

DECISION SUPPORT SYSTEMS FOR WEATHER-BASED FARMING

Sachin S. Chinchorkar*

Polytechnic in Agricultural Engineering, Anand Agricultural University, Muvaliya Farm, Dahod-389160,
Gujarat, India

*Corresponding author email: csachin.chinchorkar@gmail.com



ABSTRACT

Agriculture is highly vulnerable to weather variability, including droughts, floods, temperature extremes, and pest outbreaks. Weather-based Decision Support Systems (DSS) integrate meteorological data, weather forecasts, crop models, and expert knowledge to provide timely recommendations for irrigation, sowing, harvesting, nutrient management, and pest control. Advances in artificial intelligence, the Internet of Things, remote sensing, and machine learning have enhanced DSS accuracy and predictive capabilities. This review examines their principles, applications, and role in improving climate resilience, resource-use efficiency, risk management, and agricultural productivity under changing climatic conditions..

KEYWORDS: Climate Risk, Crop Modeling, Decision Support System, Irrigation Scheduling, Pest Forecasting, Precision Agriculture, Weather Forecasting

INTRODUCTION

Agricultural productivity is strongly influenced by weather and climate. Variations in rainfall, temperature, humidity, solar radiation, and wind conditions directly affect crop growth, yield, and quality. Extreme weather events such as droughts, floods, heat waves, and storms can cause severe agricultural losses. Consequently, farmers require timely and reliable weather information to make informed management decisions. Decision Support Systems (DSS) have emerged as valuable tools for transforming complex meteorological information into actionable agricultural recommendations. A weather-based DSS combines weather forecasts, agro-meteorological models, crop growth simulations, and expert knowledge to support operational and strategic farm decisions. These systems assist farmers in determining optimal irrigation schedules, planting dates, fertilizer applications, harvesting operations, and disease management strategies.

Modern DSS platforms increasingly integrate artificial intelligence, machine learning, remote sensing, IoT sensors, and mobile communication technologies. Such integration enables real-time monitoring,

forecasting, and location-specific advisory services. The effectiveness of a DSS depends largely on the accuracy of weather predictions, availability of local data, robustness of prediction models, and the ability to communicate recommendations in a user-friendly manner. This paper reviews the foundations, architecture, modeling approaches, applications, and evaluation methods associated with weather-based decision support systems in agriculture.

FUNDAMENTALS OF WEATHER-BASED FARMING

Effective agricultural decision-making requires accurate knowledge of future weather conditions. Although weather systems are highly complex, advances in numerical weather prediction now provide reliable forecasts ranging from one day to several weeks. However, many farmers face challenges in interpreting forecast information and applying it to farm operations.

Weather-based DSS bridges this gap by converting meteorological forecasts into practical recommendations. These systems collect, process, analyze, and interpret weather-related information to support crop management decisions. Their primary objective is to minimize production risks while maximizing productivity and resource-use efficiency.

1. Meteorological Variables and Agro-Climatic Indicators

- Several weather variables significantly influence agricultural production:
- Rainfall amount and distribution
- Maximum and minimum temperature
- Relative humidity
- Solar radiation
- Wind speed and direction
- Soil moisture status
- Evapotranspiration

These variables affect crop growth, flowering, pollination, grain filling, and maturity. They also influence the development of insects, weeds, and plant pathogens.

Rainfed farming systems are particularly vulnerable to weather variability. In developing countries, a large proportion of farmers depend on rainfall for crop production. Weather-based DSS helps such farmers make timely decisions regarding sowing, irrigation, and crop protection activities based on forecasted weather conditions.

2. Crop Requirements and Phenology

Crop phenology refers to the timing of biological growth stages such as germination, flowering, fruiting, and maturity. Phenological development is largely controlled by environmental factors, especially temperature and moisture.

Weather-based DSS often incorporates phenology models to estimate crop development stages and identify critical periods vulnerable to environmental stress. Phenological information also supports forecasting of pest and disease outbreaks because many pathogens and insects have life cycles closely linked to weather conditions.

Temperature-based growing degree day (GDD) models are widely used to predict crop development and pest emergence. More advanced DSS platforms integrate temperature, rainfall, and soil moisture variables to generate crop-specific recommendations.

ARCHITECTURE OF WEATHER-BASED DECISION SUPPORT SYSTEMS

A typical weather-based DSS consists of three major components:

1. Data acquisition and integration
2. Knowledge representation and inference
3. User interface and visualization

1. Data Acquisition and Integration

The quality of DSS recommendations depends heavily on the quality of data available. Data are obtained from multiple sources, including:

- Automatic weather stations
- Meteorological departments
- Satellite observations
- Remote sensing platforms
- IoT-based field sensors
- Historical climate databases
- Numerical weather prediction models

Data integration allows the system to combine real-time observations with short-term and seasonal weather forecasts. Modern cloud-based architectures facilitate continuous data collection and processing.

Weather forecasts are increasingly coupled with crop simulation models to evaluate potential impacts on crop growth and productivity. Integration of local observations improves forecast accuracy and enables site-specific advisories.

2. Knowledge Representation and Inference

Knowledge representation forms the intelligence layer of the DSS. Information may be represented using:

- Rule-based systems
- Expert systems
- Statistical models
- Machine learning algorithms
- Crop growth simulation models

Inference engines analyze relationships among weather variables, crop conditions, soil parameters, and management practices to generate recommendations.

For example, a DSS may combine forecasted rainfall, soil moisture content, and crop growth stage to recommend postponement of irrigation. Similarly, disease warning systems may use temperature and humidity thresholds to estimate disease risk levels.

3. User Interface and Visualization

The user interface converts complex analytical outputs into understandable information for farmers and agricultural advisors.

Important visualization features include:

- Weather dashboards
- Interactive maps
- Risk indicators
- Disease warning alerts
- Irrigation advisories

- Mobile notifications

Graphical displays simplify interpretation and facilitate rapid decision-making. Mobile applications have become particularly important because they enable real-time dissemination of weather-based advisories to farmers.

4. Interoperability and Standards

Agricultural DSS often integrate multiple software platforms and databases. Standardized protocols facilitate interoperability among weather services, crop models, remote sensing systems, and farm management platforms.

Web services and open-data standards enhance information sharing across institutions and regions. Such interoperability improves scalability and supports the development of comprehensive climate-smart agricultural advisory systems.

MODELING APPROACHES FOR WEATHER-BASED DECISIONS

Predictive models form the analytical foundation of weather-based DSS. These models transform weather information into forecasts of agricultural outcomes.

1. Predictive Weather Modeling

Weather prediction models estimate future atmospheric conditions using mathematical representations of atmospheric physics.

Forecast horizons generally include:

- Short-term forecasts (1–7 days)
- Medium-range forecasts (7–20 days)
- Seasonal forecasts (1–6 months)
- Climate projections (years to decades)

The India Meteorological Department (IMD) provides operational agricultural weather forecasts that support farm-level decision-making. Modern DSS platforms integrate these forecasts with crop-specific decision rules.

Artificial intelligence and machine learning techniques are increasingly being used to improve forecast accuracy through pattern recognition and adaptive learning.

2. Climate Risk Assessment

Climate risk assessment evaluates the probability and impact of adverse weather events on agricultural production.

Major climate risks include:

- Drought
- Flooding
- Heat stress
- Cold stress
- Salinity
- Extreme rainfall events

Historical climate datasets are analyzed to identify trends and estimate future risks under various climate scenarios. Risk maps generated through GIS and remote sensing technologies assist policymakers, insurance agencies, and farmers in climate adaptation planning.

Sensitivity analyses are frequently conducted to determine crop vulnerability under different climate scenarios such as Representative Concentration Pathways (RCPs).

3. Yield Forecasting and Phenology Modeling

Crop growth and yield forecasting models estimate production outcomes based on weather, soil, and management conditions.

Common modeling approaches include:

- Process-based crop simulation models
- Statistical regression models
- Machine learning models
- Phenological development models

These models predict flowering dates, maturity periods, biomass accumulation, and grain yield. Regional-scale forecasting supports food security planning, drought monitoring, and market intelligence.

Temperature-based thermal indices and growing degree day approaches are widely used for forecasting phenological stages of crops such as wheat, rice, mustard, and chickpea.

4. Pest and Disease Forecasting

Weather conditions strongly influence pest populations and disease development. Consequently, weather-based forecasting systems are important tools for integrated pest management.

Two major approaches are employed:

Mechanistic models: These models simulate biological processes using known relationships between weather variables and pathogen development.

Statistical models: These models use historical weather and pest occurrence data to identify predictive relationships.

Risk forecasting enables farmers to optimize pesticide applications, reduce costs, and minimize environmental impacts. Weather-based disease warnings are particularly useful for crops susceptible to fungal diseases under humid conditions.

DECISION SUPPORT FOR FARM MANAGEMENT

The practical value of weather-based DSS lies in its ability to support farm-level decisions.

1. Irrigation Scheduling

Water management is one of the most important applications of weather-based DSS.

Irrigation recommendations are generated using:

- Weather forecasts
- Evapotranspiration estimates
- Soil moisture measurements
- Crop water requirements

When rainfall is forecasted, irrigation can be postponed, thereby reducing water use and energy costs. Smart irrigation systems increasingly integrate weather forecasts with IoT-based soil moisture sensors for automated decision-making.

2. Planting and Harvest Management

Weather forecasts assist farmers in selecting suitable planting windows and harvest periods.

Benefits include:

- Improved crop establishment
- Reduced seedling mortality

- Avoidance of rainfall during harvest
- Better grain quality

Temperature accumulation models help estimate crop maturity dates and schedule harvesting operations. Seasonal forecasts can also support strategic crop selection decisions.

3. *Fertilization and Nutrient Management*

Nutrient-use efficiency is highly influenced by weather conditions.

Weather-based DSS supports nutrient management by:

- Predicting nutrient losses due to rainfall
- Estimating crop nutrient demand
- Optimizing fertilizer application timing
- Reducing environmental pollution

Integrated systems combine weather forecasts with crop growth models to generate precise fertilizer recommendations.

4. *Disease and Pest Risk Mitigation*

Disease and pest outbreaks frequently occur under favorable weather conditions. DSS platforms provide early warning systems that help farmers implement preventive measures.

Typical advisory outputs include:

- Disease risk levels
- Spray timing recommendations
- Pest monitoring alerts
- Integrated pest management strategies

Such systems reduce crop losses while minimizing unnecessary pesticide applications.

EVALUATION, VALIDATION, AND UNCERTAINTY MANAGEMENT

Reliable DSS performance requires rigorous validation and uncertainty assessment.

1. *Validation Methodologies*

Different components of DSS require different validation approaches.

Examples include:

- Comparing forecasted and observed weather variables
- Validating crop phenology predictions against field observations
- Comparing predicted and actual yields
- Assessing disease forecasts using field surveillance data

Independent validation datasets improve model credibility and operational reliability.

2. *Uncertainty Quantification*

Uncertainty arises from:

- Weather forecast errors
- Incomplete data
- Model assumptions
- Biological variability
- Climate unpredictability

Quantifying uncertainty enables users to understand the confidence associated with recommendations. Ensemble forecasting methods are increasingly used to estimate prediction uncertainty.

3. *Performance Metrics*

Common DSS performance indicators include:

- Prediction accuracy
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Probability of Detection (POD)
- False Alarm Ratio (FAR)
- Sensitivity and specificity
- Lead time effectiveness

Evaluation metrics should reflect both technical accuracy and practical utility for farmers.

FUTURE PERSPECTIVES

Emerging technologies are transforming weather-based agricultural decision support systems. Artificial intelligence, deep learning, edge computing, IoT networks, and remote sensing are improving the precision and scalability of agricultural advisories.

Future DSS platforms are expected to incorporate:

- Hyper-local weather forecasting
- AI-powered recommendation engines
- Voice-enabled advisory systems
- Autonomous sensing networks
- Climate adaptation analytics
- Digital twin farming environments

Integration of weather analytics with precision agriculture technologies will further enhance productivity, sustainability, and resilience under changing climate conditions.

CONCLUSION

Weather-based Decision Support Systems represent a critical technological advancement for climate-smart agriculture. By integrating meteorological forecasts, crop growth models, climate risk assessments, and expert knowledge, these systems enable farmers to make informed decisions regarding irrigation, planting, fertilization, harvesting, and crop protection. The incorporation of AI, IoT, remote sensing, and machine learning has significantly improved predictive capabilities and operational effectiveness. Despite challenges related to uncertainty and data availability, continued advances in forecasting technologies and digital agriculture are expected to strengthen the role of DSS in sustainable agricultural development. Widespread adoption of weather-based DSS can improve resource-use efficiency, reduce production risks, enhance climate resilience, and support long-term food security.

REFERENCES

- Bhati, C. (2026). A study on agriculture prediction and management system. *International Journal for Research in Applied Science and Engineering Technology*, 14(4).
- Fawwaz, R. H. I., Firdaus, V., Wijayaningrum, V. N., et al. (2025). AIoT architecture for localized weather prediction. *In: Proceedings of the IEEE International Conference on Advanced Technologies for Humanity*. IEEE.
- Liang, X.-Z., Gower, D., Kennedy, J., Cibin, R., Chaubey, I., & Rhoads, B. (2024). DAWN: Dashboard for agricultural water use and nutrient management. *Bulletin of the American Meteorological Society*, 105(2), E276–E294. <https://doi.org/10.1175/BAMS-D-22-0276.1>

- Mehedi, I., Hanif, M., Bilal, M., Alshammari, N., Alqahtani, S., & Alzahrani, A. (2024). Remote sensing and decision support system applications in precision agriculture: A comprehensive review. *IEEE Access*, 12, 103456–103489. <https://doi.org/10.1109/ACCESS.2024.3394587>
- Sathyamoorthy, M. S., Dheebakaran, N. K., Ranjith Kumar, R., & Balasubramanian, M. (2024). Coupled weather and crop simulation modeling for smart irrigation planning. *Water Supply*, 24(7), 2609–2625. <https://doi.org/10.2166/ws.2024.118>
- Selvan, R.M., Gouse, B.A., Kumar, A.H., Rohith, Y.S. and Manikanta, P.S.V. (2025). AI-powered decision support system for crop, fertilizer and disease management. *In: Proceedings of the IEEE International Conference on Signal and Computing Networks*. IEEE.
- Singh, K. K., Ghosh, K., Bhan, S., Singh, K. K., Balasubramanian, R., Singh, K. K., Rathore, L. S., & Prasad, K. (2023). Decision support system for digitally climate-informed services to farmers in India. *Journal of Agrometeorology*, 25(2), 209–218. <https://doi.org/10.54386/jam.v25i2.1968>
- Sirisha, P. K., Rakesh, S., Krishna, P. H., et al. (2026). AgriSense: A multimodal AI-driven decision support ecosystem. *International Journal of Scientific Research and Archives*, 18(3).
- Tariq, M. U., Saqib, S. M., Mazhar, T., et al. (2025). Edge-enabled smart agriculture framework integrating IoT and AI. *Results in Engineering*. Advance online publication.
- Zope, V., Choudhary, M., Joshi, S., & Gupta, R. (2026). AgriNovaX: A voice-enabled AI agricultural assistant. *International Journal of Computers, Information and Control Systems*, 2(5).

How to cite:

Chinchorkar, S. S. (2026). Decision support systems for weather-based farming. Leaves and Dew Publication, New Delhi 110059. *Agri Journal World* 6 (2): 55-65.

*****XXXXXX*****