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AI and Remote Sensing for Crop Micrometeorological Applications in Indian Agriculture

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Crop micrometeorology is concerned with the exchange of energy, water, momentum, and gases between the crop canopy, soil, and lower atmosphere. Unlike conventional meteorological observations, which are commonly recorded at standard weather-station heights, crop micrometeorology focuses on the microenvironment experienced by plants. Variables such as canopy temperature, humidity, radiation, wind, soil moisture, and vapour pressure deficit vary across fields and directly influence crop growth processes, including photosynthesis, transpiration, flowering, and maturation. In India, diverse agro-climatic conditions, monsoon variability, and rising temperature extremes make accurate microclimate assessment essential for irrigation, heat-stress monitoring, disease forecasting, and climate-resilient agriculture. Conventional weather stations provide accurate point observations but cannot adequately represent field-scale spatial variability. Remote sensing provides a complementary solution by observing land and crop properties over large areas, while AI can transform complex, multi-source observations into predictive information. A systematic review of machine-learning-driven RS applications in Indian agriculture found that RS and machine learning have already been applied extensively to crop, soil and water management, including crop classification, yield prediction, drought and water-stress assessment, and resource management (Sharma et al., 2023). The integration of AI and RS is therefore highly relevant to crop micrometeorology because it allows the conversion of spatially distributed environmental observations into indicators of the actual atmospheric and water conditions experienced by crops.

AI and Remote Sensing Applications in Crop Micrometeorology

1. Monitoring crop microclimate

- Remote sensing provides indirect information about the crop microenvironment through spectral, thermal and microwave observations. Optical sensors provide vegetation reflectance, thermal sensors provide surface and canopy temperature, while microwave sensors can provide information related to soil moisture.
- Important RS-derived variables include: Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), Land Surface and canopy temperature, leaf area index (LAI), soil moisture, evapotranspiration, vegetation water content, crop phenology.
- The combination of these variables with ground observations allows researchers to characterize spatial variability in crop microclimate. For example, areas with high canopy temperature and low vegetation indices may indicate inadequate water availability or stomatal closure.
- Recent developments in high-resolution RS are particularly promising. Current approaches combine visible, near-infrared, thermal-infrared and microwave observations with AI-based downscaling to produce increasingly fine-scale soil-moisture and ET

information. High-resolution products can potentially characterize land-atmosphere interactions at field scales of approximately 3–30 m for soil moisture and even finer scales for some ET applications (Huan.g et al., 2025).

2. Land surface temperature and canopy-temperature monitoring

Temperature is one of the most important micrometeorological variables because crop transpiration provides a cooling effect. When soil water becomes limiting, stomatal closure reduces transpiration and canopy temperature increases. Therefore, the difference between canopy and air temperature can provide an indication of crop water stress.

Thermal remote sensing from Landsat, ECOSTRESS, UAVs and other platforms can be used to estimate land surface temperature (LST) and canopy-temperature patterns. The Crop Water Stress Index (CWSI) is particularly relevant because it relates canopy temperature to atmospheric conditions and crop water status. AI can improve the interpretation of thermal imagery by learning relationships between temperature, vegetation indices, soil moisture and crop stress. A recent study at ICAR-IARI, New Delhi, integrated soil-moisture stress with CWSI for winter-wheat irrigation scheduling and demonstrated the value of combining atmospheric/canopy information with soil-water conditions for irrigation management.

3. Evapotranspiration (ET) estimation and irrigation management

Evapotranspiration is a central component of crop micrometeorology because it links atmospheric demand with crop water use. Traditional ET estimation requires meteorological observations such as air temperature, relative humidity, wind speed, solar radiation, and rainfall. However, these observations are often unavailable at sufficient spatial density in agricultural regions. RS can overcome this limitation by providing spatial information about vegetation, surface temperature and land characteristics. Algorithms such as SEBAL, METRIC and related surface-energy-balance models use remotely sensed information to estimate actual ET. AI can further improve ET estimation by learning relationships between ET and meteorological, vegetation and thermal variables. Recent research in northern India evaluated Random Forest, artificial neural networks and LSTM models for daily reference evapotranspiration under limited meteorological-data conditions. LSTM performed particularly well among the tested models, demonstrating the potential of AI for locations where complete weather observations are unavailable (Shaloo et al., 2025). Thus, AI–RS-based ET estimation can contribute to: field-specific irrigation scheduling; drought monitoring; water-productivity assessment; groundwater conservation; irrigation-system optimization; and climate-resilient crop management.

4. Soil-moisture estimation

Soil moisture strongly regulates crop transpiration and therefore connects soil conditions with crop micrometeorology. Microwave sensors such as Sentinel-1 can provide soil-moisture information even under some cloudy conditions where optical observations are restricted.

AI algorithms can establish nonlinear relationships between radar backscatter, vegetation characteristics, soil properties and measured soil moisture. Such approaches can support: irrigation scheduling, drought monitoring, crop-water-stress prediction, soil-water balance modelling, crop-growth models, and watershed-scale water management. Recent research across India's agro-ecological regions also demonstrates that precipitation, ET, vegetation and vapour-pressure-related variables make different contributions to surface and root-zone soil-moisture variability depending on climatic zone and season.

5. Crop water-stress detection

Crop water stress is a direct consequence of the interaction between atmospheric demand and available soil water. High temperature, high VPD and low soil moisture can increase crop stress, particularly during sensitive growth stages. RS-based stress detection can use: canopy temperature, LST, NDVI, EVI, NDWI, thermal indices, soil-moisture estimates, and hyperspectral information.AI models such as Random Forest, Support Vector Machine, artificial neural networks, convolutional neural networks (CNNs), recurrent neural networks and transformer-based architectures can classify or predict stress.

6. AI-based drought monitoring and forecasting

Conventional drought assessment often relies on rainfall and meteorological indices, but agricultural drought depends on the interaction among rainfall, soil moisture, crop condition, temperature and atmospheric demand. AI can combine these variables with satellite observations to develop predictive drought-monitoring systems. In India, the SukhaRakshak AI initiative developed by IWMI in collaboration with ICAR and CRIDA integrates AI, satellite Earth observation, probabilistic weather forecasts and localized contingency plans to provide anticipatory drought advisories. Such systems represent an important transition from conventional meteorological monitoring toward anticipatory crop micrometeorological decision support, where the objective is not merely to determine what has happened but to predict emerging stress and recommend management actions.

7. Crop growth, phenology and yield prediction

Crop growth is closely related to accumulated temperature, radiation, water availability and atmospheric conditions. AI models can combine weather observations with satellite-derived vegetation indices and phenological indicators to estimate crop development and yield. For example, time-series NDVI can identify crop emergence, peak vegetative growth, senescence and harvesting stages. Thermal data can provide additional information about heat and water stress. When these variables are combined with weather data, AI models can potentially forecast crop yield before harvest. The Indian systematic review by Sharma et al. (2023) found that crop classification and yield prediction were among the major applications of ML and RS in Indian agriculture.

8. Disease and pest-risk assessment

Microclimatic conditions such as temperature, humidity, leaf wetness and canopy density strongly influence pathogen development and pest populations. Although many of these variables cannot be directly observed from conventional satellite data, AI-RS systems can provide indirect indicators of crop and environmental conditions. For example, vegetation indices can identify abnormal crop responses, while thermal and hyperspectral observations can detect physiological changes before symptoms become visible. AI models can then classify disease-risk zones. The integration of crop microclimate data with RS and AI therefore provides a pathway toward early-warning systems rather than symptom-based disease management.

9. UAV and hyperspectral applications

UAVs (unmanned aerial vehicle) bridge the spatial gap between satellite imagery and ground observations. They can acquire high-resolution RGB, multispectral, thermal and hyperspectral imagery at the farm scale. UAV-based thermal imaging can also identify within-field temperature variation that may be hidden by the coarser spatial resolution of satellite imagery. Hyperspectral sensing is particularly useful for identifying subtle changes in: chlorophyll, nitrogen, water content, pigment composition, plant stress, and biochemical characteristics.

10. Integration of AI, IoT and ground-based micrometeorological observations

Ground sensors can measure air temperature, relative humidity, soil moisture, radiation and wind speed. UAVs can provide high-resolution canopy observations, while satellites provide repeated regional observations. AI models can integrate these datasets to produce spatially continuous estimates. ICAR has recently highlighted this direction through precision-agriculture initiatives involving sensors, drones, satellites, AI and ICT. ICAR-CIARI has also developed the Dweep Microclimate Monitor, an IoT-enabled system capable of vertically profiling temperature and humidity, transmitting observations remotely and supporting field-level microclimate research and agrometeorological advisories.

Government Initiatives Supporting AI in Agriculture

- Bharat-VISTAAR: Proposed in Budget 2026–27 as a multilingual AI system to provide farmers with personalised advice and reduce farming risks.

- Digital Agriculture Mission & AgriStack: Creates a digital foundation using farmer, land and crop data, AI, analytics and remote sensing.
- Krishi Decision Support System (KDSS): Uses satellite, weather, soil and crop data for crop mapping, yield estimation and drought/flood assessment.
- AI in Crop Insurance: Technologies like YES-TECH and CROPIC use AI, remote sensing and photographs to improve crop-yield and damage assessment.
- Agri-startups: Government supports startups working in precision farming, AI/IoT, mechanisation, supply chains and post-harvest technology.
- Agricultural Robotics: ICAR-IARI is developing robots for soil sampling, sowing, harvesting and crop monitoring.

Limitations

- Spatial and temporal resolution: Satellite data may lack sufficient spatial or temporal resolution to capture rapidly changing crop conditions.
- Cloud and atmospheric interference: The Indian monsoon creates persistent cloud cover, particularly during the kharif season therefore optical and thermal satellite observations can have significant data gaps.
- Ground-truth limitations: AI models require reliable training and validation data. However, high-frequency measurements of canopy temperature, soil moisture, humidity, radiation and ET are not available uniformly across Indian agricultural regions.
- Model transferability: An AI model developed for one crop, soil type or agro-climatic zone may not perform equally well elsewhere & can reduce model generalization.
- Explainability: For scientific crop-micrometeorological research, it is important to understand not only whether a model predicts stress accurately but also why it predicts stress. Explainable AI and physically informed machine learning are therefore important.
- Data heterogeneity: Satellite, UAV, sensor and weather-station data have different spatial and temporal scales. Integrating them requires careful preprocessing, co-registration, calibration and uncertainty analysis.
- Cost and technical capacity: Advanced sensors, UAVs, and computing infrastructure can be expensive for small institutions and farmers.
- Farmer adoption: Highly sophisticated AI models do not translate into practical agricultural benefits. Outputs must be converted into simple recommendations, such as when to irrigate, how much water to apply, or when heat/disease risk is likely to increase.
- Uncertainty: RS and AI estimates of ET, soil moisture, LST, and crop stress contain measurement and model uncertainties.

Conclusion

Artificial intelligence and remote sensing are emerging as powerful technologies for advancing crop micrometeorology in Indian agriculture. Their importance arises from their ability to move agricultural monitoring from isolated point observations toward spatially distributed, continuous and predictive information. A particularly promising direction is the development of digital twins of agricultural fields, in which real-time satellite, UAV, weather, soil and crop observations continuously update a dynamic representation of crop condition. Such systems could forecast water stress, heat stress and yield several days or weeks in advance. India is also moving toward institutional use of AI and remote sensing in agricultural monitoring, with AI/ML, IoT, remote sensing, smart soil monitoring, precision irrigation, automated agrometeorological advisories and improved satellite/UAV resolution emerging as important areas for agricultural research.

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