DOI 10.5162/EUROSENSORSXXXVI/PT1.1

A Support Vector Machine Learning Prediction Model of Evapotranspiration using Real-Time Sensor Node Data

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Summary:

An IoT-enabled smart sensor node has been developed to acquire real-time field data and formulate an adaptable prediction model to predict crop Evapotranspiration (ETc) using a Support Vector Machine (SVM) learning algorithm. Integrating the SVM algorithm with real-time sensor nodes offers great potential to improve spatial and temporal resolution of water data uncertainty. In the model development, key input features are measured in real-time and computed using mathematical equations such as Penman-Monteith, which include soil-environmental parameters.

Keywords: Evapotranspiration, FAO56, KNIME, Machine learning, RStudio, SVM, Sensors, Water

Title

A Support Vector Machine Learning Prediction Model of Evapotranspiration using Real-Time Sensor Node Data.

Headlines

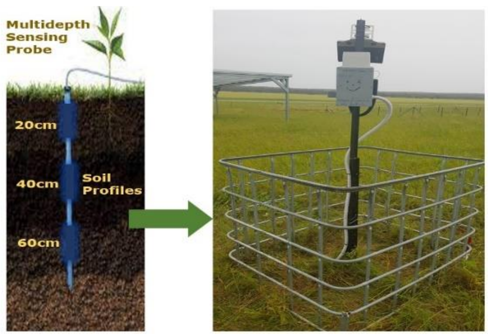
The paper outlines the existing Evapotranspiration estimation methods, machine learning modeling techniques, data collection and pre-processing, model development, and evaluation metrics, highlighting the significance of SVMs in advancing the field of ET prediction.

Background and Motivation

Water is the most critical resource for sustainable agriculture and hydrological ecosystems. According to WaterNSW and Natural-Resources-Access-Regulator 25–30% of NSW, Australia's groundwater data is unaccounted for due to the majority of monitoring sites being manually logged with minimal sensor integration, while ground bores are also expensive necessitating the need to develop a cost-effective automated system [1].

Description of the Developed Sensor Node

The current method is focused on developing an IoT-enabled low-cost embedded microcontroller system capable of delivering real-time sensor node data on a cloud server utilizing a LoRaWAN communication protocol [2]. The primary data is then analyzed to measure the statistical significance of the study parameters. The field data is then processed to model water loss in soil mainly by Evapotranspiration function using a machine learning algorithm. Furthermore, the research also focuses on the integration of a fabricated electromagnetic sensor with a microcontroller system to measure soil organic carbon which would significantly enhance the system's evaluation potential [3].



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Preliminary Results

Initially, in-situ lab testing and sensor calibrations were performed as a baseline to validate sensor nodes' performance in the real field.

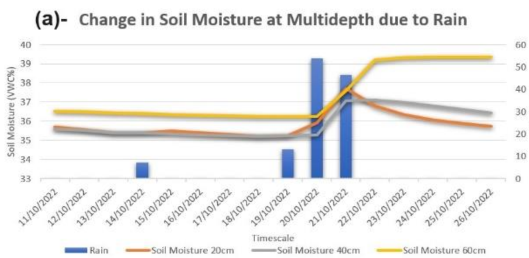

Fig. 2. Change in soil moisture content at subsequent depths after a rain event.

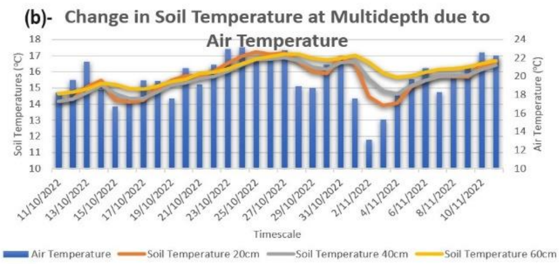

Fig. 3. Change in soil temperature at multi-depth due to varying air temperature.

Model Construction

The crop-evapotranspiration (ET_C-mm/d) prediction model was constructed based on the Support Vector Machine (SVM) Learning algorithm [4] in which various parameters are measured from the deployed sensor node and computed using mathematical equations in an R-programming tool, such as; Air Temperature (°C), Barometric Pressure (hPa), Wind Speed (Km/h), Relative Humidity (%), Rain (mm), Solar Exposure (MJ/m2), Soil Temperature (°C), and change in Soil Moisture (%VWC).

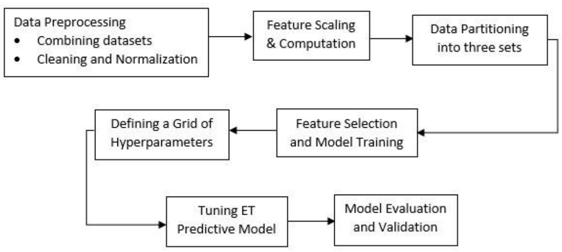

Fig. 4. Model Implementation Flowchart

The reference-evapotranspiration (ET_O-mm/d) was computed using the Penman-Monteith equation (1) [5].

$$ET_o = \frac{0.408\Delta(R_s - G) + \gamma\left(\frac{900}{T+273}\right)u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

Where,

Δ = Slope of Saturation Vapor Pressure Curve (kPa/°C)
Rs = Solar Radiation (MJ/m2 day-1)
G = Soil Heat Flux ≈ 0
ϒ = Psychrometric Constant
T = Air Temperature (℃)
u2 = Wind Speed (km/h)
es = Saturation Vapor Pressure (kPa)
ea = Actual Vapor Pressure (kPa)

Model Results

The results demonstrate the robustness and high predictability of the developed model based on the performance evaluation metrics: R^2, RMSE, and MAE [6]. The effectiveness of the proposed ET model in capturing complex relationships within soil and environmental parameters provides insights into its potential applications for water resource management and hydrological ecosystems.

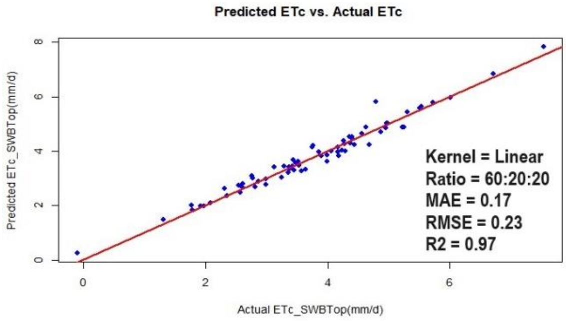

Fig. 5. Illustrating Evapotranspiration Prediction Model of the SVM Linear Kernel, (60:20:20)

Table 1. Evaluation Metrics for the ET Model with Best Hyperparamters Grid.

Kernel Function: Linear	Data Partition: 60:20:20	
Evaluation Metrics		
MAE	RMSE	R^2
0.17	0.23	0.96

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