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Crop Water Stress Index for Managing Irrigation Water

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Introduction

When there is a limited supply of water, irrigation water management using an automated irrigation decision support system (IDSS) as a smart irrigation scheduling tool can increase crop production and water efficiency. The current study compared the predicted Crop Water Stress Index (CWSI) and Crop Evapotranspiration (ET_c) using the calculated single crop coefficient FAO56 ET_c and Jackson's theoretical CWSI, respectively, to the predictions made by various AI algorithms and their ensembles. During the growing seasons of 2020 and 2021, soil moisture, canopy temperatures (T_c), and the Normalized Difference Vegetation Index (NDVI) were all measured from irrigated and unirrigated maize plots in West Central Nebraska. For ET_c and CWSI predictions, fifteen and twelve input combinations were used. These combinations had input variables like soil moisture and weather, as well as ancillary variables like NDVI, reference evapotranspiration (ET_r), and cumulative growing degree days (CGDDs). The coefficient of determination (r^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were the four statistical performance indicators used to evaluate the models. In addition, ranking scores were applied to statistical results in order to identify the optimal model for each input combination. The most accurate model for predicting CWSI was CatBoost, with an RMSE between 0.06 and 0.09 unitless, while the most accurate model for estimating ET_c was Stacked Regression, with an RMSE between 0.27 and 0.72 mm d^1. In order to establish soil water and plant stress feedback for automated irrigation scheduling, future research will look into designing and evaluating an IDSS using the best machine learning models that have been identified.

Description

In arid or semi-arid climate regions, irrigation can be essential to food production systems and economies. Since there is a possibility that a lack of freshwater resources will not be able to meet the demand for water, effective scheduling strategies are desirable in order to maximize crop yields with a limited supply of water. Using irrigation schedulers that can link physical interactions between air, soil, and plant as a continuum can improve water use efficiency in intensively irrigated areas. However, scheduling tools are frequently chosen by producers due to their low cost, adaptability to changing conditions, and, most importantly, ability to provide near-real-time information on crop water requirements and/or water stress. The majority of irrigation scheduling tools, including process-based agricultural models, soil and plant sensors, and soil water balance models, necessitate local soil, crop, and climate data. Even though localized and in-field methods, particularly soil and plant sensors, are less likely to make mistakes, they still need to be set up and maintained, which can be costly. Furthermore, the majority of approaches lack both spatial and temporal resolution. In order to inform and possibly automate their irrigation scheduling decisions in real time, producers require user-friendly and well-designed irrigation decision support systems (IDSS).

Due to its non-destructive nature and adaptability to larger fields, infrared thermometry has received increased interest in IDSS. With the crop water stress index, infrared thermometry is commonly used to monitor water stress, but it has also been extended to estimate crop evapotranspiration (ET_c). However, the high costs of sensors, the need to program and wire dataloggers, and issues with data quality may make it difficult to implement thermometry-based scheduled decision on producer fields. Additionally, CWSI baselines cannot be extended to other climates because the collection of canopy temperature (T_c) is limited to a specific time of day (midday hours) [1,2].

Using multiple linear regressions to create lower or unstressed baselines for corn and soybeans in order to facilitate the localization-independent calculation of CWSI in irrigation management. However, if there are non-linear relationships, the use of climatic variables and plant growth parameters to model CWSI can be more complicated, necessitating robust models for better predictions. Mentioned that it would be worthwhile to think about algorithms that would eliminate the need to create baselines in order to normalize T_c to microclimatic conditions or even the need to avoid taking T_c measurements at particular times during the day in order to promote CWSI in irrigation scheduling. However, producers haven't taken advantage of ET_c or soil moisture-based methods, which are considered accurate. A major obstacle to the adoption of ET_c-based irrigation models is still the availability of weather stations and knowledge or access to a specialist who understands how to interpret data into an irrigation decision. As a result, automated irrigation scheduling tools may benefit from soliciting additional straightforward but dependable models that can automatically forecast or estimate ET_c. They require data of high quality that is relevant to the local area, which is one factor [3-5].

Conclusion

It is interesting to note that datasets generated from calibrated process-based agricultural models like the Root Zone Water Quality Model (RZWQM2) and AQUACROP model have now been used to monitor soil moisture content in the rooting zone in support of irrigation scheduling. These datasets were generated using neural network (NN) models such as Long-Short Term Memory (LSTM) and Artificial Neural Network (ANN). As a result, those datasets for model training can be generated by calibrated process-based agricultural models. A study by used fuzzy NN to determine irrigation time and volume and ANN to predict changes in soil moisture based on daily weather. As opposed to traditional process-based models, AI models can easily identify associations between input and response variables without much input from the modeler. Ensembling ML models can also be used to combine them to boost their prediction performance and accuracy

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