Review of: "Determination of Evapotranspiration and Crop Coefficients of Irrigated Legumes on Different Soil Textures Using the FAO56 Approach"

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The present study investigated water usage and crop coefficients (Kc) of legumes cultivated on three distinct soil textures in southern Nigeria, aiming to enhance crop and water management practices [1]. The research revealed crucial insights into legume water consumption patterns, influenced by factors such as climatic conditions, months, and seasons of the year. While the study provides valuable insights, it is essential to acknowledge its limitations, such as the conduct of a one-time trial. To enhance the reliability and applicability of the findings, it is recommended to repeat the study during multiple planting seasons and validate the obtained coefficients within and beyond the study area. Moreover, the adoption of Artificial Intelligence (AI) and Machine Learning (ML) models for the estimation of reference evapotranspiration (ETp) and crop evapotranspiration (ETc), and consequently Kc, could further enhance the accuracy of the results [2][3][4][5]. Employing less human-dependent methods to monitor changes in soil moisture content over time is also advisable to ensure the collection of error-free data.

As discussed, the present study can be enhanced by integrating insights from the emerging roles of AI-ML methods in crop water monitoring and management, which are discussed henceforth. The forecasting of Vapor Pressure Deficit (VPD) using ensemble learning-based modeling, as a case study in different regions of Egypt [6], provides valuable information for understanding the climatic factors influencing evapotranspiration (ET) and water management in semi-arid environments. By incorporating the findings of this study into the research on crop coefficients and evapotranspiration of legumes cultivated on different soil textures, several enhancements can be achieved [7][8]. By incorporating VPD forecasts into the FAO56 approach, the precision of ET estimation can be improved, leading to more efficient water management practices. In fact, the insights gained from forecasting VPD across different regions in Egypt can be extrapolated to other semi-arid environments, including regions where the study on legume crop coefficients was conducted. By integrating the recommended Random Forest (RF) model or a similar dynamic model into the methodology of determining crop coefficients, researchers can leverage its superior performance to enhance the accuracy of ET calculations [9].

The study on meteorological data fusion approaches for modeling Crop Water Productivity (CWP) based on ensemble machine learning [10] can enhance the utility of the present study. By leveraging ML methods for modeling CWP, researchers can enhance the accuracy and efficiency of CWP estimation for legume crops on different soil types. Incorporating meteorological data fusion techniques into the FAO56 approach enables the development of more robust models that capture the complex interactions between climatic variables and crop water productivity. The application of ensemble machine learning methods, such as RF, Support Vector Regression (SVM), Bagged Trees (BT), Boosted Trees (BoT), and Gaussian Process (MG), offers alternative approaches to modeling CWP. Integrating these methods with the FAO56 approach allows for the exploration of diverse modeling techniques and the selection of the most suitable model for accurately estimating CWP across different soil textures and climatic conditions. Moreover, the identification of optimal input variables for CWP modeling provides valuable insights for refining the input parameters of the FAO56 approach. By selecting relevant meteorological variables based on their significance in predicting CWP, researchers can streamline the input data requirements of the FAO56 approach and improve its efficiency in estimating crop water productivity for legume crops and other crops [11].

The present study can further benefit from forecasting actual evapotranspiration without climate data based on stacked integration of Deep neural Network (DNN) and meta-heuristic models [12]. The stacked integration of DNN with meta-heuristic models, such as RF, Random Subspace (RSS), M5 Burned Tree (M5P), and Reduced Error Pruning Tree (REPTree), provides a data-driven approach to ET modeling [13]. Integrating these models with the FAO56 approach allows for the exploration of alternative methods for estimating crop coefficients and evapotranspiration rates based on machine learning techniques, which can improve the accuracy and efficiency of water management practices for irrigated legumes. The capability of DNN-based hybrid models, particularly the DNN-RF algorithm, for long-term predictions of actual evapotranspiration (AET) values presents an opportunity to enhance the utility of the FAO56 approach over extended time periods [14].

In conclusion, the implications of this study extend to various stakeholders, including irrigation engineers, agriculturists, soil scientists, and environmentalists. The findings offer valuable guidance for improving irrigation scheduling, water management practices, enhancing crop and water productivity, and evapotranspiration forecasting in agriculture, particularly in regions with a climate similar to southern Nigeria. Overall, these researches contribute significantly to the advancement of sustainable agricultural practices and water resource management in the region.

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