CSE 707
Distributed Computing Systems

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Paper Title

“Distributed and Parallel simulation methods for pest control and crop monitoring with IoT assistance”

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Introduction

- Modern Agriculture embraces advanced technology for pest control and crop monitoring.
- A Distributed and Parallel Simulation Framework (DPSF) with IoT support is proposed for this purpose.
- DPSF utilizes a multi-threading concept for collaboration among GPU cores.
- Four layers manage specific tasks: Crop management, Pest detection and control, Output functions, and Input functions.
- DPSF optimizes task distribution and reduces GPU workload.
- The system enhances data management, allowing effective pest classification and control.

Module system acquisition

- Artificial intelligence supports remote control applications.
- IoT devices enable the sensing of field variables like relative humidity, humidity, and pH through wireless communications.
- Real-time atmospheric data processing involves various sensors, including thermometers, precipitation sensors, and soil temperature sensors.
- Historical weather and humidity data are collected through standard datasets.
- Some of this data is obtained from farmers.

Module for data treatment

- Reduction is a paradigm for efficiently gathering vast amounts of data in decentralized environments.
- It's possible to parallel process data using this paradigm.
- The Hadoop Control Framework, a free software, supports mapping models for reduction.
- Encoding extensive information on traditional hardware servers can be challenging.
- Processing personal data involves techniques like description and estimation.

Proposed DPSF with IoT Assistance

- Data is collected in various formats, including weather, precipitation, soil, and pH sensing for accuracy.
- Historical data is gathered through regular data sets.
- Local producer responses contribute to a collection of big data.
- Clustering and identification technology categorize field specifications and results.
- Integrating statistical and machine technology in agriculture promotes sustainability and higher production.
- Artificial intelligence enhances remote control, with IoT devices sensing field factors like humidity and pH.
- Different sensors enable real-time atmospheric data analysis.
- Data sets collect historical weather and moisture data.

Proposed DPSF with IoT Assistance

- DPSF with IoT Assistance system architecture is depicted in Figure 1.
- Organized and unorganized data sets are used in cultivation for various purposes.
- Climatological service holds organized weather and climate data, while unorganized data comes from sensors.
- Device implementation extracts essential primary information using a justice system.
- The system includes a forum for crop management through Cloud Computing and ICT.
- DPSF employs multi-threading for efficient task handling across GPU cores in four layers.
- Simulation analysis shows the efficiency of DPSF with IoT support in pest management.
- Analyzing disorganized data sets helps identify crop constraints and guide future agricultural technologies.
- Data is stored in a local cloud infrastructure, and web services are provided for family farms when needed.

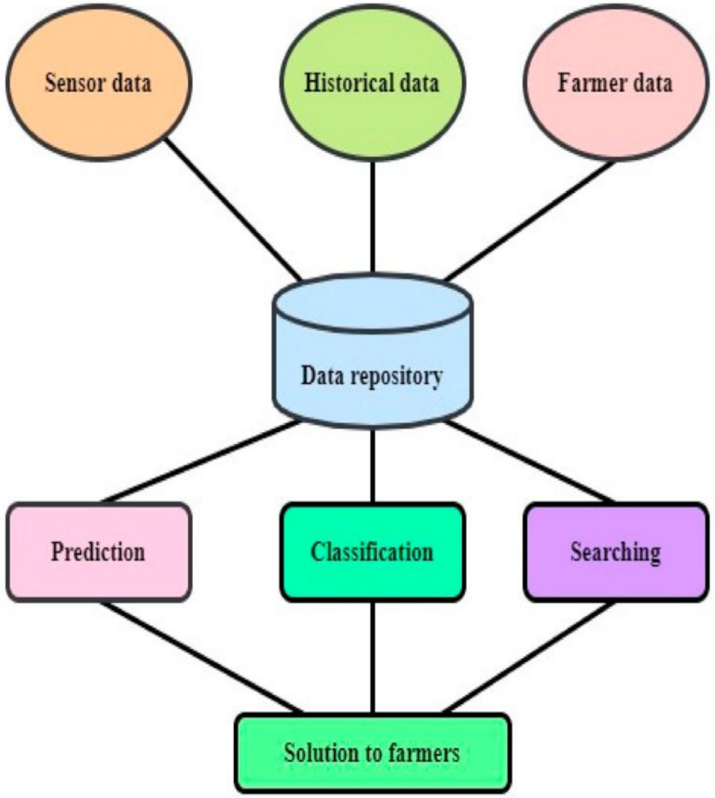

Figure 1. DPSF with IoT Assistance system architecture.

Measurement of the features of crop production

- Ecological factors and pests influence crop development.
- In-field surveillance and various methods like criteria extraction are used.
- VARIrededge and GNDVI are used to assess plant characteristics.
- Data collection formats include sensors for weather, rain, soil, and pH.
- Historical data is gathered through regular data sets.
- Local producers contribute to a significant data pool.
- Clustering and identification techniques categorize field requirements.
- The integration of statistical and machine technology is beneficial for agriculture.

$$GNDVI = \frac{(Rnir - Rg)}{(Rnir + Rg)} \quad (1)$$

$$VARIrededge = \frac{(Rrededge - Rr)}{(Rrededge + Rr)} \quad (2)$$

- Equations (1) and (2) calculate GNDVI and VARIrededge, reflecting plant characteristics based on reflectance values.

Measurement of the features of crop production

- Figure 2 illustrates GNDVI graphically.
- Rnir and Rg represent near-infrared and green leaf reflectance.
- Grain and pest surveillance relies on atmospheric details.
- Landsat 8 imaging captures a wide spectral range.
- Moistness and lightness are crucial for practical conversion.

$$\begin{aligned} Wetness = {} & wt1*b1 + wt2*b2 + wt3*b3 + wt4*b4 \\ & + wt5*b5 + wt6*b6 \end{aligned} \tag{3}$$

- Wetness (Equation 3) measures water content.

$$\begin{aligned} Greenness = {} & gr1 \times b1 + gr2 \times b2 + gr3 \times b3 + gr4 \\ & \times b4 + gr5 \times b5 + gr6 \times b6 \end{aligned} \tag{4}$$

- Greenness (Equation 4) gauges crop growth.

$$T = \frac{k2}{\ln\left(\frac{k1}{L} + 1\right)} \tag{5}$$

- Mean temperature (Equation 5) assesses crop health and is obtained from Landsat imaging data (TIRS-1).
- (k1) and (k2) are translation coefficients, and L is the total crop field length used in mean temperature calculation.

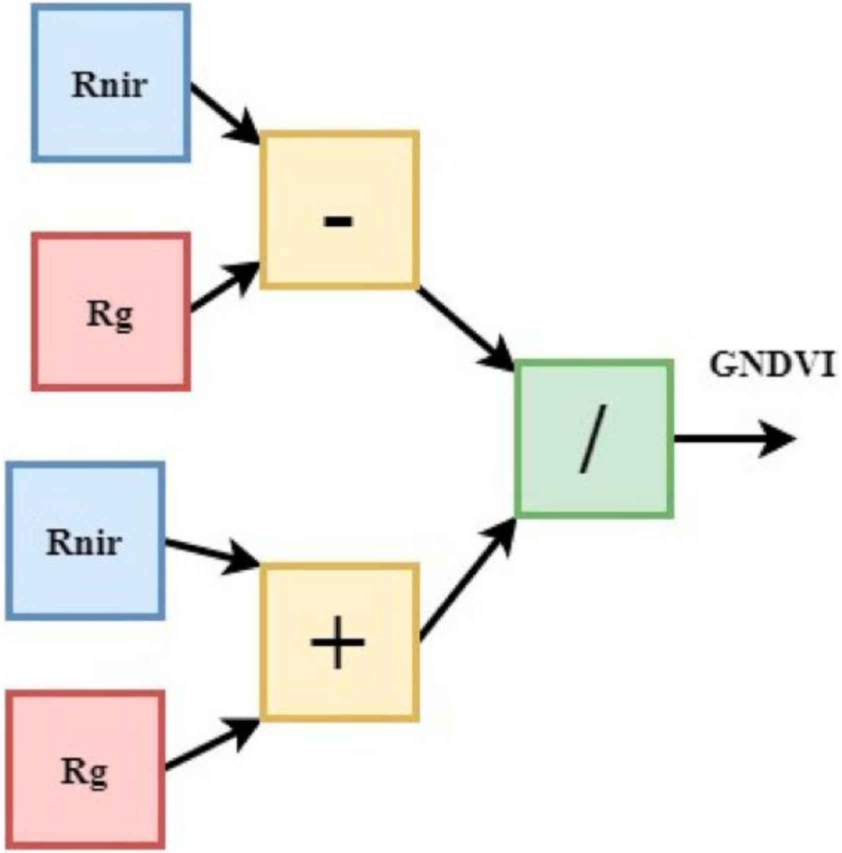

Figure 2. Pictorial representation of *GNDVI*.

Measurement of the features of crop production

- Figure 3 illustrates T, supported by the TIRS-1 group.
- Translation coefficients (k1) and (k2) are used for data conversion.
- L represents the total crop field length.
- Mean temperature, derived from Landsat imaging (TIRS-1), assesses crop health, insect and disease severity, and plant photosynthesis.

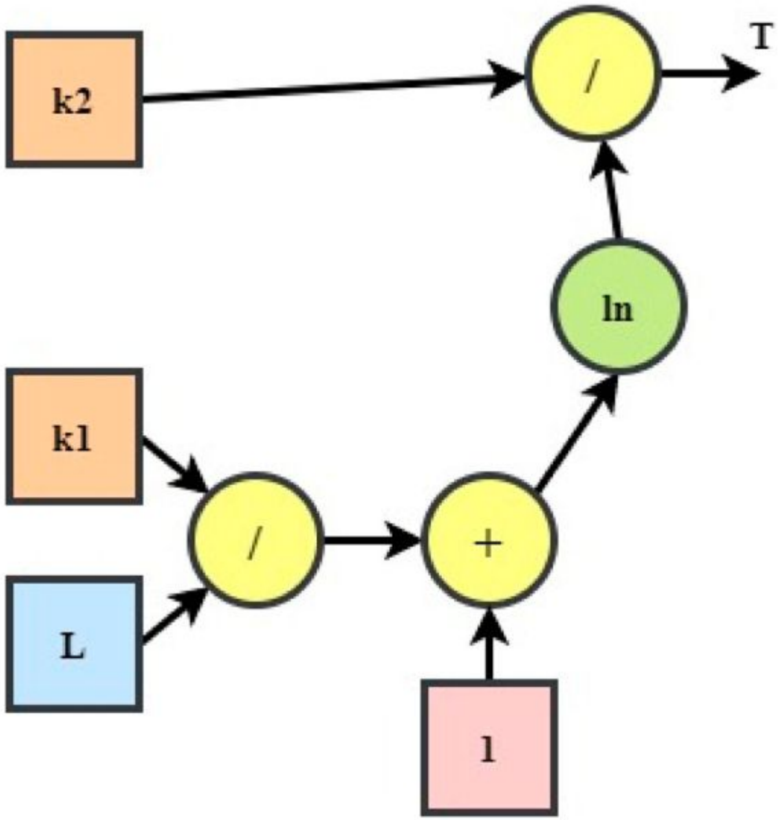

Figure 3. Pictorial representation of T.

Designing Field Conditions for Pest Habitats

- A t-test study aimed to distinguish regular and contaminated classes using specific development and ecological variables.
- Linear discriminant analysis (LDA) assessed energy and water properties for in-field crop and pesticide ecosystem measurements.
- Two approaches were used, one integrating growth features and the other including development and geographic elements.
- A confusion matrix tested prediction performance, assessing metrics like general accuracy, consumer accuracy, committee error, and faulty error.

$$B = WP \sum_{r=1}^{R} Tr \qquad (6)$$

- Crop simulation models estimated biomass output (B) using irrigation water (WP), grain sweating (Tr), and CO2 levels (Equation 6).
- Canopy Cover (CC) measured evaporation rate, related to seasonal rainfall in various countries.

A framework of Canopy Covering

- Four criteria define canopy growth and apoptosis in the optimization technique: CC0, CGC, CCx, and CDC.
- Linear Discriminant Analytic Plans are employed for in-field crop and pesticide environment data to evaluate energy and water characteristics.

$$\textit{Soil fertility} = 1.34\,(CCx) - 22.324 \qquad (8)$$

- The soil quality and soil fertility (Equation 8) affect canopy growth and crop production, with Ksccx as a function of tension.
- Recalibration of canopy production is necessary and involves re-calibrating CC0 and CGC based on soil fertility.

$$CC = CC0\ e^{CGCt} \qquad (9)$$

- The vegetation production coffee governs foliage creation, and canopy decrease is recalibrated as CC decreases (Equation 9).
- Researchers aim to provide a two-week window for reacting to potential crop damage by re-calibrating CC.

$$CDC = 3.452 \times \left(\frac{CCx + 2.29}{3.33t}\right) \qquad (11)$$

- A traditional grain cutting method is supplemented with canopy re-calibration using cell death and maturity (CDC) (Equation 11).
- Sentinel-2 NDVI data can be used for reconfiguration, with little advantage in waiting for further firmware upgrades.

Compilation of plant genomic information

- Pheno-typical data in plant pathology includes diverse data types like visible, neurotic, and infrared.
- These data sources, structured or not, provide valuable insights into crop mutations.
- Intelligent analysis covers identification, encoding, and controlling scientific information on genetic plant arrays.
- Organized and transactional text data are essential for effective management.
- Advancements in intelligent detection, measurement, and access to extensive information sources are crucial for plant pathology and genetics research.

Data collection plant morphology

- High-performance pheno-typical detection uses numerous sensors, generating vast data.
- Challenges include efficient storage, processing, and data extraction.
- Data communication can be inefficient, leading to processing strain.
- Pheno-typical data systems require organized and unstructured Big Data Solutions.
- Standardization is lacking in phenotypic data collection systems.
- Cloud-based storage is an emerging solution, offering scalability and user control.

Data collection plant morphology

- Figure 4 depicts the architecture of the DPSF with IoT Assistance system.
- The study on plant functional genomics encompasses information processing, knowledge storage, and phenotypical predictive analytics.
- Information gathering involves diverse data sources, including images, spectroscopy, climate, and global opinion indicators.
- Phenotypic data collection methods lack standardization and a unified framework.
- Data storage systems typically employ separate standards, database designs, and power supplies.
- Cloud infrastructure serves as a dynamic network for data storage, communication, and user control mechanisms.
- The system includes data, software, and communication layers with central management and online storage.
- Various software interfaces are created based on user requirements.
- The network infrastructure relies on a cloud platform for mobile data download and management.

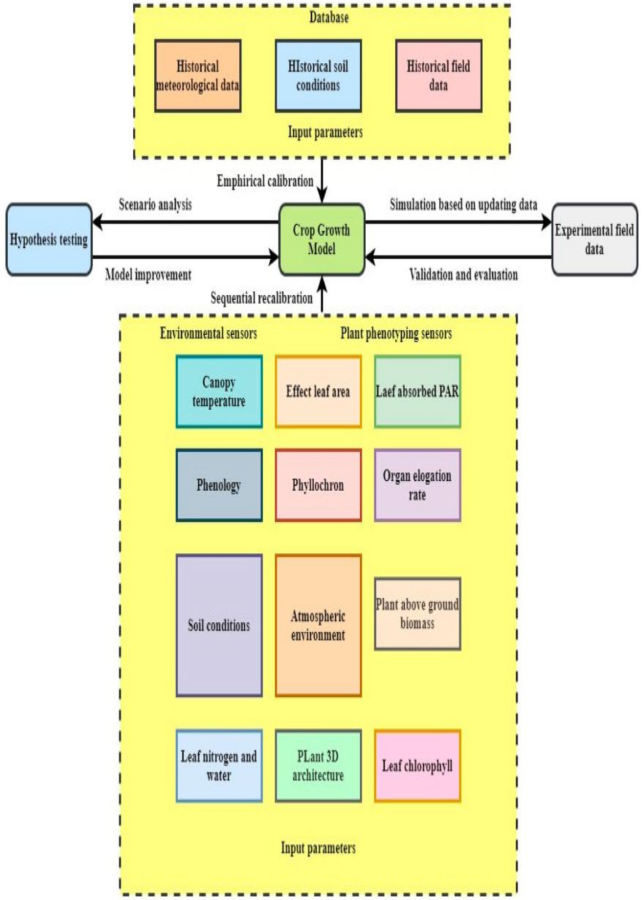

Figure 4. DPSF with IoT Assistance system architecture.

Hardware redundancies and electricity savings

- Cloud Services Benefits
- Knowledge Discovery
- Processing Framework
- Development Cycle Enhancement

Algorithm of machine learning

- Imaging translates to machine word recognition, while data recovery is the computer's language.
- Techniques like differentiation, convergence, and outline analyses are used to optimize and mine information.
- Modern architectures require not only high transaction frequencies but also handling vast amounts of data.
- Statistical analysis focuses on capturing data and gathering information for informed decision-making.

Semantic engine

- Semanticized motor relies on machine learning for effective data collection.
- Uses computer translation, emotion analytics, sentiment analysis, and other tools for expression parameters.
- Emphasizes statistical significance and industry standards for data collection and quality maintenance.
- Data aggregation serves as a constraint for usage intentions and evidence-informed policy for homogeneous microdata.

Simulating of information on plant morphology

- Learning involves constructing models from data without specific rules in AI.
- Extensive data is crucial to address complex data challenges.
- Plant mutation research is conducted at different levels due to sensor limitations.
- Semanticized engines need advanced machine learning for data collection.
- Industry standards prioritize statistical significance and data management.
- Integration of multi-scale data helps address knowledge inconsistencies.
- Plant-wide data analysis software is needed for phenotypic insights.
- Industrial IoT uses sensors and networks for agriculture and distribution.
- Smart systems improve efficiency and energy conservation in food production.
- Ahmed et al. offer technical support for efficient crop production.

Software analysis and implementation

- Omics research technology has matured with bioinformatics growth.
- Traditional omics methods focus on seed phylogenetic data.
- Researchers use AI algorithms but have limited goals in data analysis.
- Big data mining is needed for plant phenotypic data.
- Plant morphology data is complex and costly.
- Machine learning struggles with unstructured data.
- Challenges exist in information communication and preservation in seed morphology data.

DPSF with IoT Assistance: Software Implementation and Findings

- Figure 5(a), (b), and (c) compare illumination rates in the proposed DPSF with IoT Assistance system at heights of 40, 80, and 120 meters.
- Proximity of the light source to the crop affects illumination. Closeness to the crop results in higher illumination, while greater distance reduces it.
- Light source levels vary from minimum to maximum, inversely impacting illuminating intensity.

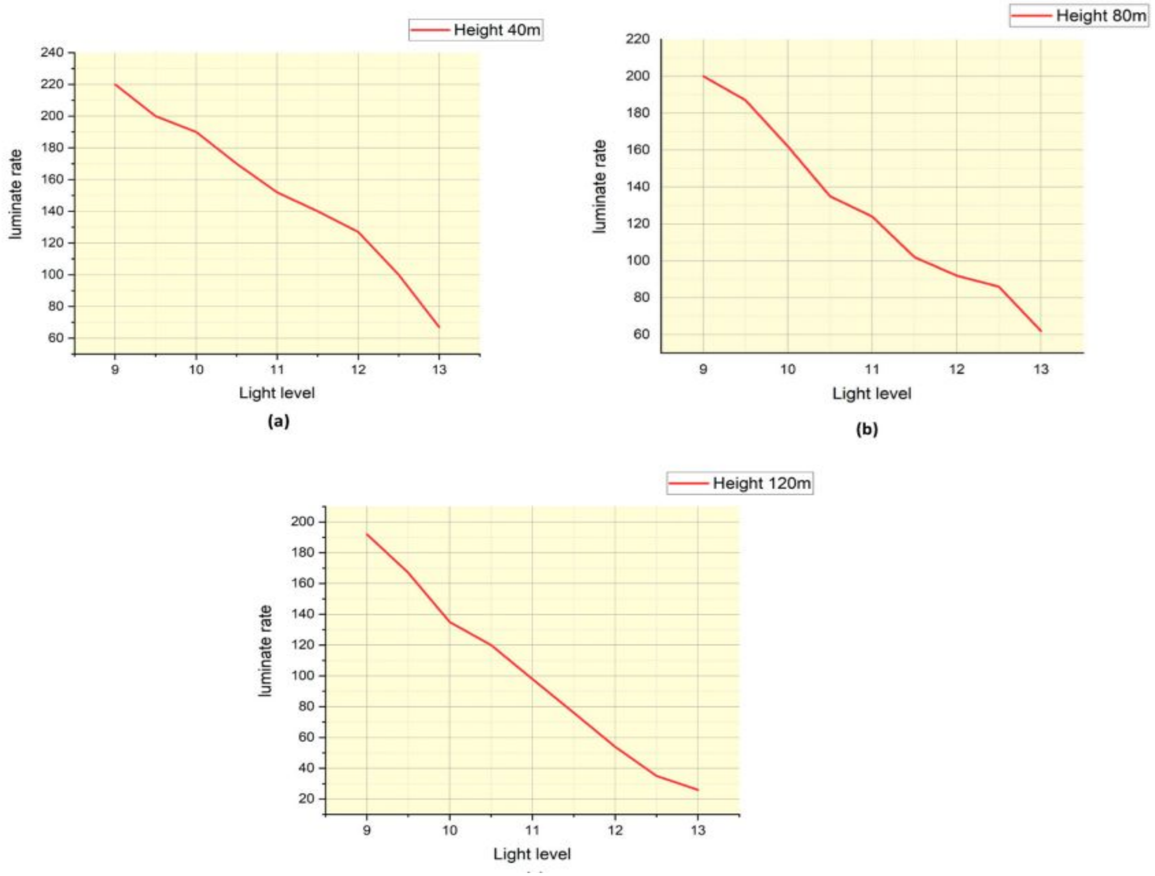

Figure 5

DPSF with IoT Assistance: Software Implementation and Findings

- Table 1 compares planting in the proposed DPSF with IoT Assistance system.
- Users vary from 1 to 10 for simulation and practical analysis.
- The table shows users' agricultural area, actual crop yield, simulated output, and predicted output for analysis.
- Smaller agricultural areas yield higher results in both simulation and practical scenarios.

Table 1. Planting a comparison of the proposed DPSF with IoT Assistance system.

			Planting	
User number	Agriculture area	Observed output (ton/ha)	Simulation output	Predicted output (%)
1	4.7	3.24	5.75	83
2	2.6	3.75	6.47	64
3	1.8	2.65	5.78	48
4	0.7	5.12	5.68	49
5	5.24	5.02	5.47	17
6	17	5.37	5.14	54
7	3.8	3.75	5.32	48
8	1.9	3.68	5.32	57
9	1.18	4.56	5.67	29
10	1.56	4.02	5.70	16

DPSF with IoT Assistance: Software Implementation and Findings

- Figure 6(a) and 6(b) display nitrogen and potash supply rates in the proposed DPSF with IoT Assistance system.
- Both nutrients' supply is analyzed in simulations and practical experiments.
- Results reveal close alignment between the proposed system's performance and predictions, demonstrating high accuracy and reliability.
- Negligible deviations exist between real-time data and the proposed system's data.

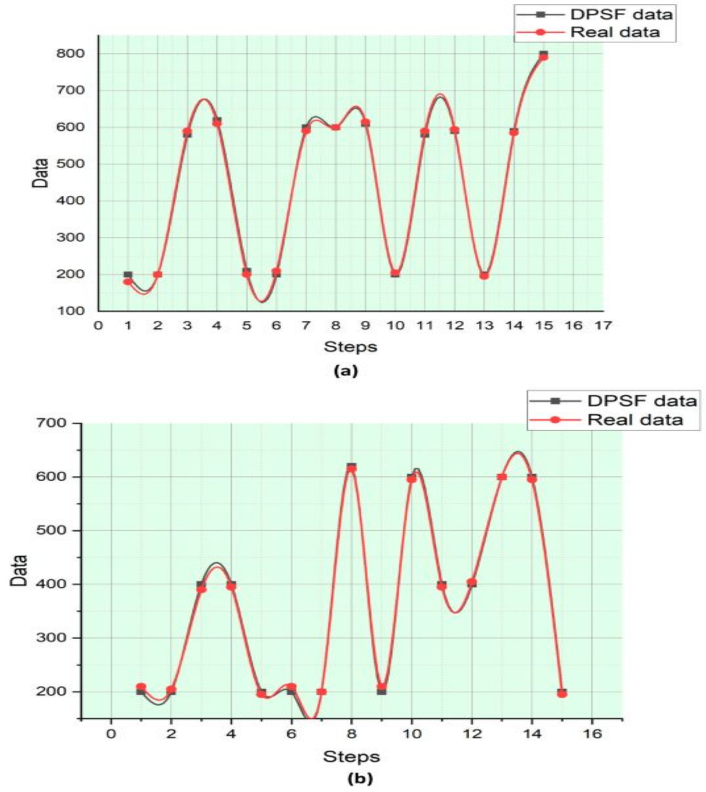

Figure 6

DPSF with IoT Assistance: Software Implementation and Findings

- Table 2 shows a full canopy comparison in the proposed DPSF with IoT Assistance system.
- Analysis includes simulations and practical experiments with users ranging from 1 to 10 and varying agriculture areas.
- Actual crop yield data is tabulated, and results are compared to predicted outputs.
- The analysis suggests that smaller agriculture areas lead to higher yields for both simulation and practical scenarios.

Table 2. Full canopy comparison of the proposed DPSF with IoT Assistance system.

User number	Agriculture area	Observed output (ton/ha)	Full canopy	
			Simulation output	Predicted output (%)
1	4.7	3.24	3.75	35
2	2.6	3.75	3.42	6
3	1.8	2.65	3.56	67
4	0.7	5.12	4.75	41
5	5.24	5.02	4.82	16
6	17	5.37	5.21	18
7	3.8	3.75	3.92	24
8	1.9	3.68	4.27	28
9	1.18	4.56	5.41	25
10	1.56	4.02	3.94	16

DPSF with IoT Assistance: Software Implementation and Findings

- Figure 7(a), (b), and (c) present a canopy cover comparison in the proposed DPSF with IoT Assistance system.
- The comparison includes scenarios of no calibration, 1 step calibration, and 2 step calibration.
- Canopy cover percentages are calculated using the formula provided in the "Proposed DPSF with IoT Assistance" section.
- Analysis involves simulations and practical experiments, considering users with varying agriculture areas.
- The results indicate that smaller agriculture areas lead to higher yields in both simulation and practical situations.

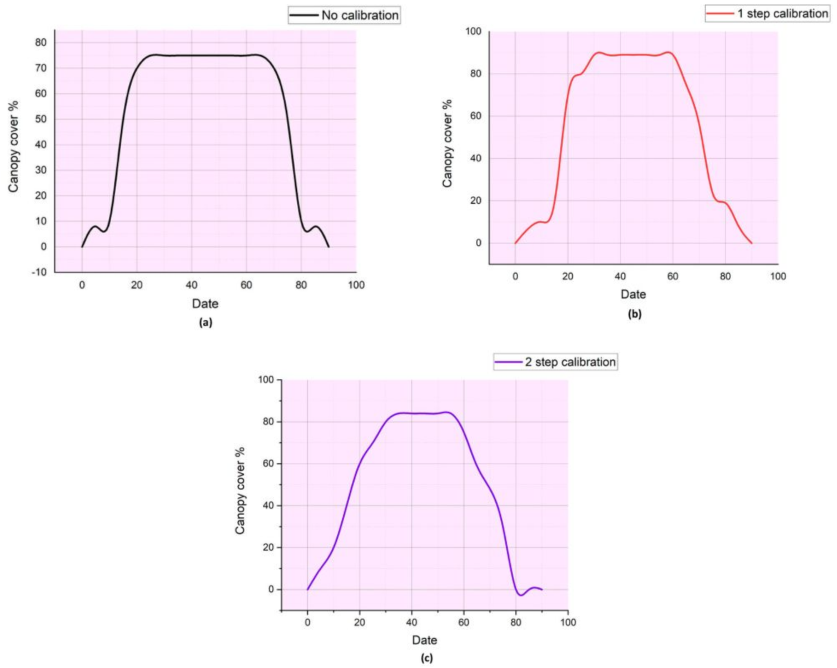

Figure 7

DPSF with IoT Assistance: Software Implementation and Findings

- Table 3 compares harvest results in the proposed DPSF with IoT Assistance system.
- The comparison considers different user numbers (1 to 10) for both simulations and practical analysis.
- The table includes data on user agriculture areas and actual crop yields.
- Smaller agriculture areas tend to yield higher results in simulations and practical applications.

Table 3. Harvest comparison of the proposed DPSF with IoT Assistance system.

User number	Agriculture area	Observed output (ton/ha)	Harvest: Simulation output	Harvest: Predicted output (%)
1	4.7	3.24	421	32
2	2.6	3.75	3.75	7
3	1.8	2.65	4.25	65
4	0.7	5.12	5.21	5
5	5.24	5.02	4.58	12
6	17	5.37	4.52	6
7	3.8	3.75	4.35	19
8	1.9	3.68	4.15	24
9	1.18	4.56	4.90	21
10	1.56	4.02	5.24	18

Conclusion

- Advanced modeling and IoT enhance crop yields.
- Development of a web-based plant surveillance system.

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