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Cutting-Edge Techniques for Accurate Crop Water Requirement Estimation and Sustainable Agriculture

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This paper examines cutting-edge approaches for assessing crop water requirements (CWR) and promoting sustainability in agriculture. It covers remote sensing-based evapotranspiration estimation, integration of weather data and climate models, crop modelling and simulation, refinement of crop coefficients, soil moisture monitoring, and machine learning for CWR prediction, and precision irrigation technologies. This review highlights challenges such as limited high-resolution weather data, cloud cover interference, and model calibration issues. Multidisciplinary approaches are emphasized to address the research gaps and advance sustainable irrigation management practices.

Introduction

Water is a vital element for life, and its effective management is essential, especially in agriculture, which is a major consumer of water resources. The precise estimation of crop water requirements is a cornerstone of efficient irrigation management, ensuring that crops receive the right amount of water at the right time, thereby optimizing yield water usage (Jangre *et al*., 2022).

Remote Sensing-Based Evapotranspiration (ET) Estimation

Evapotranspiration (ET) is a critical component of the hydrological cycle.

1. Multispectral imagery captures parameters such as leaf area index (LAI), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and biomass, which are used to estimate transpiration rates.
2. Thermal imagery shows canopy temperature, indicating water stress, as stressed plants have higher temperatures owing to reduced transpiration (Chandel et al., 2025).
3. Models for ET estimation include Mapping Evapotranspiration at High Resolution with Internalised Calibration (METRIC) and Surface Energy Balance Algorithm for Land (SEBAL), which calculate ET based on the surface energy balance using satellite imagery and meteorological data.

Integrating Weather Data and Climate Models

Weather data, such as temperature, humidity, wind speed, and solar radiation, play a critical role in CWR calculation, providing information on climatic conditions that influence crop water use and evapotranspiration rates.

1. GRASS (Geographic Resources Analysis Support System) and ERA5-Land provides high-resolution gridded weather information for CWR models.
2. CM-SAF satellite-based radiation data complement ground observations by providing continuous information on solar radiation, which is a key driver of evapotranspiration.
3. Climate models like CMIP the Coupled Model Intercomparison Project (CMIP), Representative Concentration Pathways (RCP), Shared Socioeconomic Pathways (SSP),

Budyko hydrological model, and WEAP-MABIA can project future CWR under different scenarios.

Crop modelling and simulation

Advanced crop growth models that incorporate weather data, soil characteristics, and crop physiology can be used to predict daily water requirements (Chang et al., 2025).

1. FAO-CropWat, using the Penman-Monteith equation, generally provides a more accurate estimate of irrigation requirements and scheduling.
2. Process-based models such as DSSAT, APSIM, CropSyst, EPIC, InfoCrop, and WOFOST offer advanced simulation of crop water requirements.

Crop Coefficients (Kc) and Their Refinement

Accurate Crop coefficient (Kc) values are essential for precise CWR estimation, allowing the adjustment of ET to reflect the specific water needs of crops at various growth stages (Quezada et al., 2025).

1. Vegetation indices, such as NDVI, can estimate Kc, as they correlate with crop biomass, leaf area, and transpiration rates, providing a quantitative measure of crop water use.
2. Satellite imagery provides data for Kc mapping, allowing the creation of detailed maps showing Kc variation across fields for variable-rate irrigation.

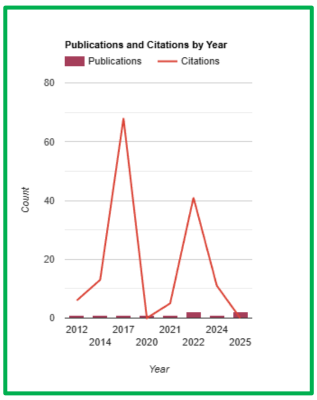
Soil Moisture Monitoring Techniques

1. In-situ soil moisture sensors and wireless sensor networks provide real-time data on soil-water content.
2. Remote sensing-based soil moisture estimation techniques, vegetation indices offer a complementary approach to in situ measurements, providing spatially continuous data across large areas.
3. Microwave remote sensing can estimate soil moisture content because microwave radiation is sensitive to the dielectric properties of the soil.
4. The combination of in situ and remote sensing data provides a comprehensive view of soil moisture.

Machine Learning Approaches for CWR Prediction

Machine learning algorithms can model the relationships between the factors affecting CWR. These models learn from data to improve CWR predictions, adapt to changing conditions, and provide reliable estimates over time (Ajith et al., 2025).

1. These include Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Random Forest (RF), and Gradient Boosting Machine (XGBoost) (Nagappan *et al.*, 2025).
2. Deep learning models like k-Nearest Neighbour (KNN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs),Density-Based Spatial Clustring of Applications with Noise (DBSCAN) have higher accuracy due to their ability to capture complex temporal dependencies
3. The application of bidirectional gated recurrent unit (Bi-GRU) networks has also shown promise in enhancing irrigation schedules by utilising soil moisture, weather, and crop data.



Examples include mango, rice, and cotton crops, for all seasons demonstrating the versatility of machine learning approaches for different crop types and environmental conditions.

Precision Irrigation Technologies and Strategies

1. Variable rate irrigation (VRI) systems enable irrigation by applying water at varying rates based on the spatial variability in CWR, accounting for differences in soil properties, topography, and crop conditions.
2. Drip irrigation, micro sprinklers, and other efficient irrigation methods offer significant advantages over traditional surface irrigation in terms of water efficiency and crop productivity.
3. Automated systems use CWR data to schedule irrigation events and optimise water use. Integration with weather forecasts allows for proactive irrigation management, enabling the system to anticipate water demand and adjust schedules accordingly.

Challenges

1. Limited access to high-quality, high-resolution weather data in many regions.
2. Cloud cover interferes with optical satellite imagery.
3. Difficulties in calibrating and validating models across diverse environments and real-time prediction.

Future Directions

1. Methods to overcome cloud cover limitation (e.g. SAR, data fusion) should be developed.
2. Improving spatial and temporal resolution of satellite-based evapotranspiration estimates.
3. The use of UAVs for high-resolution, on-demand crop monitoring can be explored.
4. Explore novel irrigation methods (e.g. subsurface drip, surge) for improved water-use efficiency.
5. Explore nexus approaches that consider water-energy-food interactions in crop production systems.

Conclusion

Addressing various research gaps will require a multidisciplinary approach involving collaboration among researchers, policymakers, and farmers. By investing in research and development in these areas, we can improve the accuracy and efficiency of crop water requirement estimations, promote sustainable irrigation management practices that ensure food security and protect water resources for future generations.

References

1. Jangre, N., Sinha, J., Raj, J., & Kamalkant, K. (2022). Estimation of crop water requirement of Kharif maize crop using CROPWAT 8.0 model in Bilaspur district. *International Journal of Environment and Climate Change*, *12*(12), 597-606.https://doi.org/10.9734/ijecc/2022/v12i121497
2. Chang, Y., Zhang, C., Huang, J., Chang, H., Wang, C., & Huo, Z. (2025). Machine Learning for Reference Crop Evapotranspiration Modeling: A State-of-the-Art Review and Future Directions. *Agronomy*, *15*(9), 2038.https://doi.org/10.3390/agronomy 15092038
3. Chandel, A. K., Khot, L. R., Stöckle, C. O., Kalcsits, L., Mantle, S., Rathnayake, A. P., & Peters, T. R. (2025). Canopy Transpiration Mapping in an Apple Orchard Using High-Resolution Airborne Spectral and Thermal Imagery with Weather Data. *AgriEngineering*, *7*(5), 154.https://doi.org/10.3390/agriengineering7050154
4. Torres-Quezada, E., Fuentes-Peñailillo, F., Gutter, K., Rondón, F., Marmolejos, J. M., Maurer, W., & Bisono, A. (2025). Remote Sensing and Soil Moisture Sensors for Irrigation Management in Avocado Orchards: A Practical Approach for Water Stress Assessment in Remote Agricultural Areas. *Remote Sensing*, *17*(4), 708.https://doi.org/10.3390/rs17040708
5. Ajith, S., Vijayakumar, S., & Elakkiya, N. (2025). Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms. *Discover Food*, *5*(1), 1-23. https://doi.org/10.1007/s44187-025-00338-1