Using Remote Sensing to Benchmark Crop Coefficients of Sweet Corn Grown in the Southeastern United States

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Abstract. *Smart irrigation is described as 'the linking of technology and fundamental knowledge of crop physiology to significantly increase irrigation water use efficiency'. Irrigation scheduling tools such as smartphone applications have become prevalent in agricultural production due to their ability to decrease water use and improve crop health and yield. A suite of irrigation scheduling apps called "SmartIrrigation Apps for Scheduling Irrigation" contains models for many agronomical and horticultural crops, however, one does not currently exist for sweet corn (Zea mays var. rugosa). In the study presented here, we used satellite-based remote sensing data to benchmark crop evapotranspiration (ETc) estimates for sweet corn grown in the southeastern United States to provide irrigation scheduling recommendations for individual fields. Initial ETc estimates were collected over four seasons, across 12 grower-managed commercial sweet corn farms located in Mitchell, Decatur, and Seminole Counties, Georgia, United States of America (USA). We benchmarked the initial ETc estimates with PlanetScope™ satellite imagery-derived Normalized Difference Vegetation Index (NDVI) data, allowing us to adjust the crop coefficient (Kc) curve to reflect crop water needs for individual fields. This information will be incorporated into the existing SmartIrrigation App Suite to create a sweet corn model.*

Keywords. *Precision Irrigation, Irrigation Scheduling, Smart Irrigation, Precision Agriculture.*

Introduction

According to the Food and Agriculture Organization (FAO), the human population is expected to reach approximately 10 billion in the next 2 decades (FAO, 2017). This increase will require current plant-based food production to double in order to feed the growing population (Ainsworth et al., 2012). When considering this drastic increase in production needs, it is clear that efficient agricultural practices are necessary (FAO, 2017; Jha et al., 2019; Abioye et al., 2020; Garcia et al., 2020; Talaviya et al., 2020). Agricultural irrigation is also responsible for over 85% of global freshwater usage (Talaviya et al., 2020). Therefore, innovative technologies and practices to ensure practical and cost-effective water conservation play a vital role in optimizing efficient agricultural production (Umair and Usmain, 2010; Vellidis et al., 2016).

Precision Agriculture and Precision Irrigation

The quickly evolving field of precision agriculture (PA) uses emerging technologies to ensure optimal application of resources in agricultural production (Bongiovanni and Lowenberg-Deboer, 2004). Precision irrigation (PI), a subset of PA, bears the goal of optimizing application of water to meet crop needs of a specific area at a specific time to achieve ideal crop health and management goals (Smith and Baillie, 2009; Pierce, 2010). PI considers varying water needs of crops, soil characteristics, precipitation, atmospheric conditions, and crop-specific attributes when making irrigation decisions (Abioye et al., 2020; Daccahe et al., 2015). When utilized efficiently, PI can increase both crop production and irrigation water use efficiency (IWUE) by up to 40% (Savitha and UmaMaheshwari, 2018; Vellidis et al., 2016).

Irrigation scheduling (IS) is a facet of PI that provides information to guide the decisions on how much irrigation water to apply and when to apply it (George et al., 2000; Broner, 2005; Wang and Cai, 2009). Implementation of IS has been shown to maximize yield while also reducing water costs and fertilizer run-off (Broner, 2005). A key concept in IS is evapotranspiration (ET) estimation. ET is defined as the cumulative water loss through evaporation from the soil surface surrounding a plant, combined with plant transpiration (Allen, 2005). Because of the value of considering ET in understanding crop water needs, ET-based IS has become prevalent, especially in crops that are sensitive to water stress, such as sweet corn (*Zea mays var. rugosa*).

Sweet Corn in Georgia

Sweet corn is one of the most popular crops, globally, and the United States of America (USA) ranks first in global sweet corn production (Tracy, 1993). Over 50 percent of global sweet corn production takes place in the state of Georgia, and of that, 50 percent is produced in Mitchell and Decatur Counties (McAvoy and Coolong, 2022). Because sweet corn is marketed as "fresh produce", quality is critical in sweet corn production. Sweet corn is sensitive to water stress and optimal soil water conditions are necessary for high yields and high quality and intensive management is necessary throughout the growing season (Kwabiah, 2004). As a result, sweet corn has relatively high-water needs (Hassanli et al. 2009). When sweet corn is grown under irrigated management conditions, it has increased yield potential (Viswandatha, 2002). IS has proven to be an effective method of improving water use efficiency, while also improving sweet corn yield (Braunworth and Mack, 1987; Hassanli et al., 2009; Datta et al., 2022). However, irrigation management for sweet corn grown in the southeastern USA is particularly difficult due to the high climatic variability and uncertainty of precipitation during the growing seasons (Stone, 2016).

The SmartIrrigation App Suite

Beginning in 2012, a group of University of Georgia (UGA) and University of Florida (UF) faculty began developing a suite of irrigation scheduling apps for a variety of crops. The suite was called

“SmartIrrigation Apps for Scheduling Irrigation” and the initial group included apps for citrus, cotton, strawberry, and residential turf. Several more apps have been added to the suite, including the SmartIrrigation CropFit App, that combines irrigation scheduling recommendations for field corn, cotton, and soybeans. Models for peanut and sweet corn irrigation scheduling will be integrated into the CropFit App in 2025. The SmartIrrigation App Suite uses the approach described in ‘Organization in Irrigation and Drainage Paper No. 56’ (also known as FAO-56) to estimate daily crop water use.

Crop Coefficients (Kc)

The FAO released FAO-56 (Allen et al., 1998) to revise the guidelines for quantifying crop water requirements. FAO-56 uses the FAO Penman-Monteith (FAO-56 PM) equation (Equation 1) to estimate crop water requirements (Kc curves) for various crops at different growth stages (Allen and FAO, 1998).

$$ETc = ETo \times Kc. \tag{1}$$

where

ETc is crop evapotranspiration,

ETo is reference evapotranspiration, and

Kc is crop coefficient.

For annual crops, Kc changes with the phenological stage and is used to proportionally modify ETo. Kc typically begins with small values after emergence and increases to 1.0 or above when the crop has the greatest water demand. This usually occurs during the crop’s reproductive stage (Shavkat Kenjabaev et al., 2020).

Allen et al. (1998) state that sweet corn maturity fluctuates between 58 and 100 days depending on growing region and season. The water needs of sweet corn increase rapidly from 40% of ETo to 110% of ETo during the peak growth stage, resulting in differing Kc values at different growth stages (Ozorez-Hampton et al., 2012). The growth stages at which Kc values peak consists of silking, tasseling, and ear development. Similarly, this is the period at which sweet corn is most sensitive to water stress (Rao, 1988). The FAO has released a Kc curve for sweet corn, the data on which the curve is based was collected from sweet corn grown in Idaho, USA., which has a different climate than the southeastern USA (Allen et al., 1998) (Figure 1).

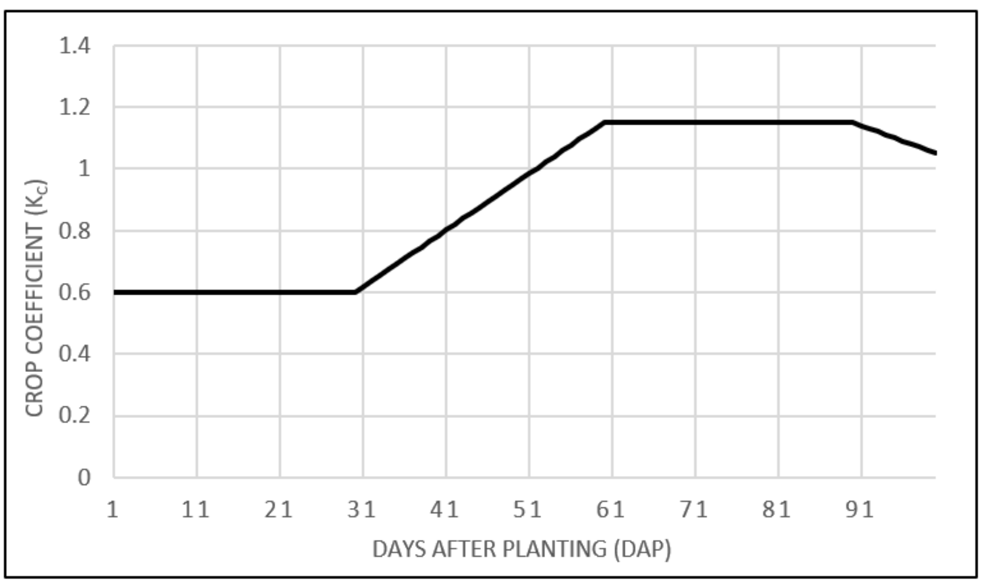

Fig 1. Crop coefficient (Kc) curve for sweet corn grown in Idaho, USA, as a function of days after planting (DAP) (adapted from Allen et al., 1998).

Due to these climatic differences and the impact they have on sweet corn growth and development, we created a revised ET-based Kc curve for sweet corn based on data collected in southwestern Georgia, USA.

Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) has proven to be a valuable tool in irrigation scheduling (Hunsaker et al., 2003; Singh et al., 2012). NDVI is the best-known and most widely used vegetation index (VI) (Rouse et al., 1974; Hobbs and Moody, 1990; Myneni et al., 1995; Pettorelli et al., 2005; Wu et al., 2019). Because NDVI has been found to be a good predictor of biomass, it is also a good predictor of Kc (Bausch and Neal, 1987; Hunsaker et al., 2003; Stone, 2016). While Kc values are indicative of irrigation requirements of a crop, Bausch and Neal (1987) and Stone (2016) found that seasonal NDVI curves resemble seasonal Kc curves. These findings show that spectrally derived Kc values may be considered a real-time Kc that illustrates the crop's response to weather, stresses, and management (Stone, 2016). NDVI-based Kc values adequately relay crop water needs, therefore, when paired with irrigation scheduling can improve WUE. The study described here evaluated the performance of NDVI as a predictor of real-time Kc values of individual sweet corn farms.

Methods

This study is comprised of three stages: (1) data collection; (2) Kc curve development, (3) evaluation of NDVI as an indicator of crop water needs (Kc values). The data collection stage entailed installing soil moisture sensor probes in grower-managed, commercial sweet corn fields to collect daily water use (DWU) data. DWU data were collected over four growing seasons– the spring and autumn growing seasons of 2022 and 2023. Our study sites were in Mitchell, Decatur, and Seminole Counties within Georgia, USA. These counties lead the state of Georgia in sweet corn production, and the climate is categorized as humid-subtropical with hot, humid summers and mild winters.

Data Collection

To collect data to develop the Kc curve, each sweet corn field was instrumented with two soil moisture probes (Sentek Sensor Technologies—Stepney SA, Australia). The 60 cm (24 in) soil moisture probes measured soil moisture as volumetric water content (VWC) at six depths, every 10 cm (4 in), beginning at 10 cm (4 in) below the soil surface. Once installed, the probes were connected to data loggers (AgSense Solutions—South Dakota, USA), that transmit data to a web interface in 30-minute intervals. For this project, the probes were used only to monitor VWC, and individual growers managed the irrigation of these fields. Precipitation, solar radiation, and wind speed were measured by Vantage Pro2 weather stations (Davis Instruments Corporation — California, USA) installed at each field location and cross referenced with meteorological data derived from the UGA weather network.

Kc Curve Development

DWU calculations for developing the Kc curve were made from VWC data that were collected between field capacity and wilting point. The calculated DWU values were assumed to be daily crop water use, or crop evapotranspiration (ETc). Only ETc values from days with solar radiation that is equal to or greater than the mean solar radiation for the period of record from the nearest UGA weather stations were used for further analysis. This was to ensure that the Kc curve represents peak water use for each phenological stage.

The remaining ETc values were paired with the corresponding daily ETo values calculated with meteorological data from the nearest weather station. The ETc and associated ETo values were then applied to Equation 2 to calculate a daily, Kc.

$$Kc=ETc/ETo \tag{2}$$

where

Kc is crop coefficient.

ETc is crop evapotranspiration,

ETo is reference evapotranspiration, and

Daily Kc values were used to create the empirically adjusted ET-based Kc curve for sweet corn grown under the climatological conditions in southern Georgia and northern Florida (Figure 2).

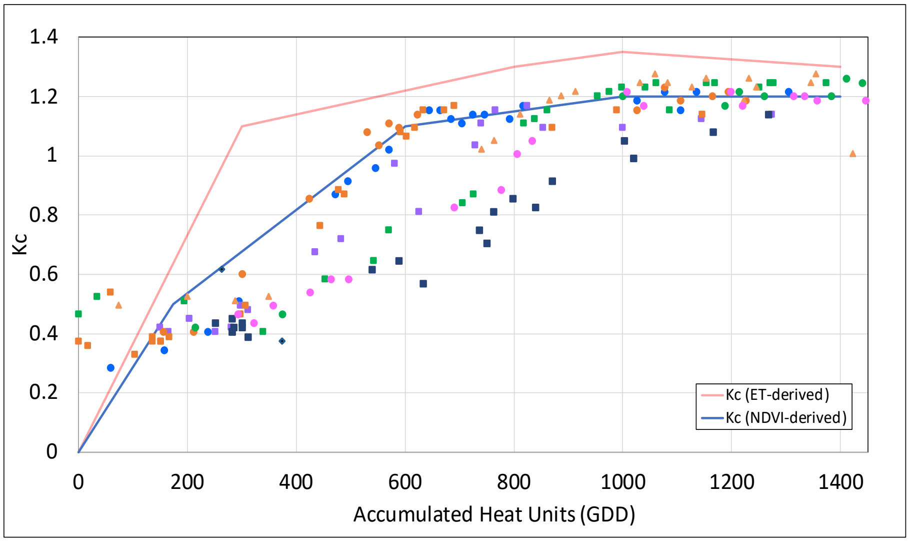

Fig 2. Crop coefficient (Kc) curves derived from DWU (ETc) measurements and on study fields and NDVI values of individual fields (indicated by various colors and shapes) from PlanetScope™.

Results

The values for ET-based Kc and NDVI-based Kc plotted as a function of GDD show that both parameters increased similarly during the early stages of crop development and had a comparable horizontal trend as the crop approached harvest. In all fields evaluated, the maximum Kc occurred around the time of effective canopy closure, when NDVI values for replicates were also highest, 0.75 or above at approximately 1000 GDD. After effective full cover, NDVI remained relatively constant within the range of 0.75-0.85 until harvest. However, NDVI-based Kc values were slightly lower than those that were based on ET. Because of this, we elected to develop a secondary Kc curve that better represented the NDVI-based Kc (Figure 2). Both Kc curves will be evaluated for IWUE at the UGA's Stripling Irrigation Research Park in Camilla, Georgia, USA during the spring and autumn seasons of 2024 and 2025 to determine their performance.

Discussion and Conclusions

Seasonal NDVI values were evaluated as predictors for seasonal Kc for sweet corn grown in the southeastern USA. An initial evaluation of the model indicated that the NDVI-based crop coefficient (Kc) provided ETc estimations that closely matched the observed ETc obtained from in-field data. The NDVI-based Kc trended lower than our ET-based Kc, therefore an adjusted Kc curve that better represents NDVI-based Kc was also developed and will be evaluated for performance. The NDVI-based Kc function used in this methodology can be easily integrated into the FAO-56 dual crop coefficient procedures, as well as the CropFit App, allowing for the application of remotely sensed observations for real-time sweet corn irrigation scheduling. Further experiments are underway at UGA's Stripling Irrigation Research Park to assess the application of the NDVI-based and ET-based Kc for scheduling irrigations for sweet corn.

The primary benefits anticipated from using real-time multispectral-based Kc to compare with conventional Kc curves include the ability to account for real-time individual field conditions. Remotely sensed Kc is expected to align with the unique developmental patterns of the crop, thereby potentially eliminating the need for field observations, assumptions, and complex procedures associated with adjusting conventional Kc curves for conditions other than optimum. Additionally, the remote sensing technique may enable the detection and quantification of differences in ETc within a single field and on a field-by-field basis.

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