socio-economic, and behavioural characteristics. Two distinct consumer segments emerged: traditional non-adopters (older, lower-income, price-sensitive, kirana shoppers) and modern adopters (younger, higher-income, quality-conscious, supermarket/online shoppers). Modern adopters demonstrated higher willingness to substitute tomato powder for fresh tomatoes (52%) and prioritized shelf-life and chemical-free attributes, whereas traditional non-adopters resisted substitution due to strong preference for fresh produce. These findings highlight the potential of AI-driven consumer analytics for informed digital agriculture interventions, targeted product positioning, and sustainable food system development.

Keywords: AI in agriculture, Consumer segmentation, Hierarchical clustering, Digital agriculture platforms, Vegetable powder adoption, Karnataka

Introduction

Vegetable powders, produced through dehydration, extend shelf-life while preserving nutritional value, addressing perishability and seasonal price volatility of fresh produce. Rapid urbanization, dual-income households, and time constraints have increased demand for convenience products, yet adoption remains heterogeneous.

Karnataka's urban households present an ideal study setting due to a combination of organized retail penetration, rising disposable incomes, and growing familiarity with value-added food products. AI-enabled consumer analytics can uncover latent patterns in adoption behaviour, informing digital agriculture platforms, supply chain planning, and precision-targeted marketing.

This study applies hierarchical clustering to segment urban consumers in Karnataka, demonstrating how AI-based insights complement agri-tech innovations to optimize production, distribution, and adoption of vegetable powder products.

Objectives

1. Apply AI-based hierarchical clustering to identify urban consumer segments for vegetable powder products in Karnataka.

2. Profile segment-specific demographic, behavioural, and attitudinal characteristics, including adoption and substitution patterns.
3. Demonstrate the utility of AI-driven analytics for digital agriculture platforms, supply chain optimization, and precision marketing strategies.

Materials and Methods

Research Design

A descriptive-analytical cross-sectional study combining primary survey data with AI-enabled hierarchical clustering to identify naturally occurring consumer segments.

Sampling and Data Collection

Population: Urban household grocery decision-makers in Karnataka's metro and tier-1 cities. **Sample:** Purposive sampling of 51 respondents aware of at least three vegetable powder products.

Instrument: Structured questionnaire capturing demographics, grocery purchase behaviour, powder usage patterns, and attribute importance (Likert scale 1–5).

Data Collection: Online and in-person survey

Data Preparation

Variables were numerically coded and standardized. Data screening confirmed completeness, consistency, and absence of outliers.

Analytical Approach

Descriptive Statistics: Frequencies, means, standard deviations, and cross-tabulations. **Hierarchical Cluster Analysis:** Ward's method with squared Euclidean distance on standardized demographic, behavioural, and attitudinal variables.

Cluster Validation: Chi-square tests for categorical variables, ANOVA for continuous variables (α=0.05).

Software: Orange Data Mining 3.36 (clustering), JASP 0.17.1 (statistical tests).

Results

Table 1: Demographic and Behavioral Characteristics of the Sample

Variable	Category	Frequency (n=51)	Percentage (%)
Age	Mean ± SD	42.4±10.6	—
Education	Postgraduate	16	31.40%
	Professional/Undergraduate	27	53.00%
	Others	8	15.60%
Monthly Income	Low (< ₹50,000)	27	53.00%
	High (> ₹50,000)	24	47.00%

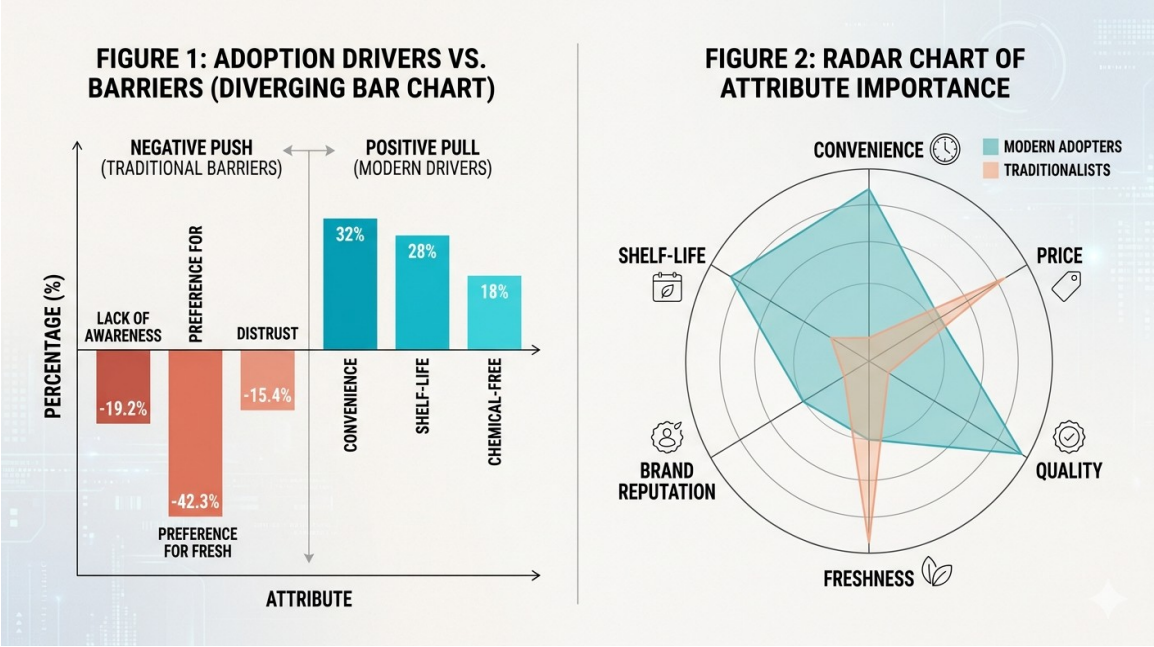
Primary Occupation	Working Professional	30	58.90%
	Homemaker/Retired	19	37.30%
	Others	2	3.80%
Preferred Store	Local Kirana	19	37.30%
	Supermarket/Online	29	56.80%
	Direct/Others	3	5.90%

From table 1, it can be observed that the sample consists of middle-aged individuals (mean age 42.4) who are predominantly well-educated working professionals with a slight preference for shopping at supermarkets or online platforms over local stores.

Table 2: Comparative Cluster Profiling and Statistical Significance

Variable	Cluster 1: Traditional (n=26)	Cluster 2: Modern (n=25)	Test Statistic (χ2/t)	p-value
Mean Age (Years)	49.2±8.4	35.3±7.9	t=6.08	< 0.001*
High Income (>₹50k)	26.90%	64.00%	χ2=21.35	< 0.001*
Retired/Homemaker	61.50%	12.00%	χ2=16.89	< 0.01*
Online/App Shopping	7.70%	44.00%	χ2=14.73	< 0.01*
Willing to Substitute	19.20%	52.00%	χ2=14.89	< 0.01*
Gender (Male %)	53.80%	56.00%	χ2=0.84	0.36 (NS)

Table 2 highlights a demographic and behavioral divide between two distinct consumer segments. Cluster 1 (Traditional) consists of older, lower-income individuals who are largely homemakers or retired and prefer offline shopping. Cluster 2 (Modern) is significantly younger, wealthier, more tech-savvy, and more open to product substitution, with gender being the only statistically insignificant factor between the two.



Discussion

Theoretical Implications

Binary segmentation aligns with innovation diffusion theory; early adoption shows bimodal distribution. Age, income, and occupation were primary discriminators, while gender was non-influential.

Practical Implications for Digital Agriculture

AI-driven segmentation informs digital agriculture platforms by predicting adoption, optimizing supply chains, and reducing post-harvest losses.

Modern Adopters: Target via e-commerce, organized retail, and digital campaigns.

Traditional Non-Adopters: Awareness-building and value-focused promotions required.

Policy and Business Implications

Insights guide startups, food processors, and policymakers in leveraging AI for precision marketing, predictive inventory management, and product innovation. Adoption of vegetable powders contributes to sustainability by extending shelf-life, reducing waste, and integrating farmers into value chains.

Conclusion

Hierarchical clustering reveals clear segmentation of urban consumers in Karnataka: modern adopters versus traditional non-adopters. AI-enabled consumer insights provide actionable intelligence for digital agriculture platforms, targeted marketing, and supply chain optimization, enabling growth in India's vegetable powder market while promoting sustainable, efficient food systems.

PP-46: Forecasting tuberose production in the selected districts of Karnataka using AItools

LALITA V MELI AND VASANTHA KUMARI, J*
*Assistant Professor, Dept. of Agri. Statistics,
CoA, UAS Dharwad, Karnataka

Abstract: Accurate forecasting of flower crop production is essential for data-driven decision-making andsustainable planning in the floriculture sector. Tuberose, a commercially valuable crop in Karnataka, is highly influenced by fluctuating agro-climatic conditions, therefore production forecasting is avital tool for growers and policymakers. For this study, three tuberose growing districts viz., Ballari, Chitradurga and Tumkur were selected and the secondary data on production of tuberose in these three selected districts is collected from Department of District Horticulture, Dharwad for the period of 1981-2023. Comparative analysis of two machine learningalgorithms viz., Support Vector Regression (SVR), K-Nearest Neighbors (KNN) and the best fitted traditional regression modelsis done.. Model performance was assessed using key evaluation metrics for machine learning models: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Logarithmic Error (MSLE),and the Coefficient of Determination (R^2). For traditional regression models RMSE and R^2 values are used. Empirical results demonstrated that the KNN model outperformedSVR and the traditional model in both Ballari and Chitradurga, achieving a lower MAE (313.13), RMSE (445.31), and MSLE (0.91) for Ballari and MAE (1075.28), RMSE (1568.07), and MSLE (0.28) for Chitradurga.The substantiallyhigher R^2 values for these two districts are0.81 and 0.77 respectively, indicating robust predictive accuracy. In Tumkur district, SVR model outperformed K-NN and the traditional model with lower MAE (85.36), RMSE (121.73), and MSLE (0.82). The R^2 value of this model is 0.84. The R^2 value of K-NN is also same as SVR in case of Tumkur and not much difference in other key evaluation matrices also. Therefore one can use K-NN model as well in order to forecast future production. The superior performance of KNN may be attributed to its ability to capture local nonlinear variationsmore effectively, which is crucial in heterogeneous agricultural environments. This study underscores theimportance of algorithm selection in crop production modeling and highlights the potential of K-NN as a reliabletool for forecasting Tuberose production. These findings offer practical implications for improving precision agricultural practices and call for further validation of machine learning models across varying agro-ecologicalcontexts to support resilient and informed floricultural development.

Key words: Machine Learning, SVR, K-NN, Traditional Regression model, Coefficient of determi

PP-47: Predicting harvest time for fruits and vegetables using artificial intelligence

AKKAMAHADEVI D AGASIMANI, SIDDARTH S SHIVAYAGOL AND SANTHOSHA H M

Department of Horticulture, College of Agriculture
University of AgriculturalSciences, Dharwad
Email:agasimaniad@uasd.in

Accurate prediction of harvest time is critical for maximizing yield, quality and market value of fruits and vegetables. Traditional methods often rely on manual observation and farmer experience, which can be subjective and influenced by environmental variability. Artificial intelligence (AI) offers a data-driven approach to improve the precision and reliability of harvest timing, enabling farmers to make informed decisions and optimize production outcomes. AI systems utilize data from multiple sources, including weather patterns, soil conditions, crop growth stages and historical yield records. Machine learning algorithms analyze these datasets to identify patterns and correlations that influence crop maturity. For instance, temperature, rainfall and sunlight exposure significantly affect the growth cycle and AI models can process these variables to forecast the optimal harvest window. Remote sensing technologies, such as satellite imagery and drone-based monitoring, further enhance prediction accuracy by providing real-time information on crop health and development.

Computer vision is another key component, where images of fruits and vegetables are analyzed to assess ripeness based on color, size and texture. Deep learning models can detect subtle changes that indicate maturity, allowing for timely harvesting. This reduces the risk of premature or delayed harvest, both of which can negatively impact quality and shelf life.AI-driven predictive tools also support farm management by generating alerts and recommendations, helping farmers plan labor, storage and transportation efficiently. This leads to reduced post-harvest losses and improved supply chain coordination. Moreover, accurate harvest predictions contribute to better market planning, ensuring that produce reaches consumers at peak quality. The integration of AI in predicting harvest time enhances agricultural productivity and sustainability. It minimizes uncertainty, improves crop quality and supports efficient resource utilization, ultimately benefiting farmers, distributors and consumers alike.

PP-48: Pricepre diction of agricultural commoditiesusing statistical methods and AI

BIRADAR S. R., BASAVARAJ HUGAR, ANITHA U
SDM College of Engineering & Technology,
Dharwad - 580 002, Karnataka
E-mail: srbiradar@gmail.com,basavarajsh.12@gmail.com,

Abstract: This paper focuses on the development of an advanced forecasting system designed to accuratelypredict commodityprices, with aparticular emphasison agriculturalproducts. The system integrates diverse data sources to provide reliable price projections that supportcritical decision-making for farmers and traders. Predict future prices of agricultural commodities with high accuracy. Identify and model seasonal trends and market cycles. It provides insights for stakeholders across the agricultural value chain. Vegetables Potato, Onion and Tomato (POT) price collected from HOPCOMS (Horticultural Producers' Cooperative Marketing and Processing Society) for prediction.The forecasting system leveragesa combination of historicalandreal-timedata.Commoditypricesforecasted yearly, monthly and weekly. Time Series Analysis is done using ARIMA and SARIMA to understand and forecast price trends. Forpredictionsdeeplearningtechnique Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) neural networks are used to capture long-term dependencies and nonlinear patterns in the data. Farmers can use price forecasts to optimize planting and harvesting and traders gain insights for inventory management and pricing strategies. This empowers stakeholders to make informed, data-driven decisions that enhance profitability and reduce market risk.

Key words: *Commodity, Forecasting, Deep Learning, RNN, LSTM, HOPCOMS, Analytics, Time Series.*

Introduction

This paper outlines the data-driven agricultural commodity price forecasting system. Designedtomitig at epersistentmarket volatility,the framework leveragesa hybrid analytical approach, integrating classical statistical time-series models with advanced deep learning neural networks. The resulting system generates highly reliable price projections, serving as a critical decision-support mechanism for stakeholders across the agricultural value chain, from local producers to regional distributors.

Market Context and Data Strategy

The Challenge of Price Volatility Agricultural markets are characterized by inherent instability. Price fluctuations are driven by a complex matrix of variables, including climatic conditions, seasonal crop cycles, and supply chain bottlenecks. This volatility creates significant risk, complicating crop planning for farmers and inventory management for traders. The proposed system synthesizes historical and real-time data to forecast market behavior, thereby reducing risk exposure.

Target Commodities: The POT Framework The forecasting model focuses on threehighlysensitive, high-demand vegetable commodities, collectivelydesignated as the POT (Potato, Onion, Tomato)

Theses pecific crops were selected due to their broad economic foot print and intenseprice sensitivity, making them ideal candidates for robust predictive modeling.

- Data Sourcing and Integrity: To ensure the models are grounded in reliable, localized realities, pricing data is sourced directly from HOPCOMS (Horticultural Producers' Cooperative Marketing and Processing Society).
- Historical Data: Establishes baseline trends, maps seasonal cycles, and trains the models on past market shock responses. Real-Time Data: Feeds current market variables into the system, enabling dynamic forecast adjustments based on immediate supply-demand shifts.

Technical Architecture

The forecastingengine utilizes a hybrid methodologyto captureboth linear market trends and complex, non-linear economic behaviors.

StatisticalTimeSeriesModeling:

- ARIMA (AutoRegressive Integrated Moving Average): Establishes a stable baseline forecast by analyzing historical dependencies and lagged pricing values under relatively consistent market conditions.
- SARIMA (Seasonal ARIMA): Extends the baseline model byexplicitlyincorporating seasonal patterns, which is critical for mapping the cyclical nature of agricultural harvests.

Deep Learning Integration: To account for unpredictable market variables and non-linear patterns, the architecture incorporates advanced neural networks:

- RNN (Recurrent Neural Networks): Optimized for sequential data, RNNs capture short-term temporal dependencies within historical price sequences.
- LSTM (Long Short-Term Memory): This advanced RNN architecture excels at learning long-term dependencies. By retaining crucial information over extended periods and filtering out market noise, LSTMs effectively model the delayed impactof complex market events.

Operational Outputand Value ChainImpact

Forecasting: The system is engineered to out put fore casts across distinct time frames, aligning with diverse operational requirements:

- Weekly Horizon: Designed fort actical decisions such asspotpricing, immediate transport scheduling, and short-term market entry.
- Monthly Horizon: Designed for operational planning, including logistics, temporary storage management, and mid-season strategy adjustments.
- Yearly Horizon: Designed for strategic planning, supporting macro-level crop selection, long-term land allocation, and annual planting decisions.

Stakeholder Impact

- Agricultural Producers: Empowers a shift from reactive farming to proactive crop management. Accurate forecasts allow for optimized planting and harvesting schedules, improving income stability.
- Traders and Distributors: Provides critical fore sight forinventory control and dynamic pricing strategies, significantly reducing spoilage rates for perishable goods.

Conclusion

By fusing localized HOPCOMS data with the predictive power of hybrid machine learning models (ARIMA, SARIMA, RNN, LSTM), this system delivers a highly scalable forecasting tool. It successfully bridges the gap between advanced artificial intelligence and practical agricultural management, ultimately enhancing profitability, reducing risk, and reinforcing the resilience of the agricultural supply chain

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Theme VII

AI in Livestock, Dairy and Fisheries

PP-49: Next-Gen farming of livestock and poultry farming in india

ANIL KUMAR G. K. AND JAYASHREE PATTAR

Department of Animal Sciences, University of Agricultural Sciences, Dharwad

E-mail: anilkumargk@uasd.in

Livestock and poultry production areone of the driving forces of Indian agriculture and allied sectors since the last decade as they are contributing significantly to Indian economy and food security. The Gross Value Added (GVA) of livestock sector is about Rs 13,55,460 crores at current prices during FY 2023-24 which is about 30.87 % of Agricultural & Allied Sector GVA. Over the pastdecade, the Gross Value Added (GVA) has nearly tripled from the year 2014–15 to 2023–24 with a growth of 12.77%. In addition, about 16.44 million workers are employed in livestock farming activities including fisheries and aquaculture. Further, it is expected that thecontinuous increase in our population, increasing purchase power and health consciousness of the middle class in our country will continue to increase the demand for livestock products such as milk, meat and eggs. The success oflivestock enterprises depends on understanding the scientific techniques of management of various livestock species, acquiring the skills by the individuals managing the farm, marketing capabilities of livestock and livestock products and better productivity of the livestock farms.

The traditional livestock farming in our country follows a low input-low output system with small unit sizes i.e., small number of animals per household/livestock farm. The productivity of the animals are usually low, the facilities provided to animals and the interventions provided to livestock and poultry are minimal. While this has worked out well in our country so far, the burgeoning population along with increased demand for the livestock products has necessitated the changes in the structure of livestock farming in the country.

Next-Gen Livestock and Poultry farming

In India, now the Livestock production is moving from a subsidiary farming to Agriculture to the primary farming. These farms with the primary goals to produce livestock products are high input-high output type of farms with large number of animals with the main focus on intensification of the production. The sustainability of these farms depends on the high production, production of quality products and productivity of farms. The use of scientific management practices, understanding the consumer preferences, production of quality livestock products and traceability of the livestock products are essential for sustenance and profitability of the intensive livestock farming. The availability of skilled labor, constant monitoring of livestock and keeping track of production at the farm are challenging when the number of livestock or poultry are in large numbers. The use of technology driven solutions such as automation and use of Artificial Intelligence driven equipments/software can be the way forward to manage the intensification of production systems in livestock and poultry farming.

Use of automation of livestock management systems

The automation of some of the management practices have been successfully incorporated into the management of livestock farms in most of the western countries. The development of sensor technology has helped in development of these technologies. Some of the automotive technologies that are essential in Indian conditions are:

1. Automation of milking in dairy farms.

The use of milking machines is one of the most successful interventions in dairy farming that has revolutionized the way the milk is collected and stored in a dairy farm. The invention of the pulsator in 1917 lead to the production of automated milking machines. In 1950's, the use of pipelines and collection of milk directly to milk tanks followed by cooling systems and monitoring of milk temperature has substantially reduced the human intervention, increased the milk quality and efficiency in milk collection. The use of robotics in milking was developed subsequently and being used in some large farms in Europe and USA.

2. Precision feeding systems.
   Precision feeding systems have been developed and used worldwide in large farms. The Calan Broadbent feeding system has been used to monitor the feed intake of ruminants and small ruminants primarily for research purposes. The use of precision feeding system would enhance the productivity of the farms by monitoring the feed intake by individual cows or group of cows.
3. Rumination monitors.
   The monitoring of number of ruminations indicates the status of digestive health of the cattle.
4. Identification of animals in heat or sick.
   Probes are used to monitor the movement of animals based on which the animals that may be in heat/estrus or may be sick are easily identified.
5. The automation of sprinklers and coolers in animal sheds will enable cooling of the sheds based on the micro-environment of the sheds. This will help control heat stress in summer.
6. Automatic body scanners and sensor based body temperature monitors.
   These will monitor the body temperature and identify animals that may have health problems. The body scanners help in body conditions scoring of the dairy cows or other livestock to follow up with immediate interventions.
7. Automated waterers for the supply of water throughout the day. The monitoring the quality of water provided and water intake level by each animal will help to maintain the health and production of the animals.
8. Facial recognition of livestock to monitor the heard strength and health of animals.
9. Efficiency of space utilization by monitoring the movement and resting period of the animals and their stress levels. This will help determine the size of a herd in a particular sized animal shed. If the animals are stressed due to more animals, we can reduce the numbers. We can have enough numbers until it does not affect the movement and resting period of each animals.

Automation in Poultry Farming

In India, of all the livestock production systems, the poultry industry is already using automation at different aspects of management. However, the AI enabled systems are expected to be incorporated in the poultry industry sooner or later. The automation of feeding and watering and temperature controlled housing has enabled handling of large number of birds in each poultry shed with minimal human intervention. The sensors, robotics and tools with artificial intelligence could be easily adopted in poultry farming.

1. Use of automated feeders and waterers.
   The feeding time and quantity can be remotely controlled and regularly dispensed to all the birds in a preplanned manner with little human intervention.
2. Segregation and grading of eggs.
3. Automated collection of eggs.
4. Automation of hatchery management.
5. Quality grading of chicks.

6. Control of micro environment of poultry housing.
7. Monitoring micro environment in the feed storage units
8. Automation of feed processing units.

Conclusion

The livestock and poultry production in India are shifting gradually to an intensified system of management. The use of automation is the way to move forward to increase the profitability of these farms as the skilled labor is one of the most expensive and limited resource that is available in India. However, the cost of mechanization is one of the limiting factors until now. The successful support for setting up of large livestock farminfrastructure and processing of livestock products through several schemes of the government is helping to change the way of livestock farming in India. However, there is not much basal data to develop Artificial Intelligence based applications as yet in India. The first priority should be to mechanize the farms, collect the data for the different types of farms and animals and then develop Artificial Intelligence driven applications for the use of equipment that are useful to Indian conditions. The automation of livestock farms using data from western countries will have to be verified before being implemented as the type of animals and the management systemsin India are quite different.

PP-50: Application of AI tools in dairy farming

JAYASHREE PATTAR., ANILKUMAR G. K., SANGEETA JADHAV., PATIL A. S., AND BHAGIRATHI B. K.

Dairy Unit, MARS, Dharwad, University of Agricultural Sciences, Dharwad - 580005, Karnataka India.

E-mail: pattarjk@uasd.in

Introduction

Nowadays conventional dairy farming is very difficult to manage as it faces lot of challenges in milk production, quality, labor, reproduction, feed wastage, lack of knowledge in balanced feeding etc. Also diagnosis of the disease in livestock is very challenging as it depends of history given by farmers, overlapping of clinical symptoms, difficulties in manual inspection which cause unnecessary stress to animals and hinder the exact diagnosis of disease. In the present era, dairy farming is rapidly counteracting these challenges by emerging AI (Artificial Intelligence) tools which helps to optimize the animal health, nutrition, milkproduction and reproduction through Internet of Things(IoT) sensors, computer vision and machine learning etc.

AI Tools and Platforms in Indian Dairy Farming: The Indian dairy sector, a pivotal contributor for national nutrition and rural livelihoods, is presently transitioning toward technology-driven modernization. The real revolution happened in recent years. In 2022, OpenAI released ChatGPT, a powerful AI language model capable of generating human-like text and assisting in various tasks.Nitara is theIndia's first AI-powered precision dairy platform which designed for individual farmers and organizations to optimize herd management and dairy operations through data. Various Indian agri-tech startups are using IoT sensors combined with machine learning to track animal behavior, detect diseases early (such as lameness), and manage feed, enhancing productivity in the unorganized sector.Computer Vision Solutions are increasingly used for monitoring cow behavior and health. Sarlaben AI App (Amul) is launched in early 2026 for 3.6 million farmers, this app provides real-time AI-powered guidance on livestock health, pregnancy, vaccination, and nutrition management.

Major applications of AI tools in dairy farming

1. **Automated monitoring of animal health and behavior**
   - Collars & Ear Tags: They are wearable sensors like Nedap SmartTag or SCR Heatime which monitor the rumination, eating, activity, heat detection, and resting time. They detect early signs of illness or stress mainly indigestion, traumatic reticular pericarditis (TRP).
   - Computer Vision (Camera Systems): Systems like CattleEye or Cainthus use cameras to monitor feeding behavior, lameness (via gait analysis), and body condition score (BCS) automatically
   - Ingestible Sensors (Boluses): These sit inside the rumen to measure internal body temperature and pH, detecting estrus (heat) or health issues with 0.1-degree precision
2. **Reproductive Management**
   - AI Heat Detection: AI algorithms analyze data from wearable sensors to determine the most fertile period for insemination, replacing manual observation.
   - Calving Alerts: Specific tools like VelPhone (Medria) or camera-based maternity systems is a highly accurate vaginal thermometer system designed to predict and monitor dairy cow calving,

providing alerts up to 48 hours in advance. This digital tool improves calf survival rates and saves farmers time by detecting the optimal time for intervention

- Genetic Selection Tools: Platforms such as Nitara Nasl is a semen scan technology which scan the semen straw to analyze genetic data and recommend the best bull semen for specific cattle traits thereby providing the efficient breeding management.

3. Robotic Milking and Feeding

- Robotic Milking Systems (AMS): The leading companies were Lely, DeLaval, GEA, BouMatic Robotics, and Fullwood Packo. These VMS is the machine where robots automatically milk cows, identify individual animals, and adjust settings per cow.Thereby enable higher milking frequencies, improved herd data management, and increased milk yield.
- AI Cameras for Parlor Practices: Cattle Care uses cameras to monitor milking parlor hygiene and behavior, flagging non-standard routines.
- Automated Feed Management: Cainthus ALUS Nutrition is AI-driven, computer vision technology designed to optimize dairy farm operations by monitoring cow nutrition and feeding behavior 24/7. There by laying a pivotal role to further increase farm profitability and sustainability.

4. Farm Management and Analytics

- **Integrated ERP Systems:** These provide a unified digital platform to manage the entire lifecycle-from milk procurement and quality testing to production, inventory, logistics, and farmer payments. These systems optimize costs and enhance traceability by automating Fat/SNF-based payments, monitoring milk quality parameters, managing shelf-life, and enabling end-to-end supply chain transparency. Solutions like Nitara, FarmPro, Navfarm, and Connecterra were the major integrated ERP systems for dairy farming.
- GauGuru (Chatbot): An AI assistant that provides instant expert advice on dairy management and cattle health.
- Cattle Valuation/Weight Analysis: AI tools that calculate a cow's weight or estimate its financial value instantly based on images or lactation data.

5. Sustainability and Waste Management

- **Methane Emission Monitoring:** AI algorithms are used to predict methane emissions based on diet and lactation stage, helping reduce the farm's carbon footprint. Methane SAT (Google Cloud/EDF), MARS-S2L (UNEP/IMEO), Shoreline AI 24x7 Ready, iFactory, Eni Gas Sensor Node (GSN) etc were the major methane emission monitors
- **Robotic Manure Collection:** Robotic manure collection systems are increasingly incorporating AI, IoT, and advanced sensors to automate barn cleaning, improve animal welfare, and enhance nutrient management. These systems, ranging from autonomous scrapers to collectors, are designed to operate 24/7, reducing labor costs and improving hygiene thereby reduce disease incidences.

In conclusion use of AI technologies in the dairy farming enables automatic feeding of balance diet, higher milk production (10-20%), reduce the man power, milk quality check, also helps in easy and early diagnosis of the disease which enabling the precision livestock farming. Despite of the major challenges like high initial cost, management skills, infrastructure gaps, lack of digital literacy etc, AI tools play a pivotal role in the future of innovative and precision dairy farming, especially in large and commercial operations Over all application of AI tools helps the farming community for sustainable dairy farming through reduced output cost (15-25%), early treatment, good quality milk, balanced nutrition and calf per year.

Theme VIII
Policy, Ethics and Socio-economic Impacts

PP-51: Mapping agricultural innovation networks: social network analysis applications in smart farming

MANJULA N., APOORVA KOLI, SHIVANAND KAMMAR, NOOLI S. S., ANILKUMAR G. K., PRAKRUTHI S. N., PRAJWAL B. P.

[1]M.Sc. Scholar, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India
[2]Ph. D. Scholar, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India
[3]Professor, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India
[4]Associate Professor, Department of Agricultural Extension Education, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India
[5]Assistant Professor and Head, Department of Animal Science, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India
[6]Scientist (Agronomy), AICRP- Sugarcane, ARS, Sankeshwar, Karnataka, India

Introduction

Modern agriculture is undergoing a fundamental transformation, shifting from isolated, individual decision-making systems towards interconnected, knowledge-driven ecosystems (Klerkx, Van Mierlo, &Leeuwis, 2012). This transition is propelled by [the] convergence of digital technologies, data analytics, and precision farming tools collectively referred to as smart farming (Wolfert, Ge, Verdouw, &Bogaardt, 2017). However, the success of these technological advancements is not determined by technology alone; rather, it is deeply rooted in the social, institutional, and informational networks that link farmers, researchers, extension agents, input suppliers, and agri-tech platforms.

Against this backdrop, Social Network Analysis (SNA) emerges as a powerful methodological framework for understanding how relationships and information flows within Agricultural Innovation Networks (AINs) shape technology adoption (Borgatti, Everett, & Johnson, 2018). It explores the application of SNA to map and analyze these networks, with the aim of identifying structural factors that either accelerate or impede the diffusion of digital agricultural technologies, particularly in developing country contexts.

Smart Agriculture: Growth and Adoption Disparities

The global smart agriculture market is witnessing unprecedented growth, projected to reach USD 80 billion by 2030 (Markets and Markets, 2023). This growth reflects the rapid integration of technologies such as remote sensing, Internet of Things (IoT) devices, artificial intelligence, drone-based monitoring, and data-driven decision support systems into farming practices. These innovations promise enhanced productivity, resource efficiency, and climate resilience.

Despite this optimistic outlook, adoption remains profoundly uneven. In developing countries, digital agriculture uptake is estimated at below 40%, a stark contrast to the technology-rich environments of advanced economies. Even within developing regions, large-scale commercial farms are significantly more likely to embrace precision agriculture technologies with nearly 60 per cent of such farms expected to adopt these tools in the near future while smallholder farmers continue to lag behind. The primary drivers of this disparity include limited access to information, inadequate infrastructure, constrained financial resources, and weak institutional support systems.

Critically, research underscores that these barriers are not purely economic or technological in nature, they are fundamentally social and relational. Farmers who lack access to well-connected networks of knowledge and support are structurally disadvantaged in their ability to discover, evaluate, and adopt new innovations regardless of whether the technologies themselves are physically accessible.

Social Network Analysis as a Methodological Framework

Key Actors in Agricultural Innovation Networks

SNA provides a systematic approach to identifying and evaluating the roles of diverse actors within AINs. These actors include farmers, agricultural extension agents, input dealers, agri-tech platform providers, government agencies, research institutions, non-governmental organizations, and financial service providers. Each actor occupies a distinct position within the network and contributes differently to the flow of knowledge, technology, and resources.

Network Metrics and Their Significance

Three core metrics lie at the heart of SNA applications in agricultural innovation contexts:

Degree Centrality: This metric measures the number of direct connections an actor has within the network. Actors with high degree centrality are influential hubs they have access to more information and are better positioned to influence the behaviour and decisions of others (Freeman, 1979).

Betweenness Centrality: This metric identifies actors who serve as bridges between otherwise disconnected parts of the network. High betweenness actors control the flow of information across sub-groups, making them strategically vital for ensuring that innovations reach peripheral or isolated farming communities. Disruption or absence of such bridge actors can significantly fragment information pathways (Borgatti *et al.,* 2018).

Network Density: Density reflects the overall interconnectedness of the network the proportion of actual connections relative to all possible connections. Denser networks facilitate faster and more reliable information diffusion, foster trust among actors, and create an environment conducive to collective learning and collaborative innovation adoption (Wasserman & Faust, 1994).

Empirical findings from studies applying SNA in agricultural contexts reveal that farmers embedded in well-connected, high-density networks are two to three times more likely to adopt new agricultural innovations compared to those operating in weak or fragmented networks.

Smart Farming as a Network-Driven Transformation

Acentral insight is that smart farming must be understood not merely as a technological shift, but as a fundamentally social and network-driven transformation (Klerkx *et al.,* 2012). The availability of precision agriculture tools, sensor technologies, or AI-based advisory systems is a necessary but insufficient condition for widespread adoption is what ultimately determines whether these technologies translate into on-farm practice is the quality, reach, and inclusiveness of the networks through which knowledge and trust are transmitted.

The role of digital extension platforms deserves particular attention in this context. Traditional extension systems relying on face-to-face knowledge transfer between extension officers and farmers are inherently limited in their scale and reach. Digital platforms, including mobile advisory applications, farmer WhatsApp groups, online marketplaces, and e-learning portals, have the potential to dramatically expand network connectivity. When leveraged effectively, these platforms can act as force multipliers, enabling high-betweenness actors to simultaneously engage with multiple farmer communities across geographically dispersed areas.

Furthermore, the presence of influential actors such as opinion leaders, progressive farmers, or well-connected agri-entrepreneurs within networks can catalyse broader adoption (Rogers, 2003). SNA provides the tools to identify these actors systematically, enabling targeted interventions that harness their influence for accelerated and more equitable technology diffusion.

Policy and Extension Implications

SNA carries significant practical implications for policymakers, development practitioners, and agricultural extension professionals. First, policy frameworks aimed at promoting smart farming must move beyond hardware and infrastructure investments to explicitly address network gaps. Identifying and strengthening weak linkages whether between research institutions and farmers, or between input dealers and smallholder communities is essential for ensuring that technological innovations permeate all segments of the agricultural sector.

Second, extension services need to adopt network-oriented intervention designs. Rather than deploying blanket outreach programmes, extension agencies can use SNA-derived insights to prioritise engagement with high-centrality actors, build new bridge connections in fragmented communities, and design digital platforms that align with existing social structures. Such targeted approaches are likely to yield a significantly higher return on investment in terms of innovation diffusion outcomes.

Third, the integration of SNA into monitoring and evaluation frameworks for agricultural development programmes can provide richer and more actionable insights into why certain interventions succeed or fail (Borgatti *et al.,* 2018). Traditional evaluation metrics tend to focus on individual adoption rates; network-level analysis can reveal systemic bottlenecks and structural barriers that would otherwise remain invisible.

Conclusion

It demonstrates that Social Network Analysis offers a robust and insightful lens through which to understand and improve the diffusion of smart farming technologies by mapping Agricultural Innovation Networks and evaluating their structural properties, SNA moves the discourse on technology adoption beyond individual-level analysis towards a systemic understanding of the relational and institutional fabric of agricultural transformation.

In an era defined by rapid digital change and mounting pressures on agricultural systems from climate change, population growth, and resource constraints, building resilient and inclusive agricultural innovation networks is not optional, it is imperative. Strengthening these networks, enhancing digital extension platforms, leveraging influential actors, and bridging structural gaps between technology availability and actual adoption will be critical to building agricultural systems that are not only more productive, but also more equitable and sustainable.

Key words: Social Network Analysis, Smart Agriculture, Technology Adoption, Agricultural Innovation Networks, Digital Agriculture, Extension Services

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Theme X
Emerging Technologies

PP-52: Innovative minds: AI- driven approach in agricultural education

MOOD TEJASWINI, GEETA TAMGALE, RAJESHWARI N AND RENUKA SALUNKE

[1]M.Sc. Scholar, Department of Extension Education and Communication Management,
College of Community Science, University of Agricultural Sciences, Dharwad- 580008
[2]Assistant Professor, Department of Extension Education and Communication Management,
College of Community Science, University of Agricultural Sciences, Dharwad- 580008
[3]Professor and Head, Department of Extension Education and Communication Management,
College of Community Science, University of Agricultural Sciences, Dharwad- 580008
[4]Professor, Department of Resource Management and Consumer Sciences,
College of Community Science, University of Agricultural Sciences, Dharwad- 580008

Abstract: Artificial intelligence(AI) in agricultural education is becoming crucial due to present demands in the educational system, but there remains a significant gap between its understanding and practical application among postgraduate students, who will later become agricultural extension professionals. The present research study investigates the knowledge and adoption of AI applications, adoption barriers, and ICT (Information and Communication Technologies) exposure of 30 postgraduate students from State Agricultural Universities. The data was collected using the questionnaire method, along with teacher-made tests. The results revealed that students spend an average of four to eight hours a day on digital tools, including WhatsApp and YouTube. Although most of them are unaware of AI in agriculture-related modules, they were familiar with popular AI tools like ChatGPT, Perplexity, and Grammarly, which results in restricted practical application in agricultural education. Adoption is driven by performance expectations and simplicity of use; AI anxiety and ethics are of least concern to the students. This survey revealed a strong theoretical understanding of AI technologies, but low actual use because of knowledge deficiencies. Exposure to ICT marginally correlated with adoption intention. However, actual usage remains limited due to proficiency gaps, while daily exposure to digital ICT tools shows a promising correlation with adoption intention. These reliable findings (Cronbach's α=0.76-0.87) highlight AI tools in agriculture education as untapped AI potential. The research indicates that even though the ICT digital tools infrastructure is strong, students are well-versed in AI and willing to use it at the postgraduate level, but the implementation of AI into practice remains limited due to skill shortages. Ethical use of AI and targeted training in agricultural educational applications are necessary to shorten the gap and empower future extension professionals.

Key words: Artificial Intelligence, Agricultural Education, Empower, ICT digital tools.

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