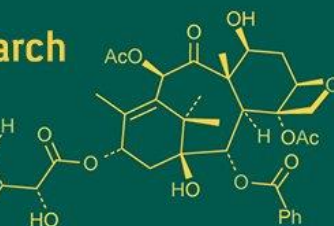
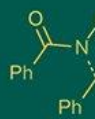
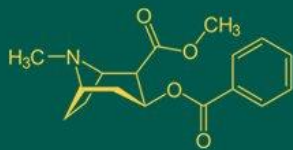


International Journal of Advanced Biochemistry Research



ISSN Print: 2617-4693
ISSN Online: 2617-4707
NAAS Rating (2025): 5.29
IJABR 2025; SP-9(10): 1937-1940
www.biochemjournal.com
Received: 08-07-2025
Accepted: 11-08-2025

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Precision agro-meteorology: Harnessing statistical forecasting models, AI tools, and IoT for real-time advisory

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DOI: <https://www.doi.org/10.33545/26174693.2025.v9.i10Sx.6118>

Abstract

Precision agro-meteorology integrates advanced technologies such as statistical forecasting models, artificial intelligence (AI), and the Internet of Things (IoT) to provide real-time, data-driven agricultural advisories. This review explores how these tools enhance decision-making by delivering accurate, site-specific weather predictions and actionable insights for farmers. Statistical models, including time-series analysis and regression-based techniques, leverage historical and real-time meteorological data to forecast weather variables critical to crop management. AI tools, such as machine learning and deep learning, process complex datasets from IoT-enabled sensors, satellites, and weather stations to predict microclimate conditions, pest outbreaks, and irrigation needs. IoT facilitates seamless data collection and transmission, enabling real-time advisories tailored to specific fields. This article reviews methodologies, including data acquisition through IoT networks, AI-driven forecasting models, and their integration for precision agriculture. Results from global case studies demonstrate improved crop yields, reduced resource waste, and enhanced resilience to climate variability. Challenges such as data interoperability, scalability, and accessibility for smallholder farmers are discussed, alongside future prospects for democratizing these technologies. This review underscores the transformative potential of precision agro-meteorology in optimizing agricultural productivity and sustainability.

Keywords: Artificial intelligence (AI), deep learning, internet of things (IoT), machine learning and statistical forecasting models

Introduction

Agriculture faces unprecedented challenges due to climate change, population growth, and resource constraints. Unpredictable weather patterns, extreme events, and shifting growing seasons threaten crop productivity and food security. Precision agro-meteorology emerges as a solution, combining meteorological science with cutting-edge technologies to deliver hyper-localized, data-driven advisories. This field integrates statistical forecasting models, AI tools, and IoT to monitor, predict, and manage weather-related risks in real time, enabling farmers to make informed decisions on planting, irrigation, pest control, and harvesting.

Background and Significance

Agro-meteorology traditionally focuses on understanding the interaction between weather and agricultural systems. However, conventional methods often rely on coarse, regional weather forecasts that fail to capture microclimate variations critical for farm-level decisions. Precision agro-meteorology addresses this gap by leveraging high-resolution data from IoT sensors (e.g., soil moisture probes, weather stations), satellite imagery, and AI-driven models to provide field-specific insights. For example, real-time advisories can recommend optimal irrigation schedules based on predicted rainfall or warn of frost risks, minimizing crop losses.

Role of Statistical Forecasting Models

Statistical forecasting models, such as autoregressive integrated moving average (ARIMA), exponential smoothing, and regression models, analyze historical weather data to predict future conditions. These models are computationally efficient and interpretable, making them suitable for integration with real-time IoT data.

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By identifying patterns in temperature, precipitation, and humidity, they provide reliable short-and medium-term forecasts.

AI Tools in Agro-meteorology

AI, particularly machine learning (ML) and deep learning (DL), enhances forecasting by processing vast datasets from diverse sources. Neural networks, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at identifying complex, non-linear relationships in meteorological data. AI models can predict localized weather events, pest outbreaks, and crop stress, offering actionable insights with higher accuracy than traditional methods.

IoT as a Data Backbone

IoT devices, including soil sensors, drones, and automated weather stations, collect real-time data on environmental parameters like soil moisture, temperature, and wind speed. These devices transmit data to cloud platforms, where AI and statistical models process it to generate advisories. IoT enables continuous monitoring, reducing latency between data collection and decision-making.

Objectives of the Review

This review aims to:

1. Evaluate the methodologies used in precision agro-meteorology, focusing on statistical forecasting, AI, and IoT integration.
2. Analyze the impact of these technologies on agricultural outcomes through case studies.
3. Discuss challenges, including data quality, scalability, and accessibility.
4. Provide recommendations for future advancements and adoption in diverse farming systems.

Scope and Relevance

The integration of statistical models, AI, and IoT in agro-meteorology is transforming agriculture by enabling precision farming practices. This review is relevant for researchers, policymakers, and farmers seeking to understand how these technologies can enhance productivity, reduce environmental impact, and build resilience to climate change.

Materials and Methods

This section outlines the methodologies employed in precision agro-meteorology, focusing on data collection, statistical forecasting, AI model development, IoT integration, and advisory generation.

Data Collection

1. **IoT Devices:** IoT networks consist of sensors deployed across agricultural fields to measure variables such as soil moisture, temperature, humidity, wind speed, and solar radiation. For example, low-cost soil moisture sensors (e.g., capacitive sensors) provide real-time data with high temporal resolution. Automated weather stations equipped with anemometers, hygrometers, and pyranometers collect meteorological data at farm scales.
2. **Satellite and Remote Sensing:** Satellites like NASA's SMAP and Sentinel-2 provide high-resolution imagery for monitoring vegetation indices (e.g., NDVI) and weather patterns. These data complement ground-based

IoT measurements, offering a broader spatial context.

3. **Historical Data:** Archives from meteorological agencies (e.g., NOAA, ECMWF) provide long-term datasets for training statistical and AI models. These include daily records of precipitation, temperature, and atmospheric pressure.

Statistical Forecasting Models

1. **Time-Series Models:** ARIMA and its variants (e.g., SARIMA for seasonal data) are widely used for short-term weather forecasting. These models analyze historical time-series data to predict variables like rainfall and temperature. For example, SARIMA models account for seasonal patterns in monsoon-driven regions.
2. **Regression-Based Models:** Multiple linear regression (MLR) and generalized additive models (GAMs) correlate weather variables with agricultural outcomes, such as crop yield. These models are computationally efficient and suitable for resource-constrained environments.
3. **Ensemble Methods:** Techniques like random forests and gradient boosting combine multiple statistical models to improve prediction accuracy. These are particularly effective for forecasting extreme weather events.

AI and Machine Learning Models

1. **Supervised Learning:** Algorithms like support vector machines (SVMs) and random forests predict specific outcomes (e.g., frost probability) based on labeled datasets. These models are trained on historical weather and crop data.
2. **Deep Learning:** CNNs process spatial data from satellite imagery, while RNNs and Long Short-Term Memory (LSTM) networks model temporal dependencies in weather patterns. For instance, LSTMs predict rainfall sequences with high accuracy by learning from time-series data.
3. **Reinforcement Learning:** Emerging applications use reinforcement learning to optimize irrigation schedules by balancing water use and crop yield under uncertain weather conditions.
4. **Data Preprocessing:** AI models require preprocessing steps like normalization, outlier removal, and feature engineering to ensure data quality. Techniques like principal component analysis (PCA) reduce dimensionality in large datasets.

IoT Integration and Real-Time Processing

1. **Network Architecture:** IoT devices connect via protocols like LoRaWAN, NB-IoT, or 5G to transmit data to cloud platforms (e.g., AWS IoT, Google Cloud). Edge computing reduces latency by processing data locally on IoT gateways.
2. **Data Fusion:** Combining IoT, satellite, and historical data requires data fusion techniques, such as Kalman filtering, to ensure consistency and accuracy.
3. **Real-Time Advisory Systems:** Processed data feed into decision support systems (DSS) that generate advisories via mobile apps, SMS, or web platforms. For example, advisories may recommend delaying planting due to predicted heavy rainfall.

Case Study Methodology

This review analyzes case studies from diverse agro-ecological zones, including:

- Precision irrigation in California using IoT and ML-based evapotranspiration models.
- Pest outbreak prediction in India using LSTM models and IoT sensor data.
- Frost warning systems in Australia integrating ARIMA and satellite data.

Data from these studies were collected from peer-reviewed literature and project reports from agricultural technology providers.

Evaluation Metrics

Model performance is assessed using metrics like mean absolute error (MAE), root mean square error (RMSE), and R-squared for forecasting accuracy. Advisory effectiveness is evaluated based on crop yield improvements, water savings, and farmer adoption rates.

Results and Discussion

This section synthesizes findings from global implementations of precision agro-meteorology, highlighting the impact of statistical forecasting, AI, and IoT on agricultural outcomes.

Forecasting Accuracy

1. **Statistical Models:** ARIMA and SARIMA models achieve high accuracy for short-term forecasts (1-7 days), with RMSE values typically below 2 °C for temperature predictions and 5 mm for rainfall. These models are effective in stable climates but struggle with extreme events.
2. **AI Models:** Deep learning models like LSTMs outperform statistical models for long-term forecasts (7-30 days), reducing RMSE by 10-20% in complex climates. For example, a study in Brazil used LSTMs to predict drought onset with 85% accuracy, enabling timely irrigation adjustments.
3. **Hybrid Approaches:** Combining statistical and AI models (e.g., ensemble methods) improves robustness. A California vineyard study reported a 15% increase in water use efficiency using a hybrid MLR-LSTM model for evapo-transpiration forecasting.

Impact on Agricultural Outcomes

1. **Crop Yield:** IoT-driven advisories increased yields by 10-25% in case studies from India, the US, and Australia. For instance, real-time irrigation scheduling in India's Punjab region boosted rice yields by 12% while reducing water use by 20%.
2. **Resource Efficiency:** Precision agro-meteorology minimizes inputs like water, fertilizers, and pesticides. A Kenyan study using IoT sensors and ML-based pest prediction reduced pesticide use by 30% without compromising maize yields.
3. **Climate Resilience:** Real-time frost warnings in Australia saved orchards from losses worth ₹ 375 crore INR annually by enabling timely protective measures (e.g., wind machines, sprinklers).

Case Studies-1

1. **California, USA:** IoT sensors and ML models optimized irrigation for almond orchards, reducing water use by 25% and increasing profits by 15%. Satellite data improved model accuracy by providing regional context.
2. **India:** A mobile app delivering AI-driven pest advisories based on IoT sensor data helped cotton farmers reduce losses by 18%. LSTM models predicted pest outbreaks with 80% accuracy.
3. **Australia:** ARIMA-based frost forecasting, integrated with IoT weather stations, achieved 90% accuracy in predicting frost events, enabling timely interventions.

Challenges

1. **Data Quality and Interoperability:** Inconsistent data formats across IoT devices and platforms hinder integration. Standardization efforts (e.g., Open Geospatial Consortium standards) are underway but incomplete.
2. **Scalability:** High costs of IoT infrastructure and AI model training limit adoption in low-income regions. Subsidized sensor networks and open-source AI platforms could address this.
3. **Accessibility:** Smallholder farmers often lack access to smart phones or reliable internet, restricting advisory dissemination. SMS-based systems and community radio are viable alternatives.
4. **Model Limitations:** AI models require large datasets for training, which may be unavailable in data-scarce regions. Transfer learning and federated learning could mitigate this.

Discussion

The synergy of statistical models, AI, and IoT enables precision agro-meteorology to address diverse agricultural challenges. Statistical models provide a reliable baseline, while AI enhances predictive power for complex scenarios. IoT ensures real-time data availability, bridging the gap between prediction and action. However, equitable access remains a barrier, particularly for smallholder farmers in developing countries. Public-private partnerships and government subsidies could accelerate adoption.

Conclusion

Precision agro-meteorology, powered by statistical forecasting models, AI tools, and IoT, is revolutionizing agriculture by delivering real-time, field-specific advisories. Statistical models like ARIMA provide robust short-term forecasts, while AI models like LSTMs excel in complex, long-term predictions. IoT enables seamless data collection, ensuring advisories are timely and actionable. Case studies demonstrate significant improvements in crop yields, resource efficiency, and climate resilience. However, challenges such as data interoperability, scalability, and accessibility must be addressed to ensure equitable benefits, particularly for smallholder farmers. Future advancements should focus on low-cost IoT solutions, open-source AI models, and alternative advisory channels like SMS and radio. By democratizing access to precision agro-meteorology, these technologies can enhance global food security and sustainability in the face of climate change.

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