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Abstract.

The agricultural sector is the largest consumer of the world's available fresh water resources. With fresh water scarcity increasing worldwide, more efficient use for irrigation water is necessary. Precision irrigation is described as the application of water to meet crop needs of a specific area, at the right amount and at the time that is optimum for crop health and management objectives. Irrigation becomes increasingly efficient through the use of precision irrigation tools. However, to maximize this efficiency, additional technologies can be applied. The main purpose of artificial intelligence (AI) is to learn from past experiences and data to perform an assigned task to solve a particular problem with efficiency and accuracy. AI is becoming pervasive in agriculture due to its ability to solve complex and unique problems. The application of AI in agriculture has the potential to greatly increase efficiency by improving our ability to manage crop inputs. When AI is utilized to implement precision irrigation, the results are economically and environmentally beneficial. Soil moisture plays a key role in crop health and productivity. In the study presented here, an AI model uses automated measurements of precipitation, estimates of evapotranspiration, and surficial soil moisture measured from satellite platforms to estimate daily crop water use (DWU) and provide irrigation scheduling recommendations. Other parameters such as soil temperature, solar radiation, and wind trends are also considered in this analysis. In this study, the machine learning model is trained and validated using in situ data collected from three farmer-managed sweet corn (Zea mays subsp. mays) farms located in Mitchell and Decatur Counties, Georgia, United States of America. Sentek™ soil moisture sensing probes are used to measure volumetric water content (VWC) of the soil. Precipitation, solar radiation, and wind speed is measured with Davis Instruments™ Vantage Pro2 weather stations installed at each field location. This poster presents the results from the first field season.

Keywords.
Precision irrigation; precision agriculture; artificial intelligence; soil moisture; irrigation scheduling

Introduction

The global human population is expected to reach approximately 10 billion by the year 2050 (FAO 2017). It is evident that optimal farming practices are imperative to feed and clothe this exponential increase in consumers (Jha et al. 2019). By ensuring proper usage of resources, conquering this feat is more easily feasible (Talaviya et al. 2020). Precision agriculture (PA) uses various technologies such as global navigation satellite systems (GNSS), remote sensing, and variable rate technology (VRT) to ensure optimal application of resources in agricultural practices ((Bongiovanni and Lowenberg-Deboer 2004). Likewise, precision irrigation (PI) is a subset of PA whose goal is to use an ideal volume of water, at the right time, for a specific area of a field (Adeyemi et al. 2017). Irrigation is an essential component of crop production (Vellidis et al. 2008). The agricultural sector is responsible for 85% of the world's freshwater consumption (Talaviya et al. 2020). This responsibility demands innovative technologies for practical and cost-effective water conservation technology in agriculture (Umair and Usmain 2010, Vellidis et al. 2008).

The major parameters that influence irrigation needs are temperature, soil composition, air humidity, solar radiation, wind, and soil moisture (Umair and Usmain 2010). Understanding soil moisture is a key component in making sound irrigation management and water conservation decisions (Talaviya et al. 2020). Soil moisture sensors are one of the most common technologies used to quantify soil moisture content (Dukes et al. 2009, Jha et al. 2019, Vellidis et al. 2008). These sensors work to gather in-situ information that is then, typically, transmitted to an irrigation controller (Quails et al. 2001, Talaviya et al. 2020). When soil moisture data is used in an expert system, specific irrigation needs can be better defined.

When PI technology is complemented with artificial intelligence (AI), the ability to relay specific solutions to complexly defined problems becomes increasingly achievable (Jha et al. 2019). Automation is imperative for optimal irrigation scheduling (Jha et al. 2019, Umair and Usain 2010). Maximum water-use efficiency can be achieved by using automated irrigation systems that monitor soil moisture at optimal levels (Umair and Usain 2010). Artificial neural networks (ANNs) are machine learning systems that mimic human decision-making processes (Kukreja et al. 2016). ANNs have been heavily adopted in water resources and have proven to be beneficial for prediction and forecasting (Jha et al. 2019, Maier and Dandy 2000).

The overarching objective of this research is to develop a user-friendly smartphone application that rapidly and efficiently estimates root zone soil moisture (RZSM) of farms by integrating in-situ soil moisture data paired with remote sensing data from satellites, meteorological data from weather monitoring networks, and soil and vegetation data from local observation. This application will be called 'RZSM View' and will aid growers in irrigation scheduling.

Methods

The study area for this research is located in southwest Georgia, United States of America. The fields of interest are located in Decatur and Mitchell counties, Georgia, USA. Six Sentek™ soil moisture probes have been installed amongst three sweet corn (*Zea mays subsp. mays*) fields, with two sensors located in each field. The 60 cm Sentek™ soil moisture probes measure volumetric water content (VWC) and soil temperature at six depths, every ten centimeters. The probes are installed in various soil types ranging from loamy sand to sand. The probes are connected to AgSense™ data loggers that transmit data to a web interface that allows the user to monitor the various metrics measured. Precipitation, solar radiation, and wind speed is being measured by Davis Instruments™ Vantage Pro2 weather stations installed at each field location. This data will be used in the development of an evapotranspiration (ET) based model for estimating DWU and a growing degree day (GDD)-based crop coefficient curve (K_c) that estimates DWU from Penman-Monteith ET (ET_o).

The National Aeronautics and Space Administration (NASA) provides global soil moisture data via a satellite-based microwave sensor (SMAP). This satellite provides soil moisture data for the top 5-10 cm of soil at a spatial resolution of 3-9 km every 2-3 days (Entekhabi et al. 2010, Kerr et al. 2001). These spatial and temporal scales are much too course to be used in irrigation management. Therefore, two ANNs will be developed to down-scale SMAP data. The first ANN will increase the temporal resolution of the SMAP data from 2-3 days to real-time. The second ANN will increase the spatial resolution of the SMAP data from 3-9 km to 1 km or better. After these ANNs convert the data into a more suitable format for this research, the data will be paired with the in-situ RZSM data gathered to aid in automated irrigation scheduling.

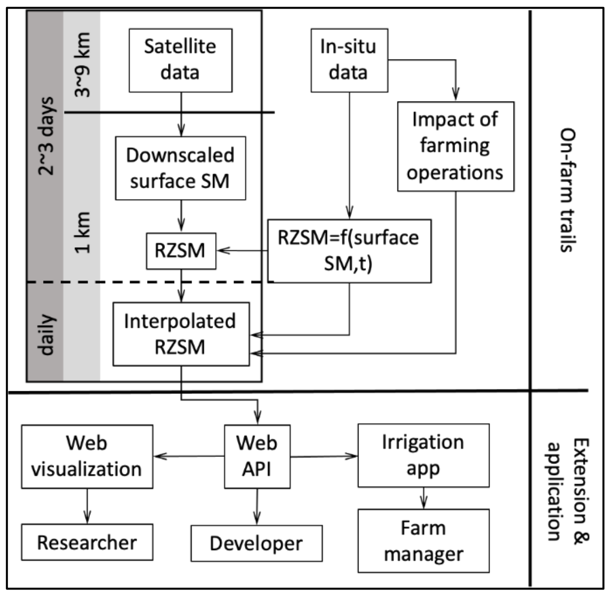

Figure 1: Project methods. (The box on the upper left corner indicates the scale change of SM information over the research development. The solid line marks the spatial resolution improvement from 9~36 km to 1 km. The dashed line implies the temporal resolution change from 2~3 days to daily. The arrows reflecting the directions of data flow and the relationships between different activities.)

Conclusion

This research will continue with on-farm trials with growers and crop consultants in Georgia, USA for years 2-5. The ANNs developed will be used to automate irrigation scheduling based on irrigation system information and crop-specific needs. This approach will be used to educate specialty crop growers on efficient irrigation practices that will result in a decrease in water and energy costs due to the resulting application's insight.

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