

DEVELOPING A DATA-DRIVEN DECISION SUPPORT TOOL TO ENHANCE
IRRIGATION WATER USE EFFICIENCY AND FRESH MARKET QUALITY OF SWEET
CORN IN THE SOUTHEASTERN UNITED STATES

by

EMILY K. BEDWELL

(Under the Direction of George Vellidis, Ph.D.)

ABSTRACT

The United States (U.S.) is the world's leading producer of fresh market sweet corn (*Zea mays* subsp. *mays* L.). In Georgia, over 9,000 ha (23,000 ac) of sweet corn are harvested annually, valued at over USD 106 million in 2023. Failure to meet crop water needs can affect yield and quality, prompting growers to over-irrigate. Over-irrigation can lead to inefficient water use and soil health problems. Science-based irrigation scheduling tools that deliver information on modern platforms are needed to improve irrigation water use efficiency and long-term sustainability. The overall goal of this study was to develop an affordable, user-friendly, and reliable irrigation scheduling tool for sweet corn adapted to growing conditions in the southeastern U.S. Two approaches were used to develop this tool. The first developed an evapotranspiration (ET) -based model using the United Nations Food and Agricultural Organization (FAO)-56 method of estimating daily crop ET (ET_c). The second approach used a model based on the normalized difference vegetation index (NDVI) to estimate ET_c. The models were evaluated with replicated field trials conducted in southwestern Georgia and compared to other irrigation scheduling approaches. Evaluation metrics included yield, irrigation water use

efficiency, and physical qualities related to the marketability of fresh market sweet corn. The best performing model was incorporated into SmartIrrigation CropFit, an irrigation scheduling tool that operates on a smartphone platform.

INDEX WORDS: Irrigation scheduling, remote sensing, normalized difference vegetation index, evapotranspiration, U.S. Fancy Grade.

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DEDICATION

I dedicate this dissertation to my beloved Mimi, Hilda “Rae” Taylor—the person who told me there was nothing I could not do enough times until I finally believed it. Your unwavering kindness and wisdom have shaped who I am today. You taught me that our purpose on this earth is to leave it better than we found it—a lesson that applies not only to how we treat one another but also to how we care for our planet and future generations. Your compassion, grace, and belief in the power of goodness despite adversity continue to inspire me every day. This work is a tribute to the values you have instilled in me and the legacy of kindness that you will leave behind.

Here’s to making the world a little better, just as you have.

“Try and leave this world a little better than you found it, and when your turn comes to die, you can die happy in feeling that at any rate, you have not wasted your time but have done your best.”

- *Robert Baden-Powell*

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CHAPTER 1

INTRODUCTION

1.1. Introduction

Sweet corn (*Zea mays* subsp. *Mayes* L.) is a globally popular crop and the third most-grown vegetable crop in the United States (U.S.) (Barros-Rios et al., 2015; Garcia y Garcia et al., 2009; Paranhos et al., 2023). The U.S. ranks first in global sweet corn production, consumption, and exportation (Dhaliwal and Williams II, 2023; FAO, 2021). Within the U.S., Georgia ranks third for national fresh market sweet corn production. In 2023, the economic value of sweet corn production in Georgia exceeded USD 106 million, with over 9,000 ha (23,000 ac) harvested (McAvoy and Coolong, 2023).

Quality is critical for sweet corn production in the U.S. because much of the production is for the fresh market, which has stringent quality standards. High yield and quality depend on the crop's water needs being met throughout the growing season, which can be difficult as sweet corn water needs increase as the season progresses, as does its sensitivity to water stress (Rao, 1988; Hassanli et al., 2009). The sweet corn varieties grown in the southeastern U.S. require between 203 and 356 mm (8-14 in) of water during the growing season, depending on variety (Allen et al., 1998; Westerfield and Eason, 2024). Although annual precipitation in the southeastern U.S. ranges from approximately 1200-1500 mm (47-60 in), the uncertainty of precipitation timing and magnitude in combination with sandy soils with low water holding capacity results in high variability in rainfed yields in this region. To reduce this risk, irrigation systems are increasingly used to avoid crop water stress (Bednarz et al., 2002; Stone et al., 2016; Sui, 2017).

Sweet corn has significantly higher yield potential when grown under irrigated management conditions (Viswandatha et al., 2002). In a study by Hassanli et al. (2009), irrigation scheduling based on soil moisture deficit led to a significant increase in sweet corn yield. When utilized in sweet corn management, irrigation scheduling ensures the crop's water needs are met strategically and efficiently, optimizing production (Braunworth and Mack, 1987; Hassanli et al., 2009; Datta et al., 2022).

1.2. Literature Review

1.2.1. Irrigation Scheduling and Sweet Corn Water Needs

Irrigation scheduling is defined as "the decision of when and how much water to apply to a field at a given time" (George et al., 2000; Broner, 2005; Wang and Cai, 2009). Irrigation scheduling improves water use efficiency by maintaining plant available soil water within an optimal range and avoiding over-and/or under-irrigation (Jones, 2004; Howell, 1996). Various factors complicate irrigation scheduling decisions, including climate, crop and soil type, and availability of irrigation water (Rao et al., 1988; Steele, 1994). In addition to stable yields, irrigation scheduling has several advantages, including improving water use efficiency, reducing fertilizer run-off and costs, and minimizing water-logging issues within the soil profile (Broner, 2005).

Irrigation scheduling techniques that use atmospheric and environmental parameters to determine daily crop water needs (also referred to as crop evapotranspiration or ET_c) are becoming increasingly available (Migliaccio et al., 2015; Vellidis et al., 2016). These techniques make effective irrigation decisions that avoid crop water stress without the need for soil moisture sensors (O'Shaughnessy and Evett, 2010).

As mentioned previously, the sweet corn varieties grown in the southeastern U.S. typically need between 203 and 356 mm (8-14 in) of water throughout the growing season, depending on the variety and meteorological factors (Westerfield and Eason, 2024). Although the annual rainfall in this region averages between 1200-1500 mm (47-60 in), the unpredictability of precipitation timing and amounts, along with sandy soils that retain little moisture, contributes to significant variability in yields from rainfed crops (Kwabiah, 2004). Many farmers utilize irrigation systems to mitigate this risk and to alleviate crop water stress, particularly for crops that are increasingly sensitive to water stress as the season progresses, like sweet corn (Bednarz et al., 2002; Stone et al., 2016; Sui, 2017).

Sweet corn's response to water stress varies depending on its growth stage, and the crop's susceptibility to yield and quality losses related to water stress increases as it approaches reproductive stages (Rao, 1988). Thus, accurately determining the phenological stage of this crop is essential for efficient irrigation management, as sweet corn water requirements can increase as much as 70%, from vegetative to the reproductive stages (Ozorez-Hampton et al., 2012).

1.2.2. Growing Degree Days

The phenological stage of a crop is a crucial factor that affects its water requirements. Accumulated heat units, commonly known as growing degree days (GDD), are vital for determining these developmental stages. GDDs forecast the timing of a plant's biological processes, which can improve the prediction of phenological events. This, in turn, helps enhance the efficiency of irrigation management (McMaster and Wilhelm, 1997). GDDs are calculated using the following equation:

$$GDD = \left[\frac{T_{max} + T_{min}}{2} \right] - T_{base} \quad (1.1)$$

where,

T_{max} = maximum daily temperature,

T_{min} = minimum daily temperature, and

T_{base} = base temperature of the crop.

The base temperature, or the threshold temperature at which plant growth begins, for sweet corn is 10°C (50°F) (Gilmore and Rodgers, 1958; Lass et al., 1993; Kara, 2011). However, sweet corn growth is also hindered and reduced by 0.5% each additional day in which the temperature is greater than 30°C (86°F) (Dhaliwal and Williams II, 2022).

1.2.3. Crop Evapotranspiration and Coefficients

Evapotranspiration (ET) estimation plays a pivotal role in irrigation scheduling, as it reflects the cumulative water loss from the soil surface and through plant transpiration (Allen et al., 2005). Crop evapotranspiration (ET_c) is quantified by a complex process that considers various environmental factors, including relative humidity, solar radiation, wind speed, temperature, and crop characteristics (Allen, 2005; Ertek and Kara, 2013). The FAO developed guidelines for estimating crop water requirements in "Organization in Irrigation and Drainage Paper No. 56" (FAO-56) that utilizes the FAO Penman-Monteith equation to estimate crop water requirements, or crop coefficients (K_c) (Allen et al., 1998) (Eq. 1.2).

$$ET_c = K_c \times ET_o \quad (1.2)$$

where,

ET_c = daily crop evapotranspiration (ET), also referred to as crop water use (mm day⁻¹),

K_c = a daily crop coefficient extracted from a crop-specific K_c curve, and

ET_o = Penman-Monteith reference ET (mm day⁻¹).

K_c varies throughout the different phenological stages of a crop. These values typically peak during the reproductive stages, when water demand is at its highest. As K_c changes according to

the phenological stage, it modifies ETo. For annual crops, Kc values start low after the crop emerges and increase to 1.0 or higher as it enters its reproductive growth stages when it requires the most water. According to Allen et al. (1998), the maturity of sweet corn can vary between 60 and 100 days, depending on the growing region and season. During its peak growth stage, water needs can increase rapidly from 40% of ETo to 110% of ETo. As a result, different Kc values are observed at various growth stages (Ozorez-Hampton et al., 2012). The growth stages during which Kc values are highest for sweet corn include silking, tasseling, and ear development, which are also the periods when sweet corn is most vulnerable to water stress (Rao, 1988). Because Kc curves that are based on GDD consider the meteorological conditions during the growing season, they typically estimate crop water needs more accurately than Kc curves that are based on days after planting (DAP) (Vellidis et al., 2016).

1.2.4. Methods for Developing Kc Curves

The traditional approach for developing Kc curves involves using weighing lysimeters to accurately estimate ETc by measuring daily changes in lysimeter mass and accounting for precipitation (Yang et al., 2000; Liu et al., 2002; Benli et al., 2006). Because weighing lysimeters are not readily available, other approaches have been developed. Vellidis et al. (2016) used matric potential soil moisture sensors in replicated plot trials to optimize cotton Kc curves developed in other regions for local conditions of the southeastern U.S. In that study, the Kc curve was modified so that using it for irrigation scheduling resulted in predetermined ranges of matric potential in the crop's root zone prior to and during the reproductive stage.

1.2.5. The SmartIrrigation Apps

Over the past four decades, an increasing number of irrigation scheduling tools based on the concepts of FAO-56 have been developed. Typically, these have been computer or web-based

models that pull the meteorological data needed for ETo calculations from weather station networks (Davis and Dukes, 2010). Within the past decade, these tools have migrated to smartphone platforms (Migliaccio et al., 2015; Vellidis et al., 2016; Miller et al., 2018).

The suite of SmartIrrigation Apps (SI Apps) (<https://smartirrigationapps.org/>) is a group of irrigation scheduling models for horticultural and agronomic crops. These models provide irrigation scheduling recommendations based on crop type, phenological stage, and real-time meteorological parameters using the FAO-56 method. The SI Apps use meteorological data to calculate daily ETo and then apply the appropriate Kc to estimate daily ETc. Models for agronomic crops (maize, cotton, peanut, and soybean) are embedded in the SmartIrrigation CropFit (SI CropFit) App. In these models, phenology and associated changes in Kc are driven by GDDs, and irrigation scheduling is based on a soil water balance model.

The SI CropFit soil water balance model uses daily ETc, precipitation received, irrigation applied, and the soil's plant available water holding capacity (AWHC) to estimate a daily root zone soil water deficit (RZSWD) in terms of percent and inches of plant available soil water. Plant available soil water is defined as the water held by the soil matrix between field capacity (FC – the point at which water no longer moves through the soil due to gravity) and the wilting point (WP – the point at which the plants can no longer effectively extract water from the soil). A 50% RZSWD or depletion of 50% of plant available soil water is a commonly accepted irrigation threshold for agronomic crops. The model calculates today's plant available soil water by subtracting yesterday's ETc from yesterday's plant-available soil water and adding precipitation received or irrigation applied.

The SI Apps pull meteorological data from several sources – state weather station networks (mesonets), Apple Weather (a commercial provider of meteorological data), and five commercial

automated rain gauge brands using application programming interfaces (APIs). Users in U.S. states with participating mesonets can select a weather station as their primary provider of meteorological data. The closest weather station is selected based on the field's coordinates. Users elsewhere utilize Apple Weather, which provides meteorological data on a 4 km (2.5 mi) grid, as their primary provider of meteorological data. The field's coordinates are used to select the appropriate source grid. Because accurate precipitation data are critical to maintaining an accurate soil water balance, an automated on-farm rain gauge that provides hyper-local precipitation data is highly recommended when SI CropFit is used for irrigation scheduling.

One of the functionalities of SI CropFit is that users can define the perimeter of their field using dropped pins. The perimeter is then used to extract soil information, including soil type, FC, and WP, from the United States Department of Agriculture (USDA) Natural Resources and Conservation Services (NRCS) Web Soil Survey (<https://websoilsurvey.sc.egov.usda.gov/App/>). The soil's plant AWHC is calculated by subtracting WP from FC. If there is more than one soil type within the field perimeter, an area-weighted average AWHC is calculated, and that value is subsequently used in the soil water balance model. SI CropFit operates primarily on a cloud server with daily updates of user-needed information to the smartphone platform. It is available for both iOS and Android platforms at no cost to the user.

The use of the SI Apps has resulted in increased yields and irrigation water use efficiency (IWUE) for many crops, including blueberry, citrus, maize, cotton, peanut, strawberry, tomato, turfgrass, soybean, and watermelon (Migliaccio et al., 2015; Vellidis et al., 2016; Ayankojo et al., 2018; Miller et al., 2018). In this study, IWUE is defined as:

$$IWUE = \frac{\text{Treatment Yield} - \text{Rainfed Yield}}{\text{Treatment Irrigation Applied} - \text{Rainfed Irrigation Applied}} \quad (1.3)$$

1.2.6. Estimating K_c with the Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is the best-known and most widely used vegetation index (Myneni et al., 1995; Pettorelli et al., 2005; Wu et al., 2019) for assessing plant vigor and biomass by utilizing the differences in reflectance between near-infrared (NIR) and red wavelengths. NDVI is calculated using Eq. 1.4.

$$NDVI = \frac{NIR+Red}{NIR-Red} \quad (1.4)$$

where,

NIR = reflected near-infrared wavelengths and

Red = reflected red wavelengths.

NDVI values range from -1 to +1, although in agricultural applications, the practical range is from 0 to 1. Higher values typically indicate more vigor / higher biomass, while lower values suggest the opposite. NDVI is particularly valuable in precision agriculture, as it allows for the assessment of the spatial variability of crop vigor within fields, thus enabling growers to make informed management decisions about the application of crop inputs (Hunsaker et al., 2003). NDVI has also proven to be a valuable tool in irrigation scheduling as NDVI can effectively indicate near-real-time crop water needs throughout the growing season (Hunsaker et al., 2003; Singh et al., 2012; Stone et al., 2016).

Research has shown that NDVI values closely correlate with crop coefficients, which represent crop water needs (Bausch and Neal, 1987; Hunsaker et al., 2003; Stone et al., 2016). These findings show that spectrally derived K_c values may be considered a real-time K_c that illustrates the crop's response to weather, stresses, and management (Stone et al., 2016).

1.2.7. U.S. Fancy Grade Fresh Market Quality Standards

Sweet corn grown within the U.S. is targeted for three markets: fresh, canning, and freezing. The fresh market accounts for over 30% of the national production and contributes to more than 65% of the economic production value (Lizaso et al., 2007; USDA-NASS, 2023). Because sweet corn produced for the fresh market is harvested at near maximum moisture and soluble sugar content, it is highly susceptible to perishability (Becerra-Sanchez and Taylor, 2021; Bayer, 2025). As a result, the U.S. established quality standards for fresh market sweet corn that also include factors associated with appearance and size. U.S. Fancy Grade is the premium grade for sweet corn and brings the highest market price (USDA, 1992).

The basic requirements of U.S. Fancy Grade sweet corn are that ears must have similar varietal characteristics, be well trimmed, and be well developed. "Similar varietal characteristics" refers to ears that have similar kernel color and character of growth, i.e., varieties of sweet corn having white kernels shall not bear characteristics of varieties that have yellow kernels. Well-trimmed describes ears that have intact husks and a shank no more than 15.2 cm (6 in), and well-developed can be defined as ears that are "fairly straight and not stunted" with no more than 38.1 mm (1.5 in) of poor-/no-tip fill (USDA, 1992). Similarly, ears must be free from smut (*Mycosarcoma maydis*), corn earworm (*Helicoverpa zea*), insect, bird and mechanical injury, decay, rust, and disease. U.S. Fancy Grade ears are also required to have kernels that are "plump and milky" and that are well covered with fresh husks. Lastly, ears shall not be clipped or be less than 15.2 cm (6 in) in length (USDA, 1992). When sweet corn faces water stress, specifically during reproductive stages, ear quality can be negatively affected (Ertek and Kara, 2013).

The standard metric for U.S. Fancy Grade sweet corn yield is measured in boxes per unit area harvested (boxes ha¹ or boxes ac¹), as this is how U.S. Fancy Grade sweet corn is harvested and

sold. In the southeastern U.S., standard boxes measure 28 cm × 28 cm (11 in × 11 in) and contain 48 ears of marketable sweet corn. An ear is considered "marketable" if it meets the U.S. Fancy Grade standards (McAvoy and Coolong, 2023; USDA, 2024). Quality is crucial in sweet corn production, especially regarding U.S. Fancy Grade Standards. The quality of sweet corn is highly influenced by an adequate water supply, which is essential for its growth and development. Therefore, effective irrigation management is vital for enhancing sweet corn's yield and quality potential (Viswandatha, 2002; Hassanli et al., 2009).

1.3. Project Goals

The overall goal of this study was to develop an affordable, user-friendly, and reliable irrigation scheduling tool for sweet corn adapted to growing conditions in the southeastern U.S. Specific objectives were to:

- (1) Develop an evapotranspiration (ET) -based irrigation scheduling model using the United Nations Food and Agricultural Organization (FAO)-56 method of estimating daily crop ET (ET_c).
- (2) Develop a normalized difference vegetation index (NDVI) -based irrigation scheduling model to estimate ET_c, and
- (3) Evaluate how different irrigation scheduling methods affect the physical qualities related to the marketability of fresh market sweet corn through replicated field trials.

Each of the above objectives corresponds to the next three chapters of this dissertation, respectively. Individual objectives which were used to pursue these goals are described in the corresponding chapters.

1.4. References

- Allen, R.G., Pereira, L.S., Raes, D., Smith, M. 1998. Crop evapotranspiration: Guidelines for computing crop water requirements. Irrigation and Drainage Paper No. 56. Food and Agricultural Organization, United Nations, Rome, Italy.
https://edisciplinas.usp.br/pluginfile.php/3887570/mod_folder/content/0/Boletim_FAO56.pdf. Accessed August 2021.
- Allen, R.G., Pereira, L.S., Smith, M., Raes, D., Wright, J.L. 2005. FAO-56 dual crop coefficient method for estimating evaporation from soil and application extensions. J. Irrigation and Drainage Engineering. 131(1), 2-13. [https://ascelibrary.org/doi/abs/10.1061/\(ASCE\)0733-9437\(2005\)131:1\(2\)](https://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9437(2005)131:1(2)). Accessed August 2021.
- Ayankojo, T. 2018. The use of SI App for irrigation scheduling in tomato production. University of Florida Water Institute, The 6th University of Florida Water Institute Symposium, Gainesville, Florida. Feb. 6-7, 2018.
<https://archives.waterinstitute.ufl.edu/symposium2018/downloads/Presentations/Ayankojo.pdf>.
- Barros-Rios, J., Romani, A., Garrote, G., Ordas, B. 2015. Biomass, sugar, and bioethanol potential of sweet corn. J. Global Change Biology Bioenergy. 7(1), 153-160.
<https://doi.org/10.1111/gcbb.12136>.
- Bausch, W., Neale, C. 1987. Crop coefficients derived from reflected canopy radiation: A concept. Trans. American Society of Agricultural and Biological Engineering. 30(3), 703-709. <https://doi.org/10.13031/2013.30463>.
- Bayer Crop Science. 2025. Sweet Corn Harvest: Quality and Safety.
https://seminisus.s3.amazonaws.com/app/uploads/2016/11/16_Sweet-Corn-Harvest-Quality-and-Safety-Seminis.pdf.
- Becerra-Sanchez, F., Taylor, G. 2021. Reducing Post-Harvest Losses and Improving Quality in Sweet Corn (*Zea mays* L.): Challenges and Solutions for Less Food Waste and Improved Food Security. J. Food and Energy Security. 10(3). <https://doi.org/10.1002/fes3.277>.
- Bednarz, C.W., Ritchie, G., Hook, G.E., Yager, R., Cromer, S., Cook, D., Griner, I. 2002. Cotton crop water use and irrigation scheduling. Georgia Cotton Research-Extension Report. Univ. of Georgia, Athens, GA. 61-64.
<http://ugacottonnews.org/vault/rer/2003/p72.pdf>. Accessed January 2022.
- Benli, B., Kodal, S., Ilbeyi, A., Ustun, H. 2006. Determination of evapotranspiration and basal crop coefficient of alfalfa with a weighing lysimeter. J. Agricultural Water Management. 81(3). 358-370. <https://doi.org/10.1016/j.agwat.2005.05.003>.
- Braunworth, W., Mack, H. 1987. Evaluation of Irrigation Scheduling Methods for Sweet Corn. J. American Society of Horticultural Science. 112(1), 29-32.
<https://pdfs.semanticscholar.org/6f05/d22d1910c71268dc90bbb1aa9c1b5d50a0a0.pdf>. Accessed January 2022.
- Broner, I. 2005. Irrigation Scheduling: Fact Sheet No. 4708. Colorado State University Extension, Crop Series 2. <https://extension.colostate.edu/docs/pubs/crops/04708.pdf>. Accessed 3 November 2021.
- Datta, D., Chandra, S., Nath, C., Kar, G., Ghosh, S., Chaturvedi, S., Bhatnagar, A., Singh, G., Singh, V. 2022. Soil-plant water dynamics, yield, quality and profitability of spring sweet corn under variable irrigation scheduling, crop establishment and moisture conservation practices. J. Field Crops Research. 279. <https://doi.org/10.1016/j.fcr.2022.108450>.

- Davis, S., Dukes, M. 2010. Irrigation scheduling performance by evapotranspiration-based controllers. *J. Agricultural Water Management*. 98(1), 19-28.
<https://doi.org/10.1016/j.agwat.2010.07.006>.
- Dhaliwal, D., Williams, M., II. 2023. An Outlook on Processing Sweet Corn Production from the Last Three Decades (1990s–2010s). *J. Horticultural Science*. 58(7), 792-796.
<https://doi.org/10.21273/HORTSCI17109-23>.
- Ertek, A., Kara, B. 2013. Yield and Quality of Sweet Corn under Deficit Irrigation. *Agricultural J. Water Management*. 129, 138–144. <https://doi.org/10.1016/j.agwat.2013.07.012>.
- Garcia y Garcia, A., Guerra, L., Hoogenboom, G. 2009. Water use and water use efficiency of sweet corn under different weather conditions and soil moisture regimes. *J. Agricultural Water Management*. 96(10), 1369-1376. <https://doi.org/10.1016/j.agwat.2009.04.022>
- George, B., Shende, S., Raghuwanshi, N. 2000. Development and Testing of an Irrigation Scheduling Model. *J. Agricultural Water Management*. 46(2), 121–136.
[https://doi.org/10.1016/S0378-3774\(00\)00083-4](https://doi.org/10.1016/S0378-3774(00)00083-4).
- Gilmore, E., Rogers, J. 1958. Heat Units as a Method of Measuring Maturity in Corn. *Agronomy Journal*. 50(10), 611–615. <https://doi.org/10.2134/agronj1958.00021962005000100014x>.
- Hassanli, A., Ebrahimizadeh, M., Beecham, S. 2009. The Effects of Irrigation Methods with Effluent and Irrigation Scheduling on Water Use Efficiency and Corn Yields in an Arid Region. *J. Agricultural Water Management*. 96(1), 93–99.
<https://doi.org/10.1016/j.agwat.2008.07.004>.
- Howell, T. Irrigation Scheduling Research and Its Impact on Water Use. 1996. Evapotranspiration and Irrigation Scheduling, Proceedings of the International Conference, Nov. 3-6, 1996, San Antonio, TX, American Society of Agricultural Engineers, St. Joseph, MI.
<https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=4216fcee2583f303cdf8cdf342c825a2c2fd7b1>.
- Hunsaker, D. Pinter Jr., P., Barnes, E., Kimball, B. 2003. Estimating cotton evapotranspiration crop coefficients with a multispectral vegetation index. *J. Irrigation Science*. 22:95-104.
<https://doi.org/10.1007/s00271-003-0074-6>.
- Jones, H. 2004. Irrigation Scheduling: Advantages and Pitfalls of Plant-Based Methods. *J. Experimental Botany*. 55(407), 2427–2436. <https://doi.org/10.1093/jxb/erh213>.
- Kara, B. 2011. Fresh ear yield and growing degree days of sweet corn in different sowing dates in southwestern Anatolia region. *Turkish Journal of Field Crops*. 16(2), 166-171.
<https://dergipark.org.tr/en/download/article-file/158720>.
- Lass, L., Callihan, R., Everson, D. 1993. Forecasting the Harvest Date and Yield of Sweet Corn by Complex Regression Models. *J. American Society for Horticultural Science*. 118(4), 450–455. https://www.researchgate.net/profile/Robert-Callihan/publication/265917092_Forecasting_the_Harvest_Date_and_Yield_of_Sweet_Corn_by_Complex_Regression_Models/links/54ff26510cf2eaf210b68484/Forecasting-the-Harvest-Date-and-Yield-of-Sweet-Corn-by-Complex-Regression-Models.pdf.
- Lizaso, J., Boote, K., Cherr, C., Scholberg, J., Casanova, J., Judge, J., Jones, J., Hoogenboom, G. 2007. Developing a Sweet Corn Simulation Model to Predict Fresh Market Yield and Quality of Ears. *J. American Society for Horticultural Science*. 132(3), 415-422.
<https://doi.org/10.21273/JASHS.132.3.415>.
- Liu, C., Zhang, X., Zhang, Y. 2002. Determination of daily evaporation and evapotranspiration of winter wheat and maize by large-scale weighing lysimeter and micro-lysimeter. *J.*

- Agricultural and Forest Meteorology. 111(2), 109-120. [https://doi.org/10.1016/S0168-1923\(02\)00015-1](https://doi.org/10.1016/S0168-1923(02)00015-1).
- McAvoy, T., Coolong, T. 2023. Shipper Sweet Corn in Southern Georgia. University of Georgia Cooperative Extension Service. Bulletin 1549. <https://extension.uga.edu/publications/detail.html?number=B1549>. Accessed 5 January 2025.
- McMaster, G. Wilhelm, W. 1997. Growing degree-days: one equation, two interpretations. J. Agricultural and Forest Meteorology. 87(4), 391-300. [https://doi.org/10.1016/S0168-1923\(97\)00027-0](https://doi.org/10.1016/S0168-1923(97)00027-0).
- Migliaccio, K., Morgan, K., Vellidis, G., Zotarelli, L., Fraisse, C., Zurweller, B., Crane, J., Rowland, D. 2015. Smartphone Apps for Irrigation Scheduling. An ASABE 2015 Meeting Irrigation Symposium Paper: 152143940. <https://doi.org/10.13031/irrig.20152143940>.
- Miller, L., Vellidis, G., Mohawesh, O., Coolong, T. 2018. Comparing a Smartphone Irrigation Scheduling Application with Water Balance and Soil Moisture-Based Irrigation Methods: Part I—Plasticulture-Grown Tomato. J. Horticultural Technology. 28(3), 354–361. <https://doi.org/10.21273/HORTTECH04010-18>.
- Myneni, R., Hall, F., Sellers, P., Marshak, A. 1995. The Interpretation of Spectral Vegetation Indexes. IEEE Transactions on Geoscience and Remote Sensing. 33(2), 481–86. <https://doi.org/10.1109/TGRS.1995.8746029>.
- O'Shaughnessy S., Evett, S. 2010. Canopy temperature-based system effectively schedules and controls center pivot irrigation of cotton. J. Agricultural Water Management. 97, 1310-1316. <https://doi.org/10.1016/j.agwat.2010.03.012>.
- Ozores-Hampton, S., Olson, S., Webb, S., Smith, S., Raid, R., McAvoy, E. 2012. Vegetable Production Handbook, Chapter 21 Sweet Corn Production in Florida. University of Florida IFAS Extension. 283-296. https://www.researchgate.net/profile/Monica-Ozores-Hampton/publication/265184286_Chapter_21_Sweet_Corn_Production_in_Florida/links/56fa9ec308ae8239f6dad110/Chapter-21-Sweet-Corn-Production-in-Florida.pdf.
- Paranhos, J., Foshee, W., Coolong, T., Hayes, B., Salazar-Gutierrez, M., Keshimer, K., Silva, A. 2023. Characterization of Sweet Corn Production in Subtropical Environmental Conditions. J. Agriculture. 13(6), 1156. <https://doi.org/10.3390/agriculture13061156>.
- Pettorelli, N., Vik, J., Mysterud, A., Gaillard, J., Tucker, C., and Stenseth, N. 2005. Using the Satellite-Derived NDVI to Assess Ecological Responses to Environmental Change. J. Trends in Ecology & Evolution. 20(9), 503–510. <https://doi.org/10.1016/j.tree.2005.05.011>.
- Rao, N., Sarma, P., Chander, S. 1988. Irrigation Scheduling under a Limited Water Supply. J. Agricultural Water Management. 15(2), 165–75. [https://doi.org/10.1016/0378-3774\(88\)90109-6](https://doi.org/10.1016/0378-3774(88)90109-6).
- Singh, R., Liu, S., Tieszen, L., Suyker, A., Verma, S. 2012. Estimating Seasonal Evapotranspiration from Temporal Satellite Images. J. Irrigation Science. 30(4), 303-13. <https://doi.org/10.1007/s00271-011-0287-z>.
- Steele, D., Stegman, E., Gregor, E. 1994. Field comparison of irrigation scheduling methods for corn. American Society of Agricultural Engineers. Transactions of the ASAE. 37(4), 1197-1203. <https://doi.org/10.13031/2013.28194>.
- Stone, K., Bauer, P., Sigua, G. 2016. Irrigation management using an expert system, soil water potentials, and vegetative indices for spatial applications. Transactions of the ASABE. 59(3), 941-948. <https://doi.org/10.13031/trans.59.11550>.

- Sui, R. 2017. Irrigation Scheduling Using Soil Moisture Sensors. *J. Agricultural Science*. 10(1), 1. <https://doi.org/10.5539/jas.v10n1p1>.
- United States Department of Agriculture (USDA) Agricultural Marketing Service (AMS). 1992. United States Standards for Grades of Sweet Corn. [https://www.ams.usda.gov/sites/default/files/media/Corn%2C Sweet Standard%5B1%5D.pdf](https://www.ams.usda.gov/sites/default/files/media/Corn%2C%20Sweet%20Standard%5B1%5D.pdf).
- United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS). 2023. *Vegetables 2022 Summary*. USDA-NASS, Washington, DC. <https://downloads.usda.library.cornell.edu/usda-esmis/files/02870v86p/hq37x121v/4b29ck28c/vegean23.pdf>
- United States Department of Agriculture (USDA). 2024. Sweet Corn Grades and Standards. <https://www.ams.usda.gov/grades-standards/sweet-corn-grades-and-standards>. Accessed 20 August 2024.
- Vellidis, G., Liakos, V., Andreis, J., Perry, C., Porter, W., Barnes, E., Morgan, K., Fraisse, C., Migliaccio, K. 2016. Development and Assessment of a Smartphone Application for Irrigation Scheduling in Cotton. *J. Computers and Electronics in Agriculture*. 127, 249–259. <https://doi.org/10.1016/j.compag.2016.06.021>.
- Viswanatha, G., Ramachandrappa, B., Nanjappa, H. 2002. Soil plant Water Status and Yield of Sweet Corn (*Zea mays* L. cv. *saccharata*) as Influenced by Drip Irrigation and Planting Methods. *J. Agricultural Water Management*, 7. [https://doi.org/10.1016/S0378-3774\(01\)00189-5](https://doi.org/10.1016/S0378-3774(01)00189-5).
- Wang, D., Cai, X. 2009. Irrigation Scheduling—Role of Weather Forecasting and Farmers’ Behavior. *J. Water Resources Planning and Management*. 135(5), 364–372. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2009\)135:5\(364\)](https://doi.org/10.1061/(ASCE)0733-9496(2009)135:5(364)).
- Westerfield, R., Eason, N. 2024. Growing Home Garden Sweet Corn. University of Georgia Cooperative Extension Service. <https://woodstock.recdesk.com/RecDeskPortal/Portals/770/Sweet%20Corn.PDF>. Accessed 27 December 2024.
- Wu, G., Miller, N., De Leon, N., Kaeppler, S., Spalding, E. Predicting *Zea Mays* Flowering Time, Yield, and Kernel Dimensions by Analyzing Aerial Images. 2019. *J. Frontiers in Plant Science*. 10:1251. <https://doi.org/10.3389/fpls.2019.01251>.
- Yang, J., Li, B., Shiping, L. 2000. A large weighing lysimeter for evapotranspiration and soil-water-groundwater exchange studies. *J. Hydrological Processes*. 14(10), 1887-1897. [https://doi.org/10.1002/1099-1085\(200007\)14:10<1887::AID-HYP69>3.0.CO;2-B](https://doi.org/10.1002/1099-1085(200007)14:10<1887::AID-HYP69>3.0.CO;2-B).

¹CHAPTER 2

AN IRRIGATION SCHEDULING MODEL FOR SWEET CORN BASED ON FAO-56¹

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2. Abstract

The United States (U.S.) leads the world in fresh market sweet corn (*Zea mays* subsp. *Mayes* L.) production. The state of Georgia is one of the leading U.S. producers, with over 9,000 ha (23,000 ac) of sweet corn harvested annually at an economic value of more than USD 106 million in 2023. Failure to meet sweet corn water needs may lead to yield and quality losses. Therefore, growers tend to over-irrigate this valuable crop to mitigate potential losses. Excess irrigation can lead to soil health problems, water table decline, nutrient and fertilizer runoff, and inefficient water use. SmartIrrigation CropFit (SI CropFit) is a smartphone application that provides irrigation scheduling recommendations for maize, cotton, peanut, and soybean based on real-time crop water needs and meteorological factors. SI CropFit makes irrigation scheduling decisions based on the Food and Agricultural Organization (FAO)-56 method of estimating daily crop water use, also described as crop evapotranspiration (ET_c), by multiplying Penman-Monteith evapotranspiration (ET_o) by a crop coefficient (K_c). This work aimed to develop an ET_c-based irrigation scheduling model for sweet corn grown in the southeastern U.S. that could be incorporated into SI CropFit. Soil moisture data gathered over four growing seasons from 12 grower-managed sweet corn fields located in southwestern Georgia was utilized to estimate daily crop water use of sweet corn. These estimates were then used to develop an empirical K_c model based on accumulated heat units (growing degree days). This model was field-tested for two growing seasons and ultimately incorporated into SI CropFit.

Keywords: smart irrigation; evapotranspiration; crop water use; irrigation water use efficiency; smartphone application.

2.1. Introduction

The United States (U.S.) ranks first in global sweet corn (*Zea mays* subsp. *Mayes* L.) production, consumption, and exportation (Dhaliwal and Williams II, 2023; FAO, 2021). Within the U.S., Georgia ranks third for national fresh market sweet corn production. In 2023, the economic value of sweet corn production in Georgia exceeded USD 106 million, with over 9,000 ha (23,000 ac) harvested (McAvoy and Coolong, 2023).

Quality is critical in sweet corn production in the U.S. because much of the production is for the fresh market, which has stringent quality standards. High yield and quality depend on the crop's water needs being met throughout the growing season (Hassanli et al., 2009). The sweet corn varieties used in the southeastern U.S. mature in 60 to 100 days and require between 203 and 356 mm (8-14 in) of water during the growing season, depending on variety (Allen et al., 1998; Westerfield and Eason, 2024). Although annual precipitation in the southeastern U.S. ranges from approximately 1200-1500 mm (47-60 in), the uncertainty of precipitation timing and magnitude in combination with sandy soils that have low water holding capacity results in high variability in rainfed yields in this region. To reduce this risk, irrigation systems are increasingly used to avoid crop water stress (Bednarz et al., 2002; Stone et al., 2016; Sui, 2017). Sweet corn has significantly higher yield potential when it is grown under irrigated management conditions (Viswandatha et al., 2002). In a study conducted by Hassanli et al. (2009), irrigation scheduling based on soil moisture deficit led to a significant increase in sweet corn yield. When utilized in sweet corn management, irrigation scheduling ensures the crop's water needs are met strategically and efficiently, optimizing production (Braunworth and Mack, 1987; Hassanli et al., 2009; Datta et al., 2022).

2.1.1. Irrigation Scheduling

Irrigation scheduling is defined as “the decision of when and how much water to apply to a field at a given time” (George et al., 2000; Broner, 2005; Wang and Cai, 2009). Irrigation scheduling improves water use efficiency by maintaining plant available soil water within an optimal range and avoiding over-and/or under-irrigation (Jones, 2004; Howell, 1996). Various factors complicate irrigation scheduling decisions, including climate, crop and soil type, and availability of irrigation water (Rao et al., 1988; Steele, 1994). In addition to stable yields, irrigation scheduling has several additional advantages, including improved water use efficiency, reduced fertilizer runoff and costs, and minimized water-logging issues within the soil profile (Broner, 2005).

Irrigation scheduling techniques that determine daily crop water needs (also referred to as crop evapotranspiration or ET_c) using atmospheric and environmental parameters are becoming increasingly available (Migliaccio et al., 2015; Vellidis et al., 2016). These techniques make effective irrigation decisions that avoid crop water stress without the need for soil moisture sensors (O'Shaughnessy and Evett, 2010).

2.1.2. Crop Evapotranspiration

ET_c is a complex process influenced by several meteorological variables, including relative humidity, solar radiation, wind speed, and air temperature (Allen et al., 2005; Ertek and Kara, 2013). Similarly, crop parameters such as variety, planting rate, and phenological growth stage play key roles in ET_c values. Soil type, fertility, salinity, and soil management also influence ET_c. Crop type and phenological stage are two key factors in ET_c estimation (Allen et al., 1998).

The Food and Agriculture Organization (FAO)'s Irrigation and Drainage Paper No. 56, commonly referred to as FAO-56 (Allen et al., 1998), provides guidelines for estimating crop water requirements. The FAO-56 method uses Eq. 2.1 to estimate daily ET_c .

$$ET_c = K_c \times ET_o \quad (2.1)$$

where,

ET_c = daily crop evapotranspiration (ET), also referred to as crop water use (mm day^{-1}),

K_c = a daily crop coefficient extracted from a crop-specific K_c curve, and

ET_o = Penman-Monteith reference ET (mm day^{-1}).

The FAO has published K_c curves for many of the world's food and fiber crops. Those curves are typically generic and are not refined for specific ecoregions. Moreover, the initial data used to develop the curves may have originated in an ecoregion with very different environmental conditions from where the curve is applied. For example, the data used to develop the FAO-56 sweet corn K_c curve (Figure 2.1) were collected from sweet corn grown in Idaho, U.S., which has a climate that differs significantly from that of the southeastern U.S.

K_c changes with the phenological stage for annual crops and proportionally modifies ET_o . K_c typically begins with small values after emergence and increases to 1.1 or above when the crop reaches peak water demand. This usually occurs during the crop's reproductive stages. Accurately assessing the crop's phenology is crucial to efficient irrigation scheduling because water demands tend to change significantly from the crop's initial growth stages to harvest (Rao et al., 1988). For example, sweet corn daily water use increases rapidly from 40% of ET_o to 110% of ET_o during its peak growth stages, resulting in proportionally increasing K_c values (Ozorez-Hampton et al., 2012). Peak water demand for sweet corn coincides with silking, tasseling, and ear development (Westerfield and Eason, 2023; Allen et al., 1998).

2.1.3. Growing Degree Days

For most annual food and fiber crops, phenological stages are driven by accumulated heat units, also known as growing degree days (GDDs). GDDs are often used to describe the timing of a plant's biological processes, which aids in crop management and irrigation (McMaster and Wilhelm, 1997). GDDs are calculated with the following equation:

$$GDD = \left[\frac{T_{max} + T_{min}}{2} \right] - T_{base} \quad (2.2)$$

where,

T_{max} = the maximum daily temperature,

T_{min} = the minimum daily temperature, and

T_{base} = the base temperature of the crop.

The base temperature, or the threshold temperature above which sweet corn actively grows, is 10°C (50°F) (Gilmore and Rodgers, 1958; Lass et al., 1993; Kara, 2011). Conversely, sweet corn growth is hindered and reduced by 0.5% each additional day in which the temperature is greater than 30°C (86°F) (Dhaliwal and Williams II, 2022). Kc curves that are based on GDDs generally perform better than Kc curves that are based on days after planting (DAP) because the climatic conditions during the growing season significantly affect the rate at which a crop moves from one phenological stage to another (Vellidis et al., 2016).

2.1.4. The SmartIrrigation Apps

Over the past four decades, an increasing number of irrigation scheduling tools based on the concepts of FAO-56 have been developed. Typically, these have been computer or web-based models that pull the meteorological data needed for ETo calculations from weather station networks (Davis and Dukes, 2010). Within the past decade, these tools have migrated to smartphone platforms (Migliaccio et al., 2015; Vellidis et al., 2016; Miller et al., 2018).

The suite of SmartIrrigation Apps (SI Apps) (<https://smartirrigationapps.org/>) is a group of irrigation scheduling models for horticultural and agronomic crops. These models provide irrigation scheduling recommendations based on crop type, phenological stage, and real-time meteorological parameters using the FAO-56 method. The SI Apps use meteorological data to calculate daily ETo and then apply the appropriate Kc to estimate daily ETc. Models for agronomic crops (maize, cotton, peanut, and soybean) are embedded in the SmartIrrigation CropFit (SI CropFit) App. In these models, phenology and associated changes in Kc are driven by GDDs and irrigation scheduling is based on a soil water balance model.

The SI CropFit soil water balance model uses daily ETc, precipitation received, irrigation applied, and the soil's plant available water holding capacity (AWHC) to estimate a daily root zone soil water deficit (RZSWD) in terms of percent and inches of plant available soil water. Plant available soil water is defined as the water held by the soil matrix between field capacity (FC – the point at which water no longer moves through the soil due to gravity) and the wilting point (WP – the point at which the plants can no longer effectively extract water from the soil). A 50% RZSWD or depletion of 50% of plant available soil water is a commonly accepted irrigation threshold for agronomic crops. The model calculates today's plant-available soil water by subtracting yesterday's ETc from yesterday's plant-available soil water and adding precipitation received or irrigation applied.

The SI Apps pull meteorological data from several sources – state weather station networks (mesonets), Apple Weather (a commercial provider of meteorological data), and five commercial automated rain gauge brands that use application programming interfaces (APIs). Users in U.S. states with participating mesonets can select a weather station as their primary provider of meteorological data. The closest weather station is selected based on the field's coordinates. Users

elsewhere utilize Apple Weather, which provides meteorological data on a 4 km (2.5 mi) grid, as their primary provider of meteorological data. The field's coordinates are used to select the appropriate source grid. Because accurate precipitation data are critical to maintaining an accurate soil water balance, an automated on-farm rain gauge that provides hyper-local precipitation data is highly recommended when SI CropFit is used for irrigation scheduling.

One of the functionalities of SI CropFit is that users can define the perimeter of their field using dropped pins. The perimeter is then used to extract soil information, including soil type, FC, and WP, from the United States Department of Agriculture (USDA) Natural Resources and Conservation Services (NRCS) Web Soil Survey (<https://websoilsurvey.sc.egov.usda.gov/App/>). The soil's plant AWHC is calculated by subtracting WP from FC. If there is more than one soil type within the field perimeter, an area-weighted average AWHC is calculated, and that value is subsequently used in the soil water balance model. SI CropFit operates primarily on a cloud server with daily updates of user-needed information to the smartphone platform. It is available for both iOS and Android platforms at no cost to the user.

The use of the SI Apps has resulted in increased yields and irrigation water use efficiency (IWUE) for many crops, including blueberry, citrus, maize, cotton, peanut, strawberry, tomato, soybean, and watermelon (Migliaccio et al., 2015; Vellidis et al., 2016; Ayankojo et al., 2018; Miller et al., 2018). In this study, IWUE is defined as:

$$IWUE = \frac{\text{Treatment Yield} - \text{Rainfed Yield}}{\text{Treatment Irrigation Applied} - \text{Rainfed Irrigation}} \quad (2.3)$$

2.1.5. Objectives

The overall goal of this study was to develop an affordable, user-friendly, and reliable irrigation scheduling tool for sweet corn adapted to growing conditions of the southeastern U.S. Specific objectives of the study were to:

1. Develop an FAO 56-based irrigation scheduling model for sweet corn,
2. Evaluate the performance of the model with replicated field trials, and
3. Incorporate the model into SI CropFit.

2.2. Materials and Methods

The study was conducted in southwestern Georgia (Figure 2.2). The area's physiographic classification is the Dougherty Plain subregion of the southeastern Coastal Plain. Soils generally range from sandy to loamy sand. The climate is categorized as humid-subtropical with hot, humid summers and mild winters. The annual precipitation for this region ranges from 1170 mm to 1270 mm (46 in to 50 in), and the annual temperature ranges from 10°C to 27°C (50°F to 80 °F). The region's climate allows for two sweet corn growing seasons – one in the spring (March to June) and one in the autumn (August to October). The study consisted of three stages: (1) collecting on-farm data, (2) developing an ET-based Kc curve, and (3) conducting field testing at the plot scale. Each stage is described in detail below.

2.2.1. On-Farm Data Collection

In this stage of the study, soil moisture sensors were installed in grower-managed sweet corn fields to collect daily crop water use (DWU) data that were used to develop a Kc curve specific to sweet corn grown in the southeastern U.S. DWU calculations were assumed to represent ETc. DWU data were collected on three grower-managed sweet corn fields during the spring and autumn growing seasons of 2022 and 2023 (four data collection seasons) for a total of 12 field-seasons of data. The study sites were located in Mitchell, Decatur, and Seminole Counties (Figure 2.2). These counties lead the state in sweet corn production.

Each sweet corn field was instrumented with two 60 cm (24 in) Sentek Drill and Drop soil moisture probes (Sentek Sensor Technologies, Stepney SA, Australia). The probes measured soil

moisture as volumetric water content (VWC) and soil temperature at six depths in 10 cm (4 in) increments, beginning at 10 cm (4 in) below the soil surface. The probes were connected to data loggers (AgSense Solutions, South Dakota, U.S.) that transmitted data to a cloud interface at 30-minute intervals. Individual growers managed the irrigation of these fields, and the soil moisture data were not used for irrigation scheduling. Precipitation, solar radiation, and wind speed were measured by Vantage Pro2 weather stations (Davis Instruments Corporation, California, U.S.) installed at each field location and were cross-referenced with meteorological data derived from the University of Georgia (UGA) weather network, which consists of 87 weather stations across the state.

2.2.2. *Kc Curve Development*

Figure 2.3 shows the VWC response of the six sensors of one probe for approximately three weeks during the Spring 2022 growing season. Each colored line in the graph represents VWC over time at a given depth. Sudden increases in VWC indicate an irrigation or precipitation event. Decreasing VWC suggests a combination of soil water redistribution, plant water use (transpiration), and evaporation. Sharp declines (steep slopes) in VWC after precipitation or irrigation events (Figure 2.3A) indicate a combination of water redistribution (drainage from saturated conditions to FC) and evapotranspiration. More gradual declines in VWC (shallower slopes) indicate that the decrease in VWC is primarily the result of evapotranspiration (Figure 2.3B). Flat slopes in the VWC curves indicate declining DWU and that the crop is entering a period of water stress (Figure 2.3C). The transition from saturated conditions with soil water redistribution (drainage) to FC is indicated by an inflection point in the slope of the VWC curve, as shown in Figure 2.3A. Diurnal changes in soil moisture (Figure 2.3D, 2.3E) are due to the redistribution of water at night when evapotranspiration and temperature effects decrease. Diurnal

changes are more apparent under wetter conditions (Figure 2.3E). Crop water use was generally limited to the soil profile's top 40 cm (16 in), as ET_c effects were not observed beyond that depth (Figure 2.3).

DWU calculations were performed using VWC data from after the inflection point (FC) and before the next irrigation or precipitation event. FC was estimated by observing the rate of change in VWC (ΔVWC) after large precipitation and irrigation events. Rate of change was calculated using Eq. 2.4.

$$\Delta VWC = \frac{VWC_{t2} - VWC_{t1}}{t2 - t1} \quad (2.4)$$

where,

ΔVWC = rate of change in VWC

VWC_{t2} = VWC at time = 2,

VWC_{t1} = VWC at time = 1,

$t2$ = time of current VWC measurement, and

$t1$ = time of previous VWC measurement.

VWC measurements were available every 0.5 hr. For the soils of the 12 grower fields, FC was defined as occurring when ΔVWC approached 0.03 hr^{-1} . DWU was then calculated as the difference in VWC at this threshold and the VWC just before the next irrigation or rain event. Because VWC readings were not always exactly 24 hours apart, the change in VWC was converted into a 24-hour DWU by dividing the difference in VWC readings by the elapsed hours between the two measurements and multiplying by 24 hours. The analysis was conducted for each measurement depth of the soil profile and the total aggregated.

Growers irrigated frequently, typically every two days, unless substantial precipitation was received. This resulted in two or, at most, three continuous DWU calculations between FC and the

next irrigation or precipitation event and ensured that the soil profile did not reach WP. Only ET_c values from days with solar radiation 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 ensured that the K_c curve represents peak water use for each phenological stage.

The remaining ET_c values were paired with the corresponding daily ET_o values calculated with meteorological data from the nearest UGA weather station and used to calculate daily K_c with Eq. 2.1. Resulting values exceeding 2.5 or below zero were excluded from the analysis. The remaining daily K_c values from the 12 fields (3 fields × 4 field seasons) were plotted, and a polynomial equation was fitted to the data (Figure 2.4). The resulting polynomial K_c curve matched the anticipated pattern with an increasing slope for approximately 70% of the growing season, with a peak at approximately 1000 GDDs followed by a gradual decline. Because sweet corn is harvested well before senescence, the K_c curve does not decrease to a low K_c value near harvest, as happens with most annual agronomic crops like maize, cotton, etc. (Vellidis et al., 2016). Because in this study soil moisture sensors were installed approximately 10 to 14 days after germination, field data were not available for the initial growth period and, consequently, the polynomial curve did not intersect the y-axis near zero in Figure 2.4. To simplify the K_c-based irrigation scheduling model, four linear models were fitted to the data to match the shape of the polynomial function, to intercept the y-axis at zero, and to allow transitions at easily observable phenological stages (Figure 2.4).

2.2.3. Sweet Corn Phenology

Beginning with the 2022 Autumn growing season, the field sites were visited weekly to quantify the crop's phenological stage. These data were associated with accumulated GDDs on the dates that observations were made and used to develop a table of phenological stage development

vs. GDDs (Table 2.1). Information from this table was used to select the beginning and end points of the linear models associated with the Kc curve. In the irrigation scheduling model, these data are used to inform the user of the crop's estimated phenological stage.

2.2.4. Soil Water Balance Model

The DWU-derived Kc curve was incorporated into a soil water balance (SWB) model (Vellidis et al., 2016) similar to the one used by SI CropFit, except that it was ran in spreadsheet mode. The soil profile was set to FC (0% soil water deficit) at planting, daily ETc calculated with Eq. 2.1 was subtracted from yesterday's soil water deficit to calculate today's soil water deficit, and precipitation and irrigation were added to the SWB. Daily ETo was extracted from a virtual field created in SI CropFit using meteorological data from the closest UGA weather station. ETo was manually entered, and a daily RZSWD was calculated using the spreadsheet. Irrigation was applied if the daily RZSWD approached or exceeded the predetermined RZSWD threshold (described later).

2.2.5. Field-Testing at the Plot Scale

The primary purpose of the field-testing was to compare the performance of the DWU-derived Kc curve to other irrigation scheduling methods. Field-testing was conducted during the Spring and Autumn 2024 seasons with a replicated plot study at the UGA's Stripling Irrigation Research Park (SIRP). SIRP is in Mitchell County, Georgia, within a few km of several of the grower fields used in the first stage of the project (Figure 2.2). The study was conducted on a 4 ha (10 ac) research field known as the Newton Lateral Field (31°16'46.24" N, 84°17'59.59" W). The field is divided into three blocks (North, Middle, and South), with each block containing 27 plots (Figure 2.5). Each plot measured 14.5 m × 14.5 m (48 ft × 48 ft or 48 ft long × 16 rows wide). The middle eight rows in each plot were used for data collection, and the four rows on either side acted as

buffers. The soil in the Newton Lateral field is classified as a Lucy Loamy Sand with AWHC of 2 mm mm⁻¹ (0.08 in in⁻¹) and 0 to 5% slope. Soil texture varies slightly across the field, with 83% sand, 10% silt, and 7% clay in the South block to 86% sand, 8% silt, and 6% clay in the North block. The North block was used for the study during the Spring 2024 and Autumn 2024 (Figure 2.5) growing seasons. The field is irrigated with a variable-rate-enabled lateral irrigation system, which can apply a unique water application rate to each of the 27 plots. A UGA weather station is located approximately 800 m (0.5 mi) from the field.

Bayer Crop Science (Leverkusen, Germany) Obsession hybrid bicolor cultivar was planted at 12,550 seeds ha⁻¹ (31,000 seeds ac⁻¹) on 30 March 2024 and harvested on 3 June 2024 (Spring 2024 season) and planted at 10,526 seeds ha⁻¹ (26,000 seeds ac⁻¹) on 21 August and harvested on 31 October 2024 (Autumn 2024 season). These planting rates mimic the typical rates used in southwestern Georgia and vary with the season to produce optimal yields and ear size and to reduce defects associated with seasonal daylight hours (McAvoy and Coolong, 2023). This cultivar was selected for the study as it is a commonly used variety for commercial production in this region of the U.S. The seed planted had a 95% germination rating, per the manufacturer's label. The actual germination estimate was 11,943 seeds ha⁻¹ (29,500 seeds ac⁻¹) in the spring and 10,000 seeds ha⁻¹ (24,700 seeds ac⁻¹) in the autumn.

2.2.6. Irrigation Treatments

For the Spring 2024 season, the study layout followed a randomized complete block design with seven treatments and three replicates for each treatment (21 plots) (Figure 2.5). The six remaining plots were cultivated but were not used in the study.

University of Georgia Smart Sensor Array (UGA SSA) soil moisture sensor probes (Liakos et al., 2017; Vellidis et al., 2008) were installed in each plot a few days after emergence. A UGA

SSA probe consists of three Irrometer Watermark sensors (The Irrometer Company—Riverside, California, U.S.) that measure soil moisture in terms of matric potential and report in units of kPa. The sensors were centered at depths of 15.2 cm (6 in), 30.5 cm (12 in), and 45.7 cm (18 in). In addition, nine Sentek probes were installed in the six plots that were irrigated using VWC threshold triggers and the three rainfed plots. These are the same Sentek probes used in the first stage of the study and measured VWC at depths of 10, 20, 30, 40, 50, and 60 cm (4, 8, 12, 16, 20, 24 in). During irrigation scheduling, sensor data were weighted by depth based on GDD to indicate root water uptake at various depths (Table 2.2). For example, from 0-300 GDD, the data from the Watermark sensor at 15 cm (6 in) in a UGA SSA probe was assigned a weight of 0.8 (80%), data from the sensor at 31 cm (12 in) assigned a weight of 0.2 (20%), and data from the sensor at 46 cm (18 in) a weight of 0.

Irrigation scheduling treatments were developed based on information available in the literature and the authors' experience with similar studies on other crops, including several years of experience with maize studies. The seven treatments used during the Spring 2024 growing season are described below and include a Grower Standard. The Grower Standard treatment followed the irrigation scheduling practices of one of the top sweet corn producers in Georgia, which has a history of using soil moisture sensors for irrigation scheduling and consistently produces high yields. In essence, the Grower Standard treatment was the benchmark against which the other irrigation treatments were compared. All other management practices, including fertilization, pest, and weed management, were applied uniformly across all treatments. Fertilization followed the practices used by the grower.

1. Grower Standard – Irrigation amount and timing matched a commercial grower's field located within 2 km (1.2 mi) of SIRP. The field was planted on the same date as the plots with the

same sweet corn variety. Soil moisture sensors were not installed in the grower's field during the plot studies, and irrigation scheduling for this treatment was based on the grower's experience. The amount of water applied at each irrigation event ranged from 8-19 mm (0.3-0.75 in).

2. VWC 14.8% – Daily VWC at 7:00 AM for the treatment was calculated by averaging the sensor readings from each depth in each of the three replicates. Those values were then used to calculate a weighted average by depth using the values shown in Table 2.2. If the weighted average approached a VWC of 14.8%, the treatment was irrigated with 19 mm (0.75 in). This was considered a “wet” treatment.
3. VWC 14%/14.4% – Daily VWC at 7:00 AM was calculated as described above, but irrigation was triggered at 14% VWC prior to the reproductive stage (tasseling) and at 14.4% from the reproductive stage (tasseling) onwards. This treatment was irrigated with 19 mm (0.75 in).
4. MP -30 kPa – Daily matric potential at 7:00 AM was calculated as described above. As the weighted average approached or exceeded a matric potential of -30 kPa, the treatment was irrigated with 19 mm (0.75 in).
5. MP -40/-30 kPa – For this treatment, matric potential was calculated as described above, but irrigation was triggered at -40 kPa prior to tasseling and at -30 kPa from tasseling onwards. This treatment was irrigated with 19 mm (0.75 in).
6. SWB ET – In this treatment, the SWB model using the Kc curve derived from DWU data was used to trigger irrigation when the RZSWD approached or exceeded 30%. This treatment was irrigated with 19 mm (0.75 in).

7. Rainfed – In this treatment, irrigation was used only for management, i.e., to promote emergence, activate herbicides, and for fertigation. These amounts applied are described in more detail below.

During the Spring 2024 season, management events included one 8 mm (0.3 in) irrigation event to promote emergence, five 4 mm (0.17 in) fertigation events, and one 9 mm (0.34 in) fertigation event) that were applied to all treatments and totaled approximately 37 mm (1.5 in). On Friday, 26 April 2024, a 10 mm (0.4 in) irrigation event was applied to all irrigated treatments to avoid crop water stress over a hot, dry weekend.

During the Autumn 2024 season, management events included six 4 mm (0.17 in) fertigation events, 8 mm (0.3 in) and 13 mm (0.5 in) irrigation events to promote emergence, and one 13 mm (0.5 in) event for herbicide activation, totaling approximately 59 mm (2.32 in).

Because scheduling with the SWB ET model during Spring 2024 resulted in more frequent irrigation than the other treatments during the first half of the growing season, the first and second segments of the tetra-linear SWB ET model were modified to reflect the irrigation timing of the MP -30 kPa treatment, which had fewer irrigation events early in the growing season but resulted in higher yield and the highest IWUE. Essentially, this meant changing the slope of the Kc curve for the first three segments, resulting in a more gradual and later increase to maximum Kc (Figure 2.1). The final segment of the curve was also modified by decreasing the maximum Kc to 1.2 from 1.4. In addition, the RZSWD was set to 40% prior to the reproductive stage and 30% from the beginning of the reproductive stage and onwards. The modified SWB ET model (SWB ET Updated) was incorporated into a beta version of SI CropFit, and irrigation scheduling decisions for this treatment during the Autumn 2024 growing season were made by checking RZSWD in

CropFit every morning at 07:00 AM. This treatment was then evaluated alongside the six other treatments used during the Spring 2024 season (Figure 2.5).

2.2.7. *Phenology, Yield, and Quality*

Sweet corn phenology was monitored weekly by assessing the current phenological stage of ten plants within the field. A USDA-certified fresh market sweet corn grader determined the optimal harvest date for the crop, as well as the grade of the ears harvested.

Plot harvest mimicked commercial sweet corn harvest as closely as possible. In commercial harvest, the upper ear (the largest on the plant) is the ear that is harvested by hand. Therefore, in this plot study, the upper ears of ten consecutive plants in the middle row (fourth row) of each plot were harvested by hand. Ears were graded as marketable or unmarketable based on the USDA U.S. Fancy Grade sweet corn standards (USDA, 2024). Ears less than 15.2 cm (6 in) in length, ears having more than 38.1 mm (1.5 in) of poor/no-tip fill, and ears with any smut, mechanical, insect or bird damage were deemed unmarketable.

Yield was calculated based on the grade of the harvested ears. For instance, if nine out of ten ears were marketable, the treatment grade would be 90%. To calculate yield, the treatment grade was multiplied by the observed germination rate (seeds ha⁻¹/seeds ac⁻¹) This was done because growers assume at least one marketable ear per plant (McAvoy and Coolong, 2023).

Several ear and plant quality parameters were measured – some immediately prior to harvest and some immediately after harvest, as various physical attributes dictate whether an ear is considered marketable. Only the results from the three quality parameters most relevant to determining yield (no-tip fill, ear length, and ear diameter) are discussed further. The remainder are presented in Bedwell et al. (2025). Ear diameter (out of husk) and no-tip fill were measured using a caliper with 0.01 mm accuracy. No-tip fill is the length of the ear without fully developed

kernels. Ear length was measured (out of husk) from the base to the tip of the ear in cm using a ruler. All three parameters were measured on the same day the ears were harvested from the field. During the measurement process, all samples were kept at 20°C (68°F) to prevent excessive moisture loss from the kernels.

2.2.8. Data Analysis

An analysis of variance (ANOVA) using irrigation totals, yields, IWUE, and ear attributes was conducted in R Studio (version 2024.04.2 + 764) (Boston, Massachusetts, U.S.) to evaluate the performance of the treatments. The ANOVA was performed using Type III sum of squares, and residual diagnostics were performed to ensure that the assumptions of the ANOVA were met.

Following the ANOVA, a Tukey post-hoc test was applied to assess pairwise differences between treatment groups. The results from the post-hoc analysis were then visualized using a compact letter display, which indicated statistically significant differences at $\alpha = 0.05$, if any were present, between the irrigation treatments.

2.3. Results

2.3.1. SWB ET Curve

The Kc curve used in the SWB ET treatment resulted in a tetra-linear model (Figures 2.1 and 2.4). The inflection points were selected based on GDD values that align with sweet corn phenological stages that indicate different water needs. The first linear segment (0 to 300 GDD) corresponds to the initial growth stage of the crop; the second segment (301 to 800 GDD) represents the crop's mid-growth stage; the third linear segment (801 to 1000 GDD) represents the early reproductive stage while the fourth segment (1001 to 1400 GDD) represents the late reproductive stage.

Figure 2.1 compares the DWU-derived (SWB ET and SWB ET Updated) K_c curves to the FAO-56 guidance curve (Allen et al., 1998). The two derived curves use GDDs to progress (bottom axis), while FAO-56 uses DAP (top axis). DAP has been matched to the corresponding GDDs in this figure for comparison. The two derived curves show that the water needs for sweet corn grown in the southeastern U.S. have a positive slope early in the growing season while the FAO-56 curve is set at $K_c = 0.6$, which could lead to over-irrigation early in the season and under-irrigation later in the season. Because of the rapid accumulation of GDDs in the southeastern U.S., the growing season for sweet corn grown in this region is shorter, thus illustrating the importance of a curve based on GDD rather than DAP. It is also essential to consider that the DWU-derived K_c curves may not accurately represent all sweet corn cultivars. However, experience with other crops suggests that these types of curves do represent most cultivars adapted to a specific region well (Vellidis et al., 2016).

2.3.2. Irrigation and Yield

Treatment irrigation amounts described below include irrigation used to promote emergence, activate herbicides, and fertigate. However, these management-related irrigation amounts were not used in calculating IWUE as shown in Eq. 2.3. In contrast, the number of irrigation events described below are indicative only of treatment irrigation events and do not include those related to promoting emergence, activating herbicides, or fertigating.

Spring 2024: During the Spring 2024 growing season, there were 16 precipitation events totaling 389 mm (15.3 in). Therefore, irrigation was required only a few times (Figure 2.6). The Grower Standard treatment resulted in seven irrigation events totaling 127 mm (5 in). In comparison, the SWB ET treatment resulted in ten irrigation events totaling 219 mm (8.6 in), which was substantially more than the other treatments (Table 2.3). The MP -30 kPa treatment

resulted in four irrigation events with a total of 105 mm (4.1 in), which was the least amount of irrigation applied in the Spring 2024 season.

The standard metric for sweet corn yield is boxes per unit area harvested (bx ha^{-1} ; bx ac^{-1}), as this is how fresh market sweet corn is harvested and sold. In the southeastern U.S., $28 \text{ cm} \times 28 \text{ cm}$ ($11 \text{ in} \times 11 \text{ in}$) boxes are standard. These boxes hold 48 ears of marketable sweet corn. An ear was deemed “marketable” if it met USDA U.S. Fancy Grade guidelines (McAvoy and Coolong, 2023; USDA, 2024). To quantify treatment yields, ten ears (upper) were harvested by hand from ten consecutive plants in the fourth row of each plot. Ears were inspected in and out of the husk for quality. The treatments with the highest numerical yield were the VWC 14.8% and the SWB ET with 1315 bx ha^{-1} (532 bx ac^{-1}). The lowest yield resulted from the Rainfed treatment at 1062 bx ha^{-1} (430 bx ac^{-1}). The Grower Standard and VWC 14%/14.4% treatments yielded 1214 bx ha^{-1} (492 bx ac^{-1}) (Figure 2.7, Table 2.3). There were no statistically significant differences in yield between treatments during the Spring 2024 season, including when Rainfed was omitted from the analysis.

The MP -30 kPa treatment resulted in the highest IWUE ($3 \text{ bx ha}^{-1} \text{ mm}^{-1}$; $30.67 \text{ bx ac}^{-1} \text{ in}^{-1}$) while the Grower Standard treatment resulted in an IWUE of $2 \text{ bx ha}^{-1} \text{ mm}^{-1}$ ($17.67 \text{ bx ac}^{-1} \text{ in}^{-1}$) and the SWB ET treatment resulted in an IWUE of $1.67 \text{ bx ha}^{-1} \text{ mm}^{-1}$ ($14.33 \text{ bx ac}^{-1} \text{ in}^{-1}$) (Figure 2.8, Table 2.3). As with yield, there was no statistically significant difference in IWUE at $\alpha=0.05$ in the Spring 2024 season.

Autumn 2024: During the Autumn 2024 growing season, there were 13 days with precipitation events totaling 251 mm (9.9 in). This is approximately half the precipitation received during the Spring 2024 growing season and is typical for the early autumn period in southwestern Georgia. October is usually the driest month of the year. Most of this precipitation (162 mm; 6.4 in) was

received during Hurricane Helene, which affected SIRP between 25-27 September, approximately halfway through the growing season (35 DAP) (Figure 2.9).

The Grower Standard treatment resulted in ten irrigation events totaling 169 mm (6.7 in) (Table 2.3). The SWB ET Updated treatment resulted in seven irrigation events totaling 192 mm (7.6 in). The VWC 14%/14.4% treatment resulted in ten irrigation events totaling 249 mm (9.8 in), which was the highest amount of irrigation applied in the Autumn 2024 season. The MP -40 kPa/-30 kPa treatment resulted in five irrigation events with a total of 154 mm (6.1 in), which was the least amount of irrigation applied in the Autumn 2024 season (Figure 2.9; Table 2.3).

The Autumn 2024 season yields were generally lower because of the 16% lower seeding rate. The Grower Standard and VWC 14.8% treatments yielded 1059 bx ha⁻¹ (429 bx ac⁻¹). The highest yields resulted from the MP -40 kPa/-30 kPa treatment (1186 bx ha⁻¹; 480 bx ac⁻¹). The SWB ET Updated treatment yielded 1102 bx ha⁻¹ (446 bx ac⁻¹) (Figure 2.10, Table 2.3), while the Rainfed treatment resulted in a yield of 636 bx ha⁻¹ (257 bx ac⁻¹) – approximately half the yield of most of the irrigated treatments, clearly indicating the need for irrigation in the autumn growing season. Similar to the Spring 2024 season there were not statistical differences in yield at $\alpha=0.05$, including when Rainfed was removed from the analysis.

In the Autumn 2024 season, the Grower Standard and the SWB ET Updated treatments resulted in the second highest IWUE of 3.67 bx ha⁻¹ mm⁻¹ (37.7 bx ac⁻¹ in⁻¹), while the MP -40 kPa/-30 kPa treatment resulted in the highest IWUE at 5.67 bx ha⁻¹ mm⁻¹ (59.67 bx ac⁻¹ in⁻¹) (Figure 2.11; Table 2.3). The VWC 14%/14.4% treatment resulted in the lowest IWUE of 1.67 bx ha⁻¹ mm⁻¹ (18.67 bx ac⁻¹ in⁻¹). There were statistically significant differences between the VWC 14%/14.4% treatment with the lowest IWUE and the MP -40 kPa/-30 kPa with the highest IWUE (Figure 2.11; Table 2.3).

2.3.3. Ear Quality Parameters

Ear length, ear diameter, and no-tip fill results for the Spring 2024 and Autumn 2024 growing seasons are shown in Table 2.4. As with yields, there were no statistically significant differences between treatments at $\alpha = 0.05$. This was not surprising as these are the three ear quality parameters that determine yield. As described earlier, ears less than 15.2 cm (6 in) in length and ears having more than 38.1 mm (1.5 in) of poor/no-tip fill were deemed unmarketable.

The Spring 2024 mean ear lengths were very similar for all treatments, with a range of only 0.6 cm (0.2 in) between the irrigated treatments (Table 2.4) and were all above the 15.2 cm (6 in) quality standard. The Grower Standard treatment resulted in a mean ear length of 18.4 cm (7.2 in). The VWC 14%/14.4% treatment had the highest mean ear length (18.8 cm; 7.4 in), while the Rainfed treatment resulted in the lowest mean ear length of 17.7 cm (7 in) (Table 2.4). Overall, Autumn 2024 mean ear lengths were 2-3 cm (0.8-1.2 in) shorter than those from Spring 2024 (Table 2.4) and had a larger range between irrigated treatments (1.1 cm; 0.4 in). The mean length of the irrigated treatments during the Autumn 2024 season was 16.25 cm (6.4 in) compared to 18.5 cm (7.3 in) for Spring 2024.

Like ear length, mean ear diameter was larger overall in Spring 2024 than in Autumn 2024 (Table 2.4). The mean diameter of the irrigated treatments was 47.43 mm (1.9 in) for Spring 2024 compared to 43.07 mm (1.7 in) for Autumn 2024. The Grower Standard treatment resulted in a mean ear diameter of 46.80 mm (1.8 in) in Spring 2024 but only 43.69 mm (1.7 in) in Autumn 2024 (Table 2.4).

No-tip fill is an important quality parameter, as ears with no-tip fill of more than 38.1 mm (1.5 in) are deemed unmarketable. No-tip fill ranged from 5.23 mm to 9.65 mm (0.21 in to 0.38 in) in the irrigated treatments for Spring 2024 and 14.33 mm to 20.19 mm (0.56 in to 0.79 in) for Autumn

2024 (Table 2.4). All the means were less than 38.1 mm (1.5 in) and, therefore, within the quality standard. However, in Spring 2024, Rainfed no-tip fill was 12.37 mm (0.49 in), and in Autumn 2024, it was 23.65 mm (0.93 in), clearly demonstrating the effect of inadequate soil moisture on ear fill (Table 2.4).

2.4 Discussion

In Spring 2024, there were no statistically significant differences in yield or IWUE across treatments (Figures 2.7, 2.8, Table 2.3), including the Rainfed treatment. Similarly, there were no statistical differences in yield when Rainfed treatment was excluded from the analysis. There are two likely explanations for this. The first is that there were 389 mm (15.3 in) of precipitation during the growing season, which exceeds estimated seasonal crop water requirements. But more importantly, much of the precipitation occurred during the reproductive stages (Figure 2.6). It is not unusual for growing season precipitation to meet or exceed crop water needs in southwestern Georgia, but it is not very common for the precipitation events to be evenly distributed throughout the growing season. This uneven distribution is why irrigation is essential for the region's sandy soils. The second likely explanation for why there were no statistically significant differences between treatment yields (Figure 2.7) is that there was high variability between the yields of replicate plots within some treatments. The cause of this variability is not clear. An interesting observation is that over-irrigation did not necessarily suppress yields in this study as it has been shown to for other crops, such as cotton and peanuts in southwestern Georgia (Vellidis et al., 2022; Hayes et al., 2024; Porter et al., 2024). For example, the SWB ET treatment had both the highest irrigation amount and the highest yield during the Spring 2024 season.

Although there were larger numerical differences between mean treatment yields in Autumn 2024 than in Spring 2024 (1186 vs. 636 bx ha⁻¹; 480 vs. 257 bx ac⁻¹), again, the differences were

not statistically significant. Similarly, there were no statistical differences in yield when Rainfed treatment was excluded from the analysis. This is likely attributed to the high variability within the replicates of the treatments (Figure 2.10). However, there was much less variability within the irrigated treatments in Autumn 2024 than in Spring 2024 (Figures 2.7 and 2.10) primarily because most of the water was applied through irrigation events that occurred at approximately the same time (Figure 2.9). Statistically analyses comparing only the irrigation scheduling treatments (excluding the Rainfed treatment) did not result in statistically significant differences for either growing season.

It is interesting to note that in the Autumn 2024 season, the Grower Standard, SWB ET Updated, and MP -40 kPa/-30 kPa treatments, which kept the soil profile a little drier during the vegetative growth stages, resulted in the highest yields and highest IWUEs. This indicates that, like other agronomic crops, sweet corn is tolerant of drier conditions during the vegetative stages. However, the MP -40 kPa/-30 kPa treatment used approximately 80% as much irrigation water as the SWB ET Updated treatment and, thus, had a statistically higher IWUE.

Between precipitation received and irrigation applied, the highest yielding Autumn 2024 treatment (MP -40 kPa/-30 kPa) received 405 mm (16 in) of water. This exceeds the total amount of water that sweet corn requires during a growing season (203-356 mm; 8-14 in). The Grower Standard treatment resulted in the same yield value as the VWC 14.8% treatment during Autumn 2024, although the amount of irrigation water applied was less than the VWC 14.8% treatment. Grower Standard irrigation amounts were nonuniform, and smaller events may have adequately met crop water needs, especially considering the fact that the Grower Standard treatment resulted in the same IWUE as the SWB ET Updated treatment but with approximately 22% less irrigation applied. Figure 2.12 shows graphs of soil water tension (the absolute value of matric potential) for

the Grower Standard, SWB ET Updated, MP -40 kPa/-30 kPa, and Rainfed treatments from the Autumn 2024 growing season. In the graphs, increasing soil water tension indicates drying soil. Beginning after the passage of Hurricane Helene on 29 September 2024, both the Grower Standard and the Rainfed treatments show increasing soil water tension, although the soils dried much quicker in the Rainfed treatment. This confirms that the smaller irrigation events used in the Grower Standard treatment did not wet the soil profile as heavily as those of the other irrigated treatments. In contrast, the other treatments maintain a moist soil profile, with the SWB ET Updated treatment consistently wetter than the MP -40 kPa/-30 kPa treatment.

Although there were no statistically significant ear quality parameter differences between the irrigated treatments within growing seasons, there were some trends. Treatments that received less irrigation tended to result in smaller ears. There were clear seasonal differences between seasons with the Autumn 2024 season, resulting in smaller ears and larger no-tip fill values despite the lower seeding rate. This was caused by cooler autumn temperatures and their impact on prolonging plant and ear growth and development.

The purpose of this study was to develop an affordable, user-friendly, and reliable irrigation scheduling tool for sweet corn adapted to growing conditions in the southeastern U.S. based on the FAO-56 method. Ultimately, this work resulted in the updated SWB ET model, which, although it yielded well during the Spring 2024 growing season, over-irrigated compared to all the other treatments. The SWB ET method applied approximately 92 mm (3.6 in) more than the Grower Standard, making it unacceptable for use. After improvements were made to the model prior to the Autumn 2024 growing season and it was incorporated into SI CropFit, it outperformed all but the MP -40 kPa/-30 kPa treatment in yield and matched or exceeded the IWUE of most other treatments during the Autumn 2024 growing season. Although the irrigation applied using

SWB ET Updated exceeded that of the Grower Standard and the MP -40 kPa/-30 kPa treatments, it was less than that of the VWC scheduling treatments. The SWB ET Updated model appears to be a reasonable irrigation scheduling method, although further evaluation is needed.

2.5 Conclusion

All the science-based irrigation scheduling treatments evaluated during this study resulted in yields greater than or comparable to the average yields from the 12 field seasons for which data were collected in the participating grower fields (spring average: 1126 bx ha⁻¹; 456 bx ac⁻¹ and autumn average: 988 bx ha⁻¹; 400 bx ac⁻¹). The VWC and matric potential approaches require the use of soil moisture sensors, which entails both the cost of purchasing the sensors and the labor for installation after planting and removal prior to harvest. In contrast, scheduling with SI CropFit requires only access to hyperlocal precipitation data for best performance, which may require the purchase and installation of an automated rain gauge. There is no additional cost to using SI CropFit. In addition, SI CropFit provides the user with information on the accumulation of GDDs and changes in crop phenology (Figure 2.13), all of which can be used to make crop management decisions – especially about scheduling harvest, which is done manually for fresh market sweet corn. SI CropFit offers the additional advantage of including irrigation scheduling models for maize, cotton, peanut, and soybean, which allows most growers in the southeastern U.S. to use a single tool for scheduling irrigation in most of the crops in their rotation.

Additional plot-scale on-farm testing is needed to assess the performance of the SI CropFit sweet corn model and to make additional improvements. For the 2025 growing seasons, the model will be made available to selected growers as a beta version for evaluation. Similarly, it will continue to be tested at SIRP and compared to other scheduling tools, including the Grower Standard. The project's goal is to publicly release the model for the 2026 growing seasons.

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2.7 References

- Allen, R.G., Pereira, L.S., Raes, D., Smith, M. 1998. Crop evapotranspiration: Guidelines for computing crop water requirements. Irrigation and Drainage Paper No. 56. Food and Agricultural Organization, United Nations, Rome, Italy.
https://edisciplinas.usp.br/pluginfile.php/3887570/mod_folder/content/0/Boletim_FAO56.pdf. Accessed August 2021.
- Allen, R.G., Pereira, L.S., Smith, M., Raes, D., Wright, J.L. 2005. FAO-56 dual crop coefficient method for estimating evaporation from soil and application extensions. *J. Irrigation and Drainage Engineering*. 131(1), 2-13. [https://ascelibrary.org/doi/abs/10.1061/\(ASCE\)0733-9437\(2005\)131:1\(2\)](https://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9437(2005)131:1(2)). Accessed August 2021.
- Ayankojo, T. 2018. The use of SI App for irrigation scheduling in tomato production. University of Florida Water Institute, The 6th University of Florida Water Institute Symposium, Gainesville, Florida. Feb. 6-7, 2018.
<https://archives.waterinstitute.ufl.edu/symposium2018/downloads/Presentations/Ayankojo.pdf>.
- Bednarz, C.W., Ritchie, G., Hook, G.E., Yager, R., Cromer, S., Cook, D., Griner, I. 2002. Cotton crop water use and irrigation scheduling. Georgia Cotton Research-Extension Report. Univ. of Georgia, Athens, GA. 61-64.
<http://ugacottonnews.org/vault/rer/2003/p72.pdf>. Accessed January 2022.
- Bedwell, E., McAvoy, T., da Silva, A., Hayes, B., McAvoy, T., Vargas, A., Yu, Z., Washington, B.J., Vellidis, G. 2025. Evaluating the impact of irrigation scheduling on quality parameters of sweet corn. *J. Horticulture Technology*. (in preparation).
- Braunworth, W., Mack, H. 1987. Evaluation of Irrigation Scheduling Methods for Sweet Corn. *J. American Society of Horticultural Science*. 112(1), 29-32.
<https://pdfs.semanticscholar.org/6f05/d22d1910c71268dc90bbb1aa9c1b5d50a0a0.pdf>. Accessed January 2022.
- Broner, I. 2005. Irrigation Scheduling: Fact Sheet No. 4708. Colorado State University Extension, Crop Series 2. <https://extension.colostate.edu/docs/pubs/crops/04708.pdf>. Accessed 3 November 2021.
- Datta, D., Chandra, S., Nath, C., Kar, G., Ghosh, S., Chaturvedi, S., Bhatnagar, A., Singh, G., Singh, V. 2022. Soil-plant water dynamics, yield, quality and profitability of spring sweet corn under variable irrigation scheduling, crop establishment and moisture conservation practices. *J. Field Crops Research*. 279. <https://doi.org/10.1016/j.fcr.2022.108450>.
- Davis, S., Dukes, M. 2010. Irrigation scheduling performance by evapotranspiration-based controllers. *J. Agricultural Water Management*. 98(1), 19-28.
<https://doi.org/10.1016/j.agwat.2010.07.006>.
- Dhaliwal, D., Williams, M., II. 2023. An Outlook on Processing Sweet Corn Production from the Last Three Decades (1990s–2010s). *J. Horticultural Science*. 58(7), 792-796.
<https://doi.org/10.21273/HORTSCI17109-23>.
- Ertek, A., Kara, B. 2013. Yield and Quality of Sweet Corn under Deficit Irrigation. *Agricultural J. Water Management*. 129, 138–144. <https://doi.org/10.1016/j.agwat.2013.07.012>.
- Food and Agriculture Organization of the United Nations. 2021. FAOSTAT statistical database. Publisher: FAO (Food and Agriculture Organization of the United Nations), Rome, Italy. <https://www.fao.org/faostat/en/#data>. Accessed 28 August 2022.

- George, B., Shende, S., Raghuwanshi, N. 2000. Development and Testing of an Irrigation Scheduling Model. *J. Agricultural Water Management*. 46(2), 121–136.
[https://doi.org/10.1016/S0378-3774\(00\)00083-4](https://doi.org/10.1016/S0378-3774(00)00083-4).
- Gilmore, E., Rogers, J. 1958. Heat Units as a Method of Measuring Maturity in Corn. *Agronomy Journal*. 50(10), 611–615. <https://doi.org/10.2134/agronj1958.00021962005000100014x>.
- Hassanli, A., Ebrahimizadeh, M., Beecham, S. 2009. The Effects of Irrigation Methods with Effluent and Irrigation Scheduling on Water Use Efficiency and Corn Yields in an Arid Region. *J. Agricultural Water Management*. 96(1), 93–99.
<https://doi.org/10.1016/j.agwat.2008.07.004>.
- Hayes, M., Porter, W., Snider, J., Reagin, K., Perry, C. 2024. Cotton Irrigation Scheduling: Which Approach is the Best Fit for Georgia? *J. Cotton Science*, 28, 136-144.
<https://doi.org/10.3146/0095-3679-51-PS1607>.
- Howell, T. Irrigation Scheduling Research and Its Impact on Water Use. 1996. Evapotranspiration and Irrigation Scheduling, Proceedings of the International Conference, Nov. 3-6, 1996, San Antonio, TX, American Society of Agricultural Engineers, St. Joseph, MI.
<https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=4216fcee2583f303cdf8cdf342c825a2c2fd7b1>.
- Jones, H. 2004. Irrigation Scheduling: Advantages and Pitfalls of Plant-Based Methods. *J. Experimental Botany*. 55(407), 2427–2436. <https://doi.org/10.1093/jxb/erh213>.
- Kara, B. 2011. Fresh ear yield and growing degree days of sweet corn in different sowing dates in southwestern Anatolia region. *Turkish Journal of Field Crops*. 16(2), 166-171.
<https://dergipark.org.tr/en/download/article-file/158720>.
- Lass, L., Callihan, R., Everson, D. 1993. Forecasting the Harvest Date and Yield of Sweet Corn by Complex Regression Models. *J. American Society for Horticultural Science*. 118(4), 450–455. https://www.researchgate.net/profile/Robert-Callihan/publication/265917092_Forecasting_the_Harvest_Date_and_Yield_of_Sweet_Corn_by_Complex_Regression_Models/links/54ff26510cf2eaf210b68484/Forecasting-the-Harvest-Date-and-Yield-of-Sweet-Corn-by-Complex-Regression-Models.pdf.
- Liakos, V., Porter, W., Liang, X., Tucker, M. A., McLendon, A., Vellidis, G. 2017. Dynamic variable rate irrigation tool for greatly improving water use efficiency. *J. Advances in Animal Biosciences*. 8(2), 557-563. <https://doi.org/10.1017/S2040470017000711>.
- McAvoy, T., Coolong, T. 2023. Shipper Sweet Corn in Southern Georgia. University of Georgia Cooperative Extension Service. Bulletin 1549.
<https://extension.uga.edu/publications/detail.html?number=B1549>. Accessed 5 January 2025.
- McMaster, G. Wilhelm, W. 1997. Growing degree-days: one equation, two interpretations. *J. Agricultural and Forest Meteorology*. 87(4), 391-300. [https://doi.org/10.1016/S0168-1923\(97\)00027-0](https://doi.org/10.1016/S0168-1923(97)00027-0).
- Migliaccio, K., Morgan, K., Vellidis, G., Zotarelli, L., Fraisse, C., Zurweller, B., Crane, J., Rowland, D. 2015. Smartphone Apps for Irrigation Scheduling. An ASABE 2015 Meeting Irrigation Symposium Paper: 152143940. <https://doi.org/10.13031/irrig.20152143940>.
- Miller, L., Vellidis, G., Mohawesh, O., Coolong, T. 2018. Comparing a Smartphone Irrigation Scheduling Application with Water Balance and Soil Moisture-Based Irrigation Methods: Part I—Plasticulture-Grown Tomato. *J. Horticultural Technology*. 28(3), 354–361.
<https://doi.org/10.21273/HORTTECH04010-18>.
- O’Shaughnessy S., Evett, S. 2010. Canopy temperature-based system effectively

- schedules and controls center pivot irrigation of cotton. *J. Agricultural Water Management*. 97, 1310-1316. <https://doi.org/10.1016/j.agwat.2010.03.012>.
- Ozores-Hampton, S., Olson, S., Webb, S., Smith, S., Raid, R., McAvoy, E. 2012. Vegetable Production Handbook, Chapter 21 Sweet Corn Production in Florida. University of Florida IFAS Extension. 283-296. https://www.researchgate.net/profile/Monica-Ozores-Hampton/publication/265184286_Chapter_21_Sweet_Corn_Production_in_Florida/links/56fa9ec308ae8239f6dad110/Chapter-21-Sweet-Corn-Production-in-Florida.pdf.
- Porter, W., Tostenson, M., Reagin, K., Tubbs, R., Smith, A. 2024. Evaluation of Soil Water Tension Trigger Levels for Optimizing Peanut (*Arachis hypogaea*) Yield and Water Use Efficiency. *J. Peanut Science*, 51(1), 100-1005. <https://doi.org/10.3146/0095-3679-51-PS1607>.
- Rao, N., Sarma, P., Chander, S. 1988. Irrigation Scheduling under a Limited Water Supply. *J. Agricultural Water Management*. 15(2), 165–75. [https://doi.org/10.1016/0378-3774\(88\)90109-6](https://doi.org/10.1016/0378-3774(88)90109-6).
- Steele, D., Stegman, E., Gregor, E. 1994. Field comparison of irrigation scheduling methods for corn. *American Society of Agricultural Engineers. Transactions of the ASAE*. 37(4), 1197-1203. <https://doi.org/10.13031/2013.28194>.
- Stone, K., Bauer, P., Sigua, G. 2016. Irrigation management using an expert system, soil water potentials, and vegetative indices for spatial applications. *Transactions of the ASABE*. 59(3), 941-948. <https://doi.org/10.13031/trans.59.11550>.
- Sui, R. 2017. Irrigation Scheduling Using Soil Moisture Sensors. *J. Agricultural Science*. 10(1), 1. <https://doi.org/10.5539/jas.v10n1p1>.
- United States Department of Agriculture (USDA). 2024. Sweet Corn Grades and Standards. <https://www.ams.usda.gov/grades-standards/sweet-corn-grades-and-standards>. Accessed 20 August 2024.
- Vellidis, G., Tucker, M., Perry, C., Kevin, C., Bednarz, C. 2008. A real-time wireless smart sensor array for scheduling irrigation. *J. Emerging Technologies for Real-Time and Integrated Agriculture Decisions*. 61(1), 44-50. <https://doi.org/10.1016/j.compag.2007.05.009>
- Vellidis, G., Liakos, V., Andreis, J., Perry, C., Porter, W., Barnes, E., Morgan, K., Fraisse, C., Migliaccio, K. 2016. Development and Assessment of a Smartphone Application for Irrigation Scheduling in Cotton. *J. Computers and Electronics in Agriculture*. 127, 249–259. <https://doi.org/10.1016/j.compag.2016.06.021>.
- Vellidis, G. 2022. BMPs & precision ag tools in GA: reducing inputs while maintaining yields [Informational flyer].
- Viswanatha, G., Ramachandrappa, B., Nanjappa, H. 2002. Soil plant Water Status and Yield of Sweet Corn (*Zea mays L. cv. saccharata*) as Influenced by Drip Irrigation and Planting Methods. *J. Agricultural Water Management*, 7. [https://doi.org/10.1016/S0378-3774\(01\)00189-5](https://doi.org/10.1016/S0378-3774(01)00189-5).
- Wang, D., Cai, X. 2009. Irrigation Scheduling—Role of Weather Forecasting and Farmers’ Behavior. *J. Water Resources Planning and Management*. 135(5), 364–372. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2009\)135:5\(364\)](https://doi.org/10.1061/(ASCE)0733-9496(2009)135:5(364)).
- Westerfield, R., Eason, N. 2024. Growing Home Garden Sweet Corn. University of Georgia Cooperative Extension Service. <https://woodstock.recdesk.com/RecDeskPortal/Portals/770/Sweet%20Corn.PDF>. Accessed 27 December 2024.

2.8 Tables and Figures

Table 2.1. Estimated phenological stages for sweet corn based on growing degree days (GDD) based on data collected over two spring and two autumn seasons of Bayer Crop Science (Leverkusen, Germany) Obsession hybrid bicolor cultivar grown in southwestern Georgia, United States (U.S.).

GDDs	Phenology
0 - 70	Planting to Emergence
71 - 140	Emergence to V1
141 - 195	V1 to V2
196 - 255	V2 to V3
256 - 300	V3 to V4
301 - 355	V4 to V5
356 - 415	V5 to V6
416 - 490	V6 to V7
491 - 565	V7 to V8
566 - 645	V8 to V9
646 - 695	V9 to V10
696 - 770	V10 to V11
771 - 840	V11 to V12
841 - 890	V12 to V13
891 - 935	V13 to Tasseling
936 - 1050	Tasseling to Silking (R1)
1051 - 1190	Silking to Blister (R1 to R2)
1191 - 1345	Blister to Milk (R2 to R3)
1346 – 1400 +	Milk to Harvest

Table 2.2. Weighting factors used for sensor depths. Factors were based on growing degree days (GDDs) which were indicative of rooting depth.

Root Depth Weighting									
GDD	UGA SSA			Sentek					
	15 cm	31 cm	46 cm	10 cm	20 cm	30 cm	40 cm	50 cm	60 cm
0-300	80%	20%	0%	40%	40%	10%	10%	0%	0%
301-800	50%	30%	20%	25%	25%	15%	15%	10%	10%
801-1000	50%	25%	25%	25%	25%	12.5%	12.5%	12.5%	12.5%
1001-Harvest	40%	30%	30%	20%	20%	15%	15%	15%	15%

Table 2.3. Yield, irrigation amounts, and irrigation water use efficiency (IWUE) of Spring 2024 and Autumn 2024 treatments. There was statistical significance at $\alpha = 0.05$ only for IWUE during the Autumn 2024 growing season.

Treatment	Yield ² (bx ha ⁻¹)		Irrigation Applied ⁵ (mm)		IWUE ⁴ (bx ha ⁻¹ mm ⁻¹)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	1214	1059	127	169	2.00	3.67 ^{ab}
VWC 14.8%	1315	1059	143	230	2.33	2.33 ^a
VWC 14%/14.4%	1214	975	124	249	2.00	1.67 ^a
MP -30 kPa	1265	932	105	211	3.00	2.33 ^a
MP -40 kPa/-30kPa	1164	1186	124	154	1.33	5.67 ^b
SWB ET / Updated ¹	1315	1102	219	192	1.67	3.67 ^{ab}
Rainfed	1062	636	37 ³	59 ³	-	-

1SWB ET for Spring 2024 and SWB ET Updated for Autumn 2024.

2Spring 2024 and Autumn 2024 seeding rates were 12,550 and 10,526 ha-1, respectively.

3 Indicates irrigation applied to promote emergence (Spring: one event; Autumn: two events), activate herbicide (Spring: 0, due to precipitation; Autumn: one event), and fertigate (Spring: six events; Autumn: six events).

4Does not include irrigation related to emergence, herbicide activation, or fertigation.

5Includes amounts related to treatment irrigation, emergence, herbicide activation, and fertigation.

Table 2.4. Mean ear length, diameter, and no-tip fill of Spring and Autumn 2024 growing seasons. There was no statistical significance at $\alpha = 0.05$ during either the Spring or Autumn 2024 growing season.

Treatment	Ear Length (cm)		Ear Diameter (mm)		No-Tip Fill (mm)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	18.4	16.8	46.80	43.69	8.73	14.33
VWC 14.8%	18.6	15.7	47.75	41.35	5.43	19.53
VWC 14%/14.4%	18.8	16.7	47.45	42.82	9.65	20.19
MP -30 kPa	18.2	16.2	47.11	43.56	5.98	17.97
MP -40 kPa/-30kPa	18.3	15.8	47.77	43.31	6.71	16.41
SWB ET / Updated ¹	18.4	16.3	47.67	43.66	5.23	17.49
Rainfed	17.7	15.4	46.90	41.68	12.37	23.65

¹SWB ET for Spring 2024 and SWB ET Updated for Autumn 2024.

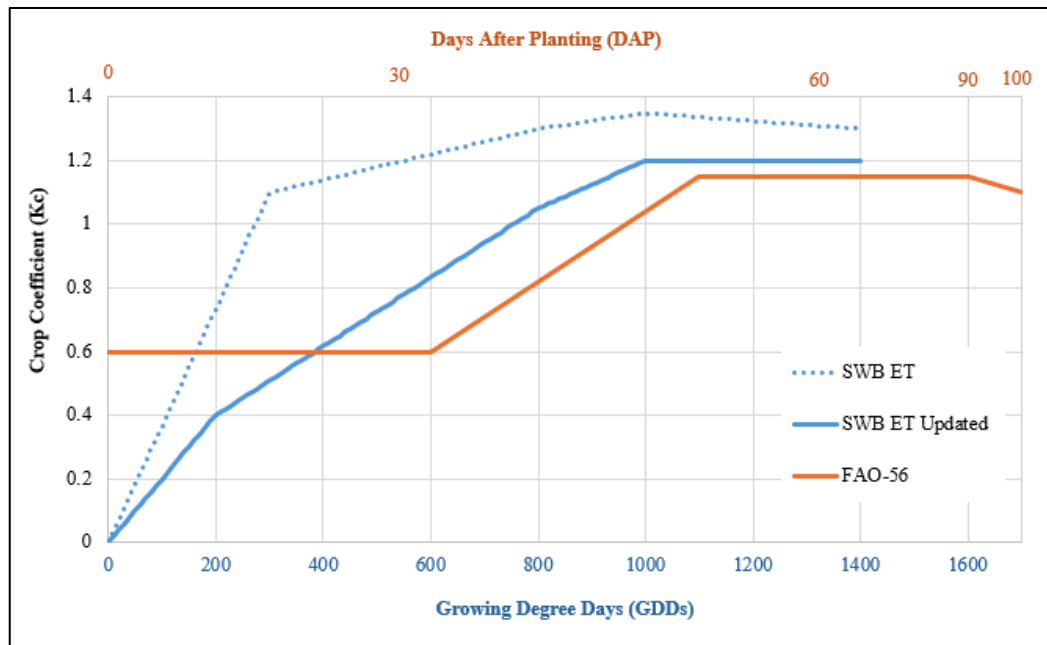


Figure 2.1. Line chart of crop coefficient (K_c) curves for sweet corn used in this study (shown as a function of growing degree days (GDD)) and the FAO-56 curve developed with data from Idaho, U.S. (shown as a function of days after planting (DAP)) (*adapted from Allen et al., 1998*).

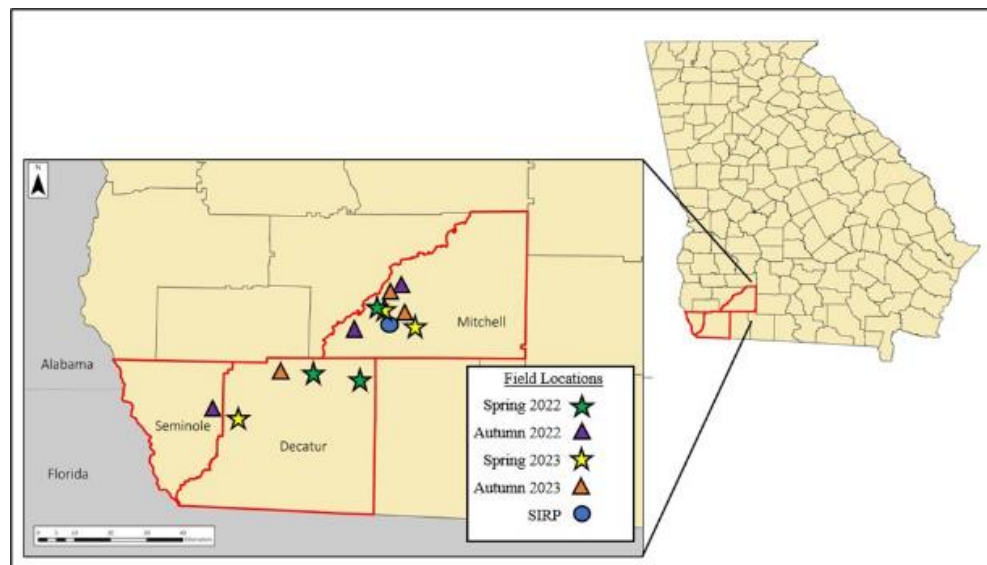


Figure 2.2. Map indicating approximate locations of 12 grower managed sweet corn fields and University of Georgia's Stripling Irrigation Research Park (SIRP).

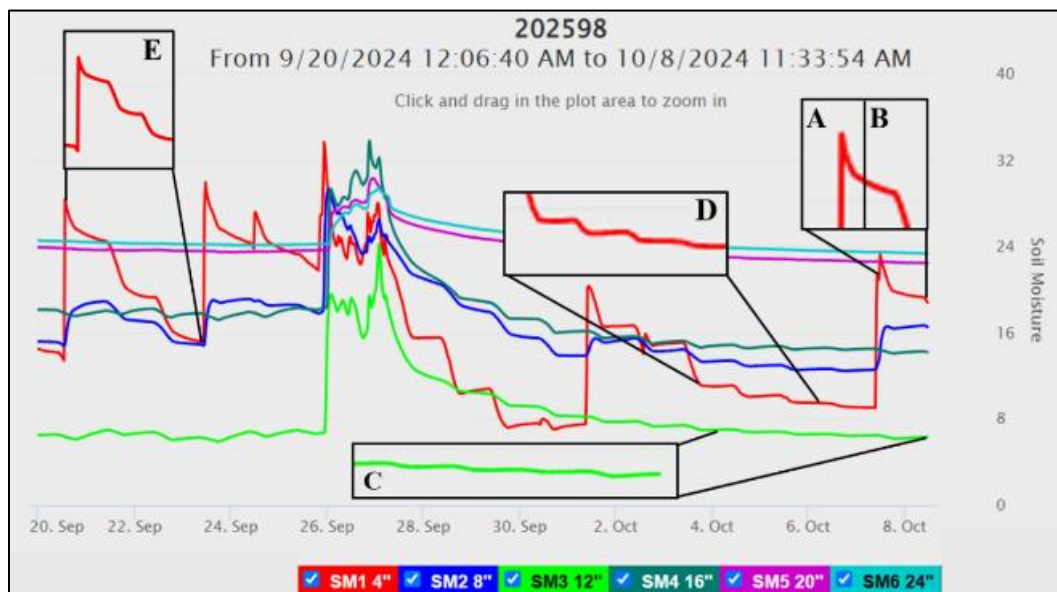


Figure 2.3. AgSense Solutions web interface depicting VWC at 10, 20, 30, 40, 50, and 60 cm (4, 8, 12, 16, 20, and 24 in) in Field 3. Saturation to field capacity is illustrated in window A while daily water use is illustrated by B, and approach to wilting point in window C. Diurnal soil moisture changes in a drier soil are illustrated in window D, with more apparent diurnal soil moisture changes in a wetter soil in window E.

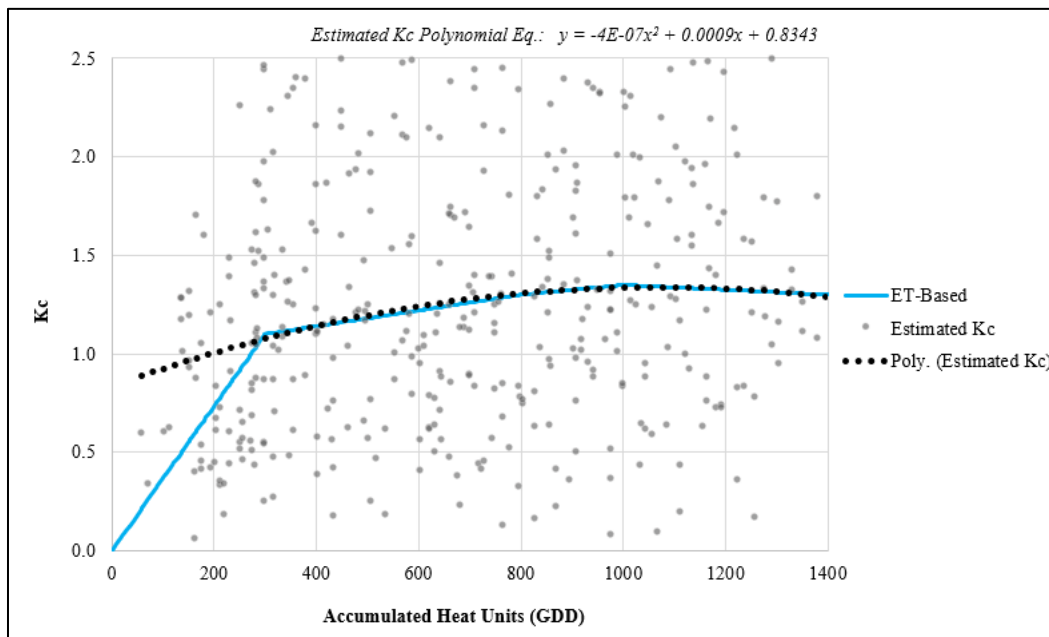


Figure 2.4. Scatter plot indicating estimated evapotranspiration-based crop coefficient (Kc) values with polynomial function of $y = -4E-07x^2 + 0.0009x + 0.8343$ and four linear interpolations to match the function.

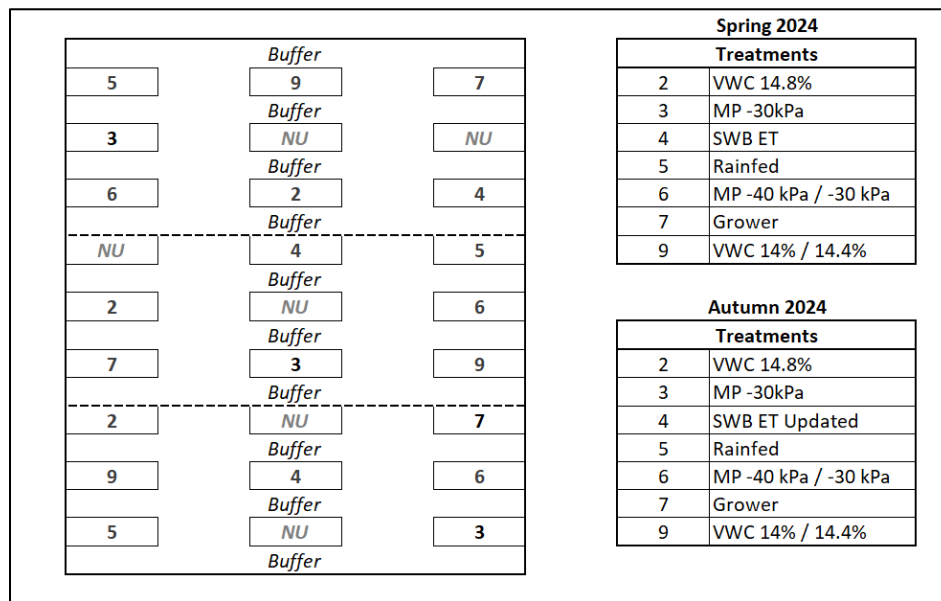


Figure 2.5. Spring and Autumn 2024 randomized complete block design experimental layout and treatments at University of Georgia’s Stripling Irrigation Research Park (SIRP). The rectangles indicate the eight data rows within each plot while *Buffer* indicates the eight buffer rows between data rows. Numbers within the plots indicate treatment and the dashed lines separate the treatment blocks (replicate). Plots labeled “NU” were not used in the study.

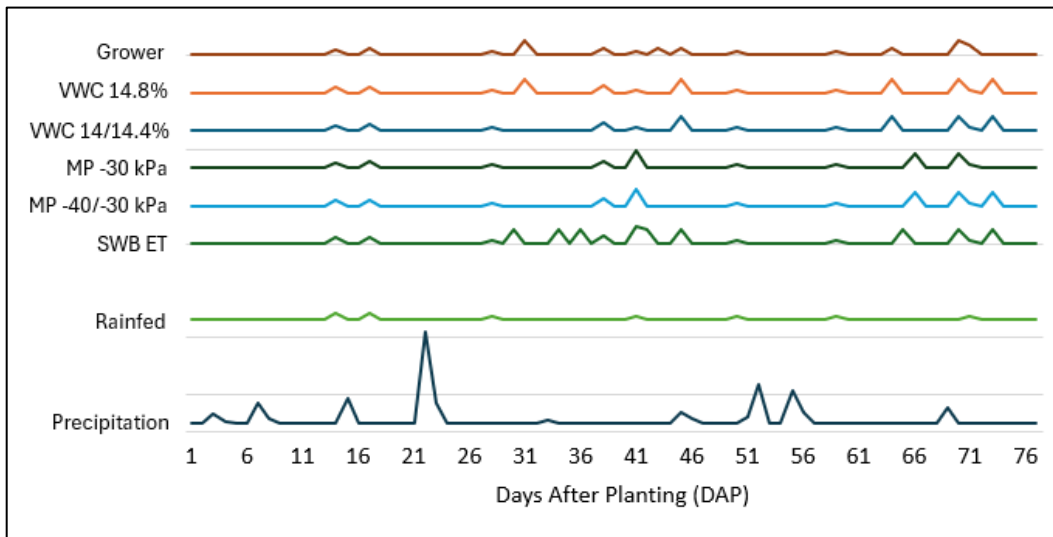


Figure 2.6. Combined line charts indicating frequency and magnitude of Spring 2024 irrigation events for each treatment and precipitation event. There were 16 days with precipitation events totaling 389 mm (~15 in).

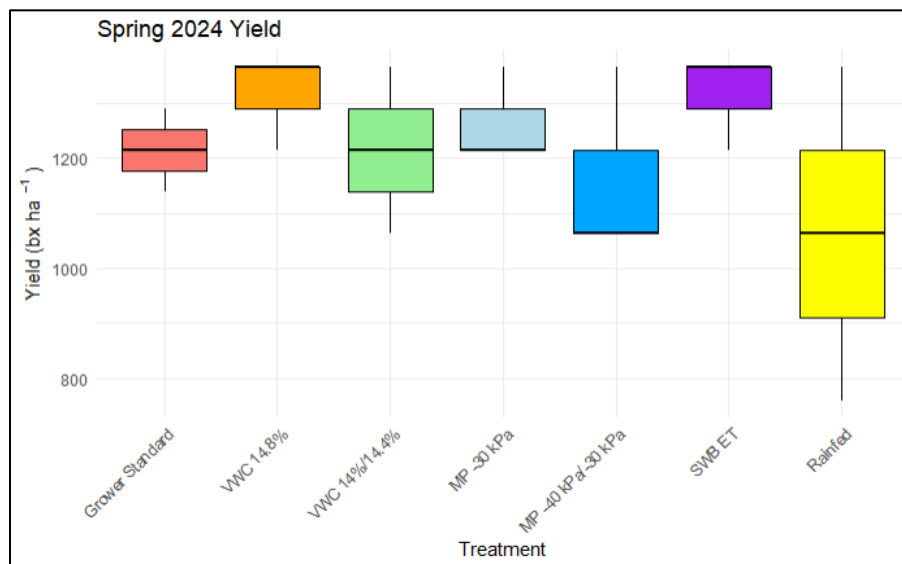


Figure 2.7. Box and whisker plot of Spring 2024 yield per treatment (in bx ha^{-1}) (no statistically significant differences between treatments at $\alpha = 0.05$).

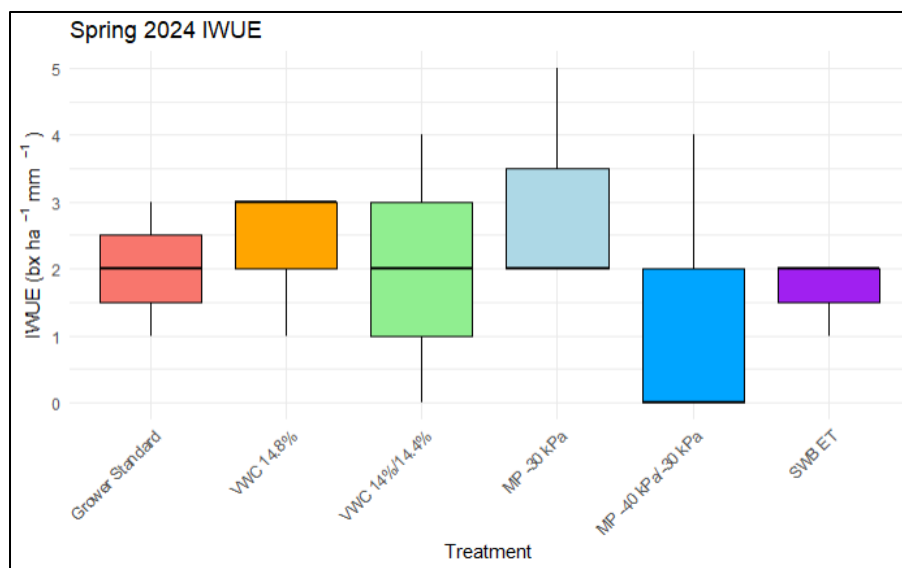


Figure 2.8. Box and whisker plot of Spring 2024 irrigation water use efficiency (IWUE) per irrigated treatment (in $\text{bx ha}^{-1} \text{mm}^{-1}$) (no statistically significant differences between treatments at $\alpha = 0.05$).

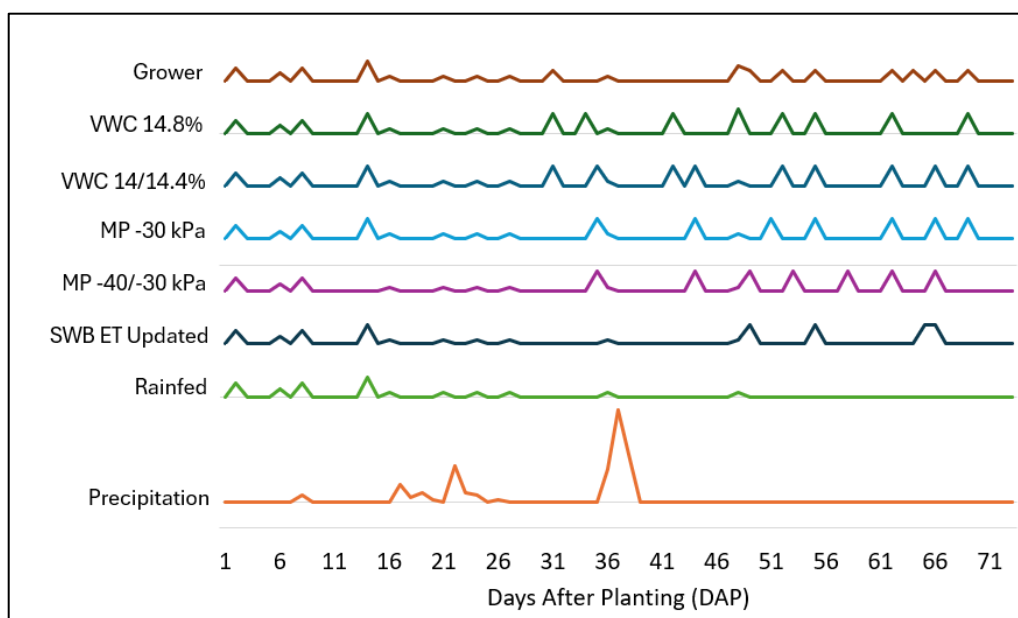


Figure 2.9. Combined line charts indicating frequency and magnitude of Autumn 2024 irrigation events for each treatment and precipitation event. There were 13 days with precipitation events totaling 251 mm (10 in). Most of the precipitation (162 mm; 6.4 in) was received between 35-37 DAP and was associated with Hurricane Helene.

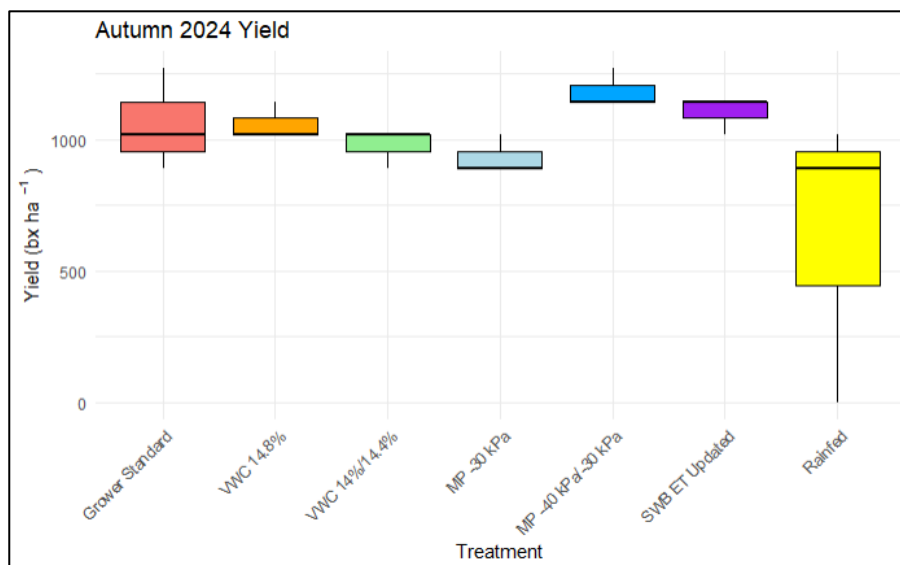


Figure 2.10. Box and whisker plot of Autumn 2024 yield per treatment (in bx ha⁻¹) (no statistical significance between treatments at $\alpha = 0.05$).

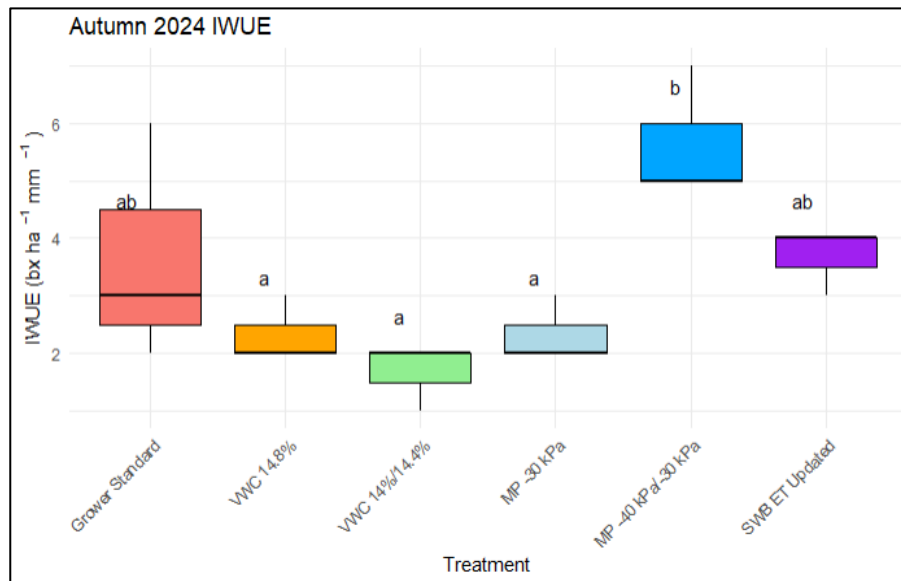


Figure 2.11. Box and whisker plot of Autumn 2024 irrigation water use efficiency (IWUE) per irrigated treatment (in bx ha⁻¹ mm⁻¹) (statistical significance between treatments at $\alpha = 0.05$ indicated by letters).

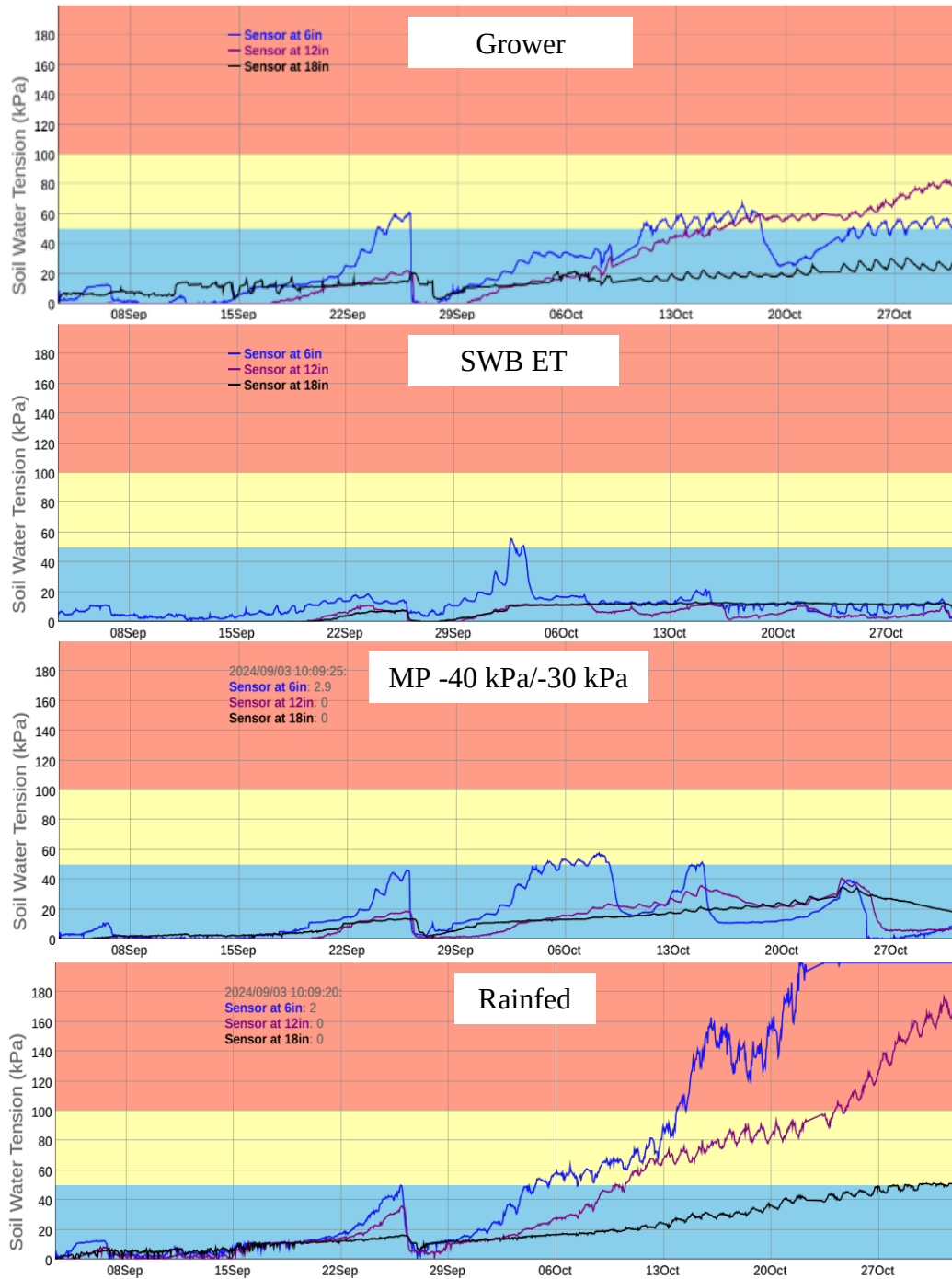


Figure 2.12. Line graphs of soil water tension (the absolute value of matric potential) for four treatments from the Autumn 2024 growing season. The maximum soil water tension recorded by the Watermark sensors used in the UGA SSA probes is 200 kPa. Each curve on the graph indicates soil water tension at the depth shown in the legend. The sensors were centered at depths of 15.2 cm (6 in), 30.5 cm (12 in), and 45.7 cm (18 in).

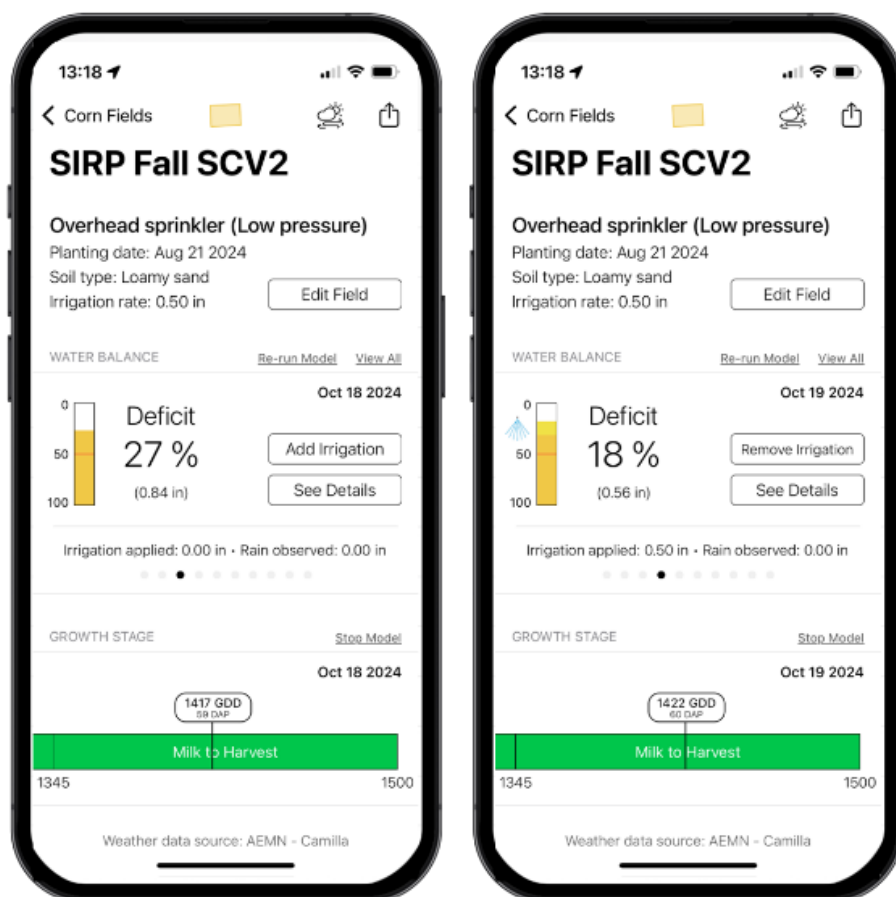


Figure 2.13. Screenshots from SI CropFit showing the main user screen including current RZSWD, crop phenology, accumulated GDDs, and DAP. The screenshot on the left shows the RZSWD approaching the 30% reproductive stage threshold while the screenshot on the right shows the change in the RZSWD after irrigation was applied.

²CHAPTER 3

USING REMOTE SENSING TO DEVELOP A CROP COEFFICIENT CURVE FOR SWEET CORN²

²Bedwell, E., Lacerda, L., Ortiz, B., da Silva, A., Hayes, B., McAvoy, T., Snider, J., Yu, Z.,
Vellidis, G. To be submitted to the *Journal of Remote Sensing in Agriculture*.

3. Abstract

Meeting the water requirements of sweet corn (*Zea mays* subsp. *Mayes* L.) is critical to achieving high yields and meeting the quality standards of fresh market produce in the United States. Therefore, growers tend to over-irrigate this economically valuable crop to ensure that water is not a limiting factor. Science-based irrigation scheduling tools that deliver information on modern platforms are needed to improve irrigation water use efficiency (IWUE) and long-term sustainability. This study applied the Food and Agricultural Organization (FAO)-56 method of estimating daily crop water use to develop an irrigation scheduling tool for sweet corn. The FAO-56 method calculates crop evapotranspiration (ET_c) by multiplying Penman-Monteith evapotranspiration (ET_o) by a crop coefficient (K_c). Past research has shown that the normalized difference vegetation index (NDVI) correlates well with K_c. This study used NDVI values from 12 grower fields over four growing seasons (Spring and Autumn in 2022 and 2023) to develop an NDVI-based K_c curve for sweet corn. A total of 195 multispectral satellite images were sourced from the PlanetScope satellite platform. Mean field NDVI values from each image were used to calculate K_c values using a K_c-NDVI relationship for maize that was available from the literature. The K_c values were plotted as a function of accumulated heat units, and a polynomial equation was fitted to the data. For ease of further programming, the polynomial was represented by four linear models that were incorporated into a soil water balance model (SWB). The SWB model was compared to soil moisture sensor-based irrigation scheduling and a grower standard with replicated plot trials during the 2024 Spring and Autumn growing seasons. There were no statistically significant differences in sweet corn yield or quality between treatments, although the sensor-based method resulted in statistically higher IWUE during the Autumn 2024 growing season. Overall, the NDVI-derived K_c curve that was incorporated into the SWB model resulted in high sweet corn

yields and good quality during both growing seasons but applied more irrigation water than the sensor-based method and the Grower Standard treatment, indicating that further refinement is needed. The NDVI-based methodology used in this study to develop a Kc curve for sweet corn appears to be a simpler but reliable approach to developing Kc curves compared to traditional approaches of estimating daily ETc using weighing lysimeters or soil moisture sensors.

Keywords: smart irrigation; evapotranspiration; normalized difference vegetation index; irrigation water use efficiency; irrigation scheduling.

3.1. Introduction

3.1.1. *Agricultural Irrigation and Precision Irrigation*

The Food and Agriculture Organization (FAO) projects that the global population will reach approximately 10 billion within the next two decades (FAO, 2017). To meet the food demands of this expanding population, plant-based food production must double (Ainsworth et al., 2012). This substantial rise in production requirements underscores the necessity for efficient agricultural practices (FAO, 2017; Jha et al., 2019; Abioye et al., 2020; Garcia et al., 2020; Talaviya et al., 2020). A significant challenge lies in increasing the efficiency of agricultural irrigation, which accounts for over 85% of global freshwater consumption (Talaviya et al., 2020). Given this substantial contribution, developing and implementing innovative technologies and practices for effective and economical water conservation are crucial for optimizing agricultural production (Umair and Usmain, 2010; Vellidis et al., 2016).

In the context of increasing agricultural efficiency, precision agriculture has emerged as a transformative approach that utilizes advanced technologies, such as remote sensing, to optimize resource use in agricultural production (Bongiovanni and Lowenberg-Deboer, 2004). Precision irrigation, a subset of precision agriculture, aims to improve irrigation water use efficiency (IWUE) and crop yield by considering crop water needs as a function of crop growth and development, soil properties, precipitation patterns, and environmental conditions. This approach is particularly ideal for crops that are sensitive to water stress (Savitha and UmaMaheshwari, 2018; Vellidis et al., 2016).

3.1.2. *Sweet Corn in Georgia, U.S.*

Sweet corn (*Zea mays* subsp. *Mayes* L.) is a globally popular crop and the third most-grown vegetable crop in the United States (U.S.) (Barros-Rios et al., 2015; Garcia y Garcia et al., 2009;

Paranhos et al., 2023). The U.S. leads in global sweet corn production, with Georgia playing a significant role as the third-largest producer of fresh market sweet corn nationally (McAvoy and Coolong, 2023). In 2023, the economic value of sweet corn production in Georgia surpassed USD 106 million, with over 9,000 ha (23,000 ac) harvested (McAvoy and Coolong, 2023). Quality is a critical aspect of sweet corn production. Quality heavily depends on adequate water supply, which is a limiting resource for sweet corn growth and development (Hassanli et al., 2009). Therefore, effective irrigation management is key to increasing sweet corn's yield potential (Viswandatha, 2002). Depending on variety, sweet corn grown in the southeastern U.S. typically requires between 203 and 360 mm (8-14 in) of water during the growing season (Westerfield and Eason, 2024).

However, irrigation management for sweet corn in the southeastern U.S. presents challenges due to significant climatic variability and precipitation uncertainty (Stone, 2016; Paranhos et al., 2023). To address these issues, irrigation scheduling has emerged as an effective method for improving both IWUE and sweet corn yield and quality. Research shows that irrigation scheduling based on soil moisture deficit can increase yield by ensuring that sweet corn water needs are met strategically and efficiently (Braunworth and Mack, 1987; Hassanli et al., 2009; Datta et al., 2022).

3.1.3. Irrigation Scheduling in the Southeastern U.S.

Despite a humid-subtropical climate with a regional average annual precipitation of approximately 1200-1500 mm (47-60 in), the uncertainty of precipitation timing and magnitude paired with sandy soils that have low water holding capacity leads to high variability in rainfed yields in this region and has spurred the widespread adoption of irrigation systems (Bednarz et al., 2002; Stone, 2016; Sui, 2017). Effective irrigation scheduling maintains plant available soil water within an optimal range for the crop at each phenological stage (Jones, 2004; Howell, 1996).

Dynamic environmental conditions as well as differences in soil types and crop water needs make this particularly challenging (Rao et al., 1988; Steele, 1994).

3.1.4. Crop Evapotranspiration and Coefficients

Evapotranspiration (ET) estimation plays a pivotal role in irrigation scheduling, as it reflects the cumulative water loss from the soil through evaporation and plant transpiration (Allen, 2005). ET is quantified by a complex process that considers various environmental factors, including relative humidity, solar radiation, wind speed, temperature, and crop characteristics (Allen, 2005; Ertek and Kara, 2013). The FAO developed guidelines for estimating crop water requirements in "Organization in Irrigation and Drainage Paper No. 56" (FAO-56) that utilizes the FAO Penman-Monteith equation to estimate crop water requirements, or crop coefficients (K_c) (Allen et al., 1998) (Eq. 3.1).

$$ET_c = K_c \times ET_o \quad (3.1)$$

where,

ET_c = daily crop evapotranspiration (ET), also referred to as crop water use (mm day^{-1}),

K_c = a daily crop coefficient extracted from a crop-specific K_c curve, and

ET_o = Penman-Monteith reference ET (mm day^{-1}).

K_c varies throughout the different phenological stages of a crop. These values typically peak during the reproductive stages, when water demand is at its highest. For annual crops, K_c values begin near zero at crop emergence and increase to 1.0 or higher as the crop enters its reproductive growth stages, when it requires the most water. During its peak growth stage, water needs can increase rapidly from 40% of ET_o to 110% of ET_o (Ozorez-Hampton et al., 2012). The growth stages during which K_c values are highest for sweet corn include silking, tasseling, and ear

development, which are also the periods when sweet corn is most vulnerable to water stress (Rao, 1988).

3.1.5. Growing Degree Days

Phenological stages are driven by accumulated heat units or growing degree days (GDD) and fundamentally influence crop water needs (McMaster and Wilhelm, 1997). GDD calculations help predict a plant's biological processes, which can improve irrigation management.

GDD are calculated with the following equation:

$$GDD = \left[\frac{T_{max} + T_{min}}{2} \right] - T_{base} \quad (3.2)$$

where,

T_{max} is the maximum daily temperature,

T_{min} is the minimum daily temperature, and

T_{base} is the base temperature of the crop.

The base temperature, or the threshold temperature at which plant growth begins, for sweet corn is 10°C (50°F) (Gilmore and Rodgers, 1958; Lass et al., 1993; Kara, 2011). However, sweet corn growth is also hindered and reduced by 0.5% each additional day in which the temperature is greater than 30°C (86°F) (Dhaliwal and Williams II, 2022). Because Kc curves that are based on GDD consider the meteorological conditions during the growing season, which significantly affect the rate at which a crop develops, they typically estimate crop water needs more accurately than Kc curves that are based on days after planting (DAP) (Vellidis et al., 2016). For example, the sweet corn growing season may vary between 60 and 100 days, depending on the growing region and season (Allen et al., 1998).

3.1.6. *Methods for Developing Kc Curves*

The traditional approach for developing Kc curves involves using weighing lysimeters to accurately estimate ETc by measuring daily changes in lysimeter mass and accounting for precipitation (Yang et al., 2000; Liu et al., 2002; Benli et al., 2006). Because weighing lysimeters are not readily available, other approaches have been developed. Vellidis et al. (2016) used matric potential soil moisture sensors in replicated plot trials to optimize cotton Kc curves developed in other regions for local conditions of the southeastern U.S. In that study, the Kc curve was modified so that using it for irrigation scheduling resulted in predetermined ranges of matric potential in the crop's root zone prior to and during the reproductive stages.

Bedwell et al. (2025a) developed an ETc-based model for sweet corn for the southeastern U.S. using a Kc curve derived empirically from soil moisture data. Twelve grower-managed commercial sweet corn fields in southwestern Georgia (Figure 3.1) were each instrumented with two volumetric water content sensor probes across four growing seasons (Spring and Autumn 2022 and 2023). Daily differences in volumetric water content were used to estimate the daily ETc of sweet corn. These ETc estimates were then used to develop an empirical Kc vs GDD curve. The Kc curve was incorporated into a soil water balance model similar to the one described further below and was evaluated by comparing it to five soil moisture sensor-based irrigation scheduling methods and a Grower Standard method in replicated plot trials. During the Spring 2024 growing season, scheduling with the ETc-based model resulted in the highest yield but required more irrigation than the other scheduling methods during the first half of the growing season. The Kc curve was modified to reduce the estimate of daily ETc during this period, and it performed well during the Autumn 2024 growing season, producing the second highest yields while irrigation

applied was similar to that of the sensor-based methods. Numerical differences in yield were not statistically different during either growing season (Bedwell et al., 2025a).

3.1.7. *The SmartIrrigation CropFit App*

Over the last forty years, significant progress has been made in developing irrigation scheduling tools based on FAO-56 principles. Initially, these tools were primarily computer-based and later web-based models that leveraged meteorological data obtained from extensive weather station networks (Davis and Dukes, 2010). In the past decade, however, there has been a shift towards making these advanced tools available on smartphone platforms (Migliaccio et al., 2015; Vellidis et al., 2016; Miller et al., 2018). This evolution has not only increased accessibility but also provided users with convenient access to essential irrigation information, leading to more effective water resource management.

The SmartIrrigation CropFit App (SI CropFit) (<https://smartirrigationapps.org/>) is a smartphone-based irrigation scheduling platform that contains FAO-56-based scheduling models for maize, cotton, peanuts, and soybeans. SI CropFit uses meteorological data to determine daily ETo and the corresponding Kc to estimate daily ETc. In all four models, phenological development and Kc changes are driven by GDD.

SI CropFit applies a soil water balance (SWB) model to estimate the daily root zone soil water deficit (RZSWD) using daily ETc, precipitation, irrigation applied, and the soil's plant available water holding capacity (AWHC). AWHC refers to the moisture retained in the soil between field capacity, where gravity prevents further downward movement of water, and wilting point, where plants can no longer efficiently extract moisture. A 50% RZSWD, indicating a depletion of half the plant available soil water, is a widely accepted irrigation threshold for agronomic crops. In the SI CropFit SWB model, the current plant-available soil water is determined by subtracting

yesterday's ETc from the previous day's plant-available soil water and adding any precipitation received or irrigation applied.

SI CropFit sources meteorological data from state weather station networks (mesonets), Apple Weather, and five different brands of automated rain gauges, all accessed via application programming interfaces (APIs). Users in U.S. states that participate in mesonets can select a weather station as their main data source, with the system automatically identifying the nearest station based on the field's coordinates. Apple Weather acts as the primary data source for users outside these states, providing weather information on a 4 km (2.5 mi) grid chosen according to the field's location. The use of an automated on-farm rain gauge is highly recommended when using SI CropFit for irrigation scheduling to ensure the accuracy of the SWB model.

One of the functionalities of SI CropFit is that users can delineate the perimeter of their field using dropped pins. The perimeter is then used to extract soil information, including soil type, field capacity, and wilting point, from the United States Department of Agriculture (USDA) Natural Resources and Conservation Services (NRCS) Web Soil Survey (<https://websoilsurvey.sc.egov.usda.gov/App/>). The soil's plant AWHC is calculated by subtracting wilting point from field capacity. If there is more than one soil type within the field perimeter, an area-weighted average AWHC is calculated, and that value is subsequently used in the soil water balance model. SI CropFit operates primarily on a cloud server with daily updates of user-needed information to the smartphone platform. It is available for both iOS and Android platforms at no cost to the user.

Plot-scale and on-farm research in Alabama, Florida, Georgia, and Mississippi has shown that using SI CropFit to schedule irrigation in maize, cotton, peanut, and soybean results in 5-15% greater yields and up to 40% greater IWUE than those achieved with traditional calendar-based

irrigation scheduling methods and similar results to scheduling irrigation with soil moisture sensors (Vellidis et al., 2016; Vellidis, 2022; Gallios et al., 2023).

3.1.8. Estimating K_c with the Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is the best-known and most widely used vegetation index (Myneni et al., 1995; Pettorelli et al., 2005; Wu et al., 2019) for assessing plant vigor and biomass by utilizing the differences in reflectance between near-infrared (NIR) and red wavelengths. NDVI is calculated using Eq. 3.3.

$$NDVI = \frac{NIR+Red}{NIR-Red} \quad (3.3)$$

where,

NIR is reflected near-infrared wavelengths and

Red is reflected red wavelengths.

NDVI values range from -1 to +1, although in agricultural applications, the practical range is from 0 to 1. Higher values typically indicate more vigor and higher biomass, while lower values suggest the opposite. NDVI is particularly valuable in precision agriculture, as it allows for the assessment of the spatial variability of crop vigor within fields, thus enabling growers to make informed management decisions about the application of crop inputs (Hunsaker et al., 2003). NDVI has also proven to be a valuable tool in irrigation scheduling as NDVI can effectively indicate near-real-time crop water needs throughout the growing season (Hunsaker et al., 2003; Singh et al., 2012; Stone et al., 2016).

Research has shown that NDVI values closely correlate with crop coefficients, which represent crop water needs (Bausch and Neal, 1987; Hunsaker et al., 2003; Stone et al., 2016). These findings indicate that spectrally derived K_c values may be considered a real-time K_c that illustrates the crop's response to weather, stresses, and management (Stone et al., 2016).

Past research conducted in Arizona (Hunsaker et al., 2003) and South Carolina (Stone et al., 2016) has found empirical relationships between NDVI and Kc for cotton (*Gossypium hirsutum*) and maize (*Zea mays*), respectively. Hunsaker et al. (2003) developed a relationship between GDD, NDVI, and Kc for cotton in Arizona using two different linear regressions. During the early season, a simple linear regression was applied between Kc and NDVI driven by GDD, as both Kc and NDVI increase in parallel, with both peaking during the reproductive phase when full canopy closure typically occurs. Kc peaks at the first flower, remains constant for much of the reproductive period, and begins to decrease as the bolls develop and open, reducing water requirements. NDVI, however, typically saturates once the canopy closes and remains constant at about 0.75-0.80 until the crop begins to naturally defoliate. To address this issue, Hunsaker et al. (2003) applied a multiple regression to estimate Kc once NDVI reached a value of 0.80. The Hunsaker et al. (2003) approach was modified by Stone et al. (2016) for maize. Because NDVI values for maize decrease after reaching a peak during the reproductive period, Stone et al. (2016) were able to use the simple linear model shown in Eq. 3.4 to estimate maize Kc from NDVI.

$$Kc = 1.5 \times NDVI \quad (3.4)$$

3.1.9. Objectives

The overall goal of this study was to apply the techniques developed by Hunsaker et al. (2003) and Stone et al. (2016) to develop an NDVI-based Kc curve for sweet corn in the southeastern U.S. as an alternative to soil moisture sensor-based techniques used in other recent studies (Vellidis et al., 2016; Bedwell et al., 2025a). Specific objectives of the study were to:

1. Develop an NDVI-based Kc curve using data from sweet corn fields in Georgia.
2. Incorporate the NDVI-based Kc model into the SI CropFit soil water balance model and compare its performance to other irrigation scheduling tools.

3.2. Materials and Methods

The study was conducted in southwestern Georgia, U.S., within the Dougherty Plain subregion of the southeastern Coastal Plain (Figure 3.1). The soils in this region vary from sandy to loamy sand, and the climate is classified as humid subtropical, characterized by hot, humid summers and mild winters. Annual precipitation in the area generally ranges from approximately 1170 mm to 1270 mm (47 to 50 in), while the average annual temperature typically falls between 10°C and 27°C (50°F to 80°F). This warm, moist climate allows for two sweet corn growing seasons: in the Spring, from March to June, and in the Autumn, from August to October.

3.2.1. *Developing an NDVI-Based K_c Curve*

The 12 grower fields described by Bedwell et al. (2025a) were used in this study to develop the NDVI-based K_c curve for sweet corn. A total of 195 multispectral satellite images that represented the study fields during four growing (Spring 2022: 51 images; Autumn 2022: 26 images; Spring 2023: 56 images; Autumn 2023: 62 images) were sourced from the PlanetScope (Planet Labs Inc., San Francisco, CA, U.S.) satellite platform. The platform consists of approximately 130 satellites that capture reflected light from the Earth's surface in eight wave bands (coastal blue, blue, green I, green, yellow, red, red edge, and NIR). The temporal resolution for the location of the study was at least daily, while the spatial resolution was 3 m (9.8 ft).

Using reflectance data from the red (665-680 nm) and NIR (780-850 nm) bands, NDVI was calculated for growing season days with cloud-free images from the 12 fields using the ArcGIS (Esri, Redlands, California, U.S.) Pro Raster Calculator tool. A daily field average NDVI value was calculated using the ArcGIS Pro Zonal Statistics tool. The resulting NDVI values for specific fields on specific dates were used to calculate K_c values for that field using Eq. 3.4.

The K_c values were plotted as a function of GDD, and a polynomial equation was fitted to the data (Figure 3.2). GDD were calculated using meteorological data from the closest University of Georgia (UGA) weather stations. Only data points from $GDD \geq 250$ were used to ensure that the seedlings had emerged. The polynomial K_c curve matched the pattern of the data with an increasing slope for approximately 70% of the growing season and a peak at approximately 1000 GDD, after which they plateaued. However, the polynomial underpredicted the NDVI-derived K_c values in the pre-reproductive and early reproductive stages (600 to 1000 GDD). To address this concern, four linear models were fitted to the data that generally matched the shape of the polynomial function but better represented the higher K_c values (Figure 3.2). In addition, the first linear model was set to intercept the y-axis at zero. The transitions from one linear model to the next were set at easily observable phenological stage changes to facilitate incorporation into an irrigation scheduling model and to allow for simpler field observations.

3.2.2. Using the NDVI-Based K_c Curve for Irrigation Scheduling

The NDVI K_c curve was integrated into a spreadsheet version of the SI CropFit SWB model described earlier so that it could be used for irrigation scheduling and its performance could be compared to other irrigation scheduling tools. SI CropFit was run in parallel for a virtual maize field to provide daily GDD and ETo values, which were manually entered into the SWB model. SI CropFit used meteorological data from the nearest UGA weather station. GDD were used to calculate a corresponding K_c from the NDVI-based K_c curve, and Eq. 3.1 was used to calculate daily ET_c . At the time of planting, the soil profile was initialized to field capacity (0% RZSWD). The daily ET_c calculated using Eq. 3.1 was subtracted from the previous day's RZSWD to determine the current day's RZSWD, and precipitation and irrigation amounts were added manually to the SWB model. Irrigation was triggered if the daily RZSWD approached or surpassed

a set threshold (described later). The SWB model using the NDVI-based Kc curve was named NDVI-1.

3.2.3. Field-Testing at the Plot Scale

The goal of the field testing was to evaluate the effectiveness of the NDVI model in comparison to other irrigation scheduling methods. The study took place during the Spring and Autumn 2024 growing seasons utilizing a replicated plot study at UGA's Stripling Irrigation Research Park (SIRP) located in Mitchell County, Georgia. This site is near several of the 12 grower fields (Figure 3.1). The research was conducted on a 4 ha (10 ac) area known as the Newton Lateral Field (31°16'46.24" N, 84°17'59.59" W). The field contains 27 plots, each measuring 14.5 m × 14.5 m (48 ft × 48 ft or 48 ft long by 16 rows wide), with data collection taking place in the middle eight rows of each plot. The outer four rows serve as buffers. The soil in the Newton Lateral field is classified as Lucy Loamy Sand, with an AWHC of 2 mm mm⁻¹ (0.08 in in⁻¹) and a slope ranging from 0 to 5%. Soil texture is approximately 86% sand, 8% silt, and 6% clay. Irrigation is provided by a variable-rate lateral system capable of applying distinct water rates to each of the 27 plots. A UGA weather station is located about 800 m (0.5 mi) from the field.

The Bayer Crop Science (Leverkusen, Germany) Obsession hybrid bicolor cultivar was planted at 12,550 seeds ha⁻¹ (31,000 seeds ac⁻¹) on 30 March 2024 and harvested on 3 June 2024, during the Spring season. In the Autumn, it was planted at 10,526 seeds ha⁻¹ (26,000 seeds ac⁻¹) on 21 August and harvested on 31 October. These planting densities align with typical practices in southwestern Georgia and are adapted to seasonal variations to optimize yields and ear size while minimizing defects related to changes in daylight hours (McAvoy and Coolong, 2023). This particular cultivar was chosen due to its widespread use in commercial farming within the southeastern U.S. The seeds had a germination rating of 95%, based on the manufacturer's label.

Actual observed germination rates were estimated at 11,943 seeds ha⁻¹ (29,500 seeds ac⁻¹) in the Spring and 10,000 seeds ha⁻¹ (24,700 seeds ac⁻¹) in the Autumn.

3.2.4. Irrigation Treatments

For the Spring 2024 season, the study layout followed a randomized complete block design with four treatments and three replicates for each treatment (12 plots). During the Autumn 2024 season, the layout mirrored that of Spring 2024, with an additional treatment included, resulting in five treatments with three replications of each treatment (15 plots). The remaining plots were all planted with sweet corn and used for other irrigation scheduling studies.

University of Georgia Smart Sensor Array (UGA SSA) soil moisture sensor probes (Liakos et al., 2017; Vellidis et al., 2008) were installed in each plot a few days after emergence. A UGA SSA probe consists of three Irrometer Watermark sensors (The Irrometer Company—Riverside, California, U.S.) that measure soil moisture in terms of matric potential and report in units of kilopascal (kPa). The sensors were centered at depths of 15.2 cm (6 in), 30.5 cm (12 in), and 45.7 cm (18 in). During irrigation scheduling, sensor data were weighted by depth based on GDD to indicate root water uptake at various depths (Table 3.1). For example, from 0-300 GDD, the data from the Watermark sensor at 15 cm (6 in) in a UGA SSA probe was assigned a weight of 0.8 (80%), data from the sensor at 31 cm (12 in) assigned a weight of 0.2 (20%), and data from the sensor at 46 cm (18 in) a weight of 0.

The four treatments used during the Spring 2024 growing season are described below and included a Grower Standard. The Grower Standard treatment followed the irrigation scheduling practices of one of the top sweet corn producers in Georgia, which has a history of using soil moisture sensors for irrigation scheduling and consistently produces high yields. In essence, the Grower Standard treatment was the benchmark against which the other irrigation treatments were

compared. All other management practices, including fertilization, were applied uniformly across all treatments. Fertilization followed the practices used by the grower, and most fertilizer was applied in-season using fertigation.

1. Grower Standard – Irrigation amount and timing matched one of the grower’s commercial fields located within 2 km (1.2 mi) of SIRP. The field was planted on the same date as the plots with the same sweet corn variety. Soil moisture sensors were not installed in the grower’s field during the plot studies, and irrigation scheduling for this treatment was based on the grower’s experience. The amount of water applied at each irrigation event ranged from 8-19 mm (0.3-0.75 in).
2. NDVI-1 – In this treatment, the SWB model used the Kc curve derived from NDVI data to trigger irrigation when the RZSWD approached or exceeded 30%. This treatment was irrigated with 19 mm (0.75 in) at each event.
3. SMS (Soil moisture sensors) – Daily matric potential at 7:00 AM was calculated by averaging the Watermark sensor readings from each depth of each UGA SSA probe in each of the three replicates. Those values were then used to calculate a weighted average by depth using the values shown in Table 3.1. If the weighted average approached or exceeded a matric potential of -40 kPa prior to tasseling and approached or exceeded a matric potential of -30 kPa from tasseling onwards, the treatment was irrigated with 19 mm (0.75 in) at each event. The matric potential thresholds were based on the authors’ experience with similar irrigation scheduling studies on other crops in this environment.
4. Rainfed – In this treatment, irrigation was used only for management, i.e., to promote emergence, activate herbicides, and for fertigation. These amounts applied are described in more detail below.

During the Spring 2024 season, management events included one 8 mm (0.3 in) irrigation event to promote emergence, five 4 mm (0.17 in) fertigation events, one 9 mm (0.34 in) fertigation event) that were applied to all treatments and totaled 37 mm (1.5 in). On Friday, 26 April 2024, a 10 mm (0.4 in) irrigation event was applied to all irrigated treatments to avoid crop water stress over a hot, dry weekend. During the Autumn 2024 season, management events included six 4 mm (0.17 in) fertigation events, 8 mm (0.3 in), and two 13 mm (0.5 in) irrigation events to promote emergence and one 13 mm (0.5 in) event for herbicide activation. Irrigation treatments began following that period.

Because scheduling with the NDVI-1 model during Spring 2024 resulted in more frequent irrigation than the SMS treatment, the first, second, and third segments of the NDVI-1 Kc were modified to reflect the shape of the original polynomial curve (Figure 3.2). The revised Kc curve was incorporated into the SI CropFit soil water balance model and added as a fifth treatment (NDVI-2) during the Autumn 2024 season. The NDVI-2 treatment was irrigated as the RZSWD approached 40% prior to tasseling and 30% from tasseling until harvest, with 19 mm (0.75 in) at each event.

The total irrigation amount applied to each treatment included irrigation used to promote emergence, activate herbicides, and fertilize. However, these amounts were not included in IWUE calculations. Treatment IWUE was calculated using Eq. 3.5.

$$IWUE = \frac{\text{Treatment Yield} - \text{Rainfed Yield}}{\text{Treatment Irrigation Applied} - \text{Rainfed Irrigation}} \quad (3.5)$$

3.2.5. Yield and Quality

The plot harvest was conducted to resemble the commercial sweet corn harvesting process. In a commercial setting, the uppermost ear, which is the largest on each plant, is harvested by hand. The accepted standard for measuring sweet corn yield is boxes per unit area harvested (bx ha⁻¹; bx

ac⁻¹). In the southeastern U.S., the standard box size is 28 cm × 28 cm (11 in × 11 in), which holds 48 ears of marketable sweet corn. To assess treatment yields, ten upper ears were harvested by hand from ten consecutive plants in the fourth row of each plot. The ears underwent inspection both in and out of the husk for quality.

A USDA-certified fresh market sweet corn grader evaluated the ears as either marketable or unmarketable according to USDA U.S. Fancy Grade standards (McAvoy and Coolong, 2023; USDA, 2024). Ears were classified as unmarketable if they were shorter than 15.2 cm (6 in), had more than 38.1 mm (1.5 in) of poor/no-tip fill, or exhibited any signs of smut, mechanical damage, or insect or bird damage.

Yield was calculated based on the grade of the harvested ears. For instance, if seven out of ten ears were marketable, the treatment grade would be 70%. To calculate yield, the treatment grade was multiplied by the observed germination rate. This method follows the common assumption among sweet corn growers: that each plant produces at least one marketable ear (McAvoy and Coolong, 2023).

Several parameters related to ear and plant quality were assessed—some before the harvest and others immediately after—as various physical characteristics impact marketability. This discussion focuses on three key quality parameters directly influencing yield: no-tip fill, ear length, and ear diameter. Ear diameter and no-tip fill were recorded with a caliper with an accuracy of 0.01 mm, while ear length was measured in centimeters with a ruler. All measurements were taken on the same day as the harvest, and samples were kept at 20°C (68°F) to prevent excessive moisture loss from the kernels.

3.2.6. Data Analysis

To assess the treatments' performance, an analysis of variance (ANOVA) was performed using irrigation totals, yields, IWUE, and ear attributes in R Studio (version 2024.04.2 + 764) (Boston, Massachusetts, U.S.) The ANOVA was performed using Type III sum of squares, and residual diagnostics were performed to ensure that the assumptions of the ANOVA were met.

Following the ANOVA, a Tukey post-hoc test was applied to assess pairwise differences between treatment groups. The results from the post-hoc analysis were then visualized using a compact letter display, which indicated statistically significant differences at $\alpha = 0.05$, if any were present, between the irrigation treatments. A comprehensive assessment of quality parameters was provided by Bedwell et al. (2025b).

3.3. Results

3.3.1. Irrigation and Yield

Treatment irrigation amounts described below include irrigation used to promote emergence, activate herbicides, and fertigate. However, these management-related irrigation amounts were not used in calculating IWUE, as shown in Eq. 3.5. In contrast, the number of irrigation events described below are indicative only of treatment irrigation events and do not include those related to promoting emergence, activating herbicides, or fertigating.

Spring 2024: During the Spring 2024 growing season, 16 precipitation events contributed to a total of 389 mm (15.3 in) of precipitation. As a result, irrigation was necessary only a few times. The NDVI-1 treatment required seven irrigation events, amounting to 162 mm (6.4 in), which was higher than the other treatments (Table 3.2). In contrast, the SMS treatment had five irrigation events with a total of 124 mm (4.9 in), making it the treatment with the least irrigation applied during the Spring 2024 season (Figure 3.3). The Grower Standard treatment resulted in seven

irrigation events totaling 127 mm (5 in). Because the amount applied at each Grower Standard event was not the same, this treatment had the same number of events as the NDVI-1 treatment, but less total water was applied.

The treatment with the highest numerical yield was the Grower Standard with 1214 bx ha⁻¹ (492 bx ac⁻¹), while the Rainfed treatment yielded the least at 1062 bx ha⁻¹ (430 bx ac⁻¹) (Figure 3.4, Table 3.2). However, no statistically significant yield differences were observed between treatments, including when the Rainfed treatment was omitted from the analysis. The Grower Standard also achieved the highest IWUE (2 bx ha⁻¹ mm⁻¹; 17.67 bx ac⁻¹ in⁻¹), whereas the NDVI-1 treatment recorded the lowest IWUE (0.33 bx ha⁻¹ mm⁻¹; 4 bx ac⁻¹ in⁻¹) (Figure 3.5, Table 3.2). Like with yield, there were no statistically significant differences in IWUE.

Autumn 2024: During the Autumn 2024 growing season, there were 13 days with precipitation totaling approximately 251 mm (10 in), which is nearly half of the precipitation received during the Spring 2024 growing season and is typical for early Autumn in southwestern Georgia, as October generally marks the driest month of the year. Most of the precipitation (162 mm; 6.4 in) occurred during Hurricane Helene, which impacted SIRP from 25 September to 27, placing it about midway through the growing season (Figure 3.6).

The NDVI-1 and NDVI-2 treatments resulted in the most irrigation, with seven events totaling 192 mm (7.6 in). However, the timing of the events varied slightly (Figure 3.6). The Grower Standard treatment resulted in ten irrigation events totaling 169 mm (6.7 in). The SMS treatment resulted in five irrigation events with a total of 154 mm (6.1 in), which was the least amount of irrigation applied in the Autumn 2024 season and was substantially less than all the other irrigated treatments (Table 3.2).

Yields for the Autumn 2024 season were generally lower due to a 16% reduction in the seeding rate. The SMS treatment resulted in the highest yield at 1186 bx ha⁻¹ (480 bx ac⁻¹). The NDVI-2 treatment followed with the second highest yield of 1102 bx ha⁻¹ (446 bx ac⁻¹). The Grower Standard resulted in a yield of 1059 bx ha⁻¹ (429 bx ac⁻¹). The Rainfed treatment yielded 636 bx ha⁻¹ (257 bx ac⁻¹), which was approximately half of the yields from most irrigated treatments, highlighting the need for irrigation in the Autumn growing season (Figure 3.7, Table 3.2).

During the Autumn 2024 season, the SMS treatment achieved the highest IWUE at 5.67 bx ha⁻¹ mm⁻¹ (59.67 bx ac⁻¹ in⁻¹) (Figure 3.8, Table 3.2). The Grower Standard and SWB NDVI-2 treatments resulted in the second-highest IWUE of 3.67 bx ha⁻¹ mm⁻¹ (37.7 bx ac⁻¹ in⁻¹). The NDVI-1 treatment had an IWUE of 2.87 bx ha⁻¹ mm⁻¹ (29.49 bx ac⁻¹ in⁻¹) (Figure 3.8, Table 3.2). As with yield, there were no statistically significant differences in IWUE during the Autumn 2024 season, including when Rainfed was removed from the analysis.

3.3.2. Ear Quality Parameters

Ear length, ear diameter, and no-tip fill results for the Spring 2024 and Autumn 2024 growing seasons are shown in Table 3.3. As with yields, there are no statistically significant differences between treatments at $\alpha = 0.05$ for either season. This is not surprising as these are the three ear quality parameters that determine yield. As described earlier, ears less than 15.2 cm (6 in) in length and ears having more than 38.1 mm (1.5 in) of poor/no-tip fill were deemed unmarketable.

Spring 2024 mean ear lengths were similar for all treatments, with a range of only 0.4 cm (0.16 in) between the irrigated treatments (Table 3.3) and were all above the 15.2 cm (6 in) quality standard. The NDVI-1 treatment resulted in the highest mean ear length of 18.7 cm (7.36 in), while the Rainfed treatment resulted in the lowest mean ear length of 17.7 cm (6.96 in) (Table 3.3).

Overall, Autumn 2024 mean ear lengths were 2-3 cm (0.79-1.18 in) shorter than those from Spring 2024 (Table 3.3) but were all above the 15.2 cm (6 in) quality standard. There was a larger range between irrigated treatments (1 cm; 0.39 in). The mean length of the irrigated treatments was 16.4 cm (6.46 in) compared to 18.5 cm (7.27 in) for Spring 2024. The Rainfed treatment mean ear lengths were slightly above the marketing standard (Table 3.3), which contributed to the lower yields of this treatment (Table 3.2). The Grower Standard treatment had the largest mean ear length (16.8 cm; 6.61 in).

Similar to ear length, the mean ear diameter was greater in Spring 2024 than in Autumn 2024. For the irrigated treatments, the mean diameter was 47.16 mm (1.86 in) in Spring 2024, while it measured 43.8 mm (1.72 in) in Autumn 2024. The SMS had the highest mean ear diameter, recording 47.77 mm (1.88 in) in Spring 2024, and the NDVI-1 treatment had the largest mean ear diameter of 44.54 mm (1.75 in) in Autumn 2024. The smallest mean diameter in Autumn 2024 was from the Rainfed treatment at 41.68 mm (1.64 in) (Table 3.3).

No-tip fill is a key quality metric, as ears with more than 38.1 mm (1.5 in) of no-tip fill are considered unmarketable by U.S. Fancy Grade standards. In Spring 2024, no-tip fill for the irrigated treatments ranged from 6.71 to 8.73 mm (0.26 to 0.34 in), while in Autumn 2024, it ranged from 14.33 to 17.49 mm (0.56 to 0.69 in). All treatment means met the quality standards, although the Rainfed treatment mean of 23.65 mm (0.93 in) was closer to the threshold, likely contributing to its lower yields. In Spring 2024, the Rainfed no-tip fill was 12.37 mm and increased to 23.65 mm in Autumn 2024, highlighting the impact of insufficient soil moisture during the growing season (Table 3.3).

3.4. Discussion

3.4.1. Seasonal Impacts on Scheduling, Yield, and Quality

The effectiveness of the NDVI-based Kc curves (NDVI-1 and NDVI-2) was evaluated during the Spring and Autumn 2024 growing seasons. In Spring 2024, there were no statistically significant differences in yield between the irrigated and rainfed treatments (Figure 3.4, Table 3.2). Similarly, there were no statistically significant differences between treatments when the Rainfed treatment was removed from the analysis. Two main factors likely explain this outcome. First, the growing season experienced 16 precipitation events resulting in 389 mm (15.3 in) of precipitation, which exceeds the expected seasonal water needs for sweet corn (Figure 3.3), and most of this precipitation occurred during the reproductive stages. While it is common for precipitation during the growing season to meet or exceed sweet corn's water requirements, it is unusual for precipitation to be evenly distributed throughout the entire season. This uneven distribution highlights the importance of irrigation for the sandy soils found in the southeastern Coastal Plain. The second possible reason for the lack of statistically significant differences in yield (Figure 3.4) could be attributed to the considerable variability seen among the replicate plots in specific treatments, especially for NDVI-1 and Rainfed. The cause of this variability is still unknown. Interestingly, excessive irrigation did not negatively affect the yields recorded in this study, as has been reported by for cotton and peanut in southwestern Georgia (Vellidis et al., 2022; Hayes et al., 2024; Porter et al., 2024).

In the Autumn 2024 season, the SMS treatment maintained a slightly drier soil profile during the vegetative growth stages (Figure 3.8), yet it led to the highest yield and IWUE. This suggests that sweet corn can tolerate drier soil during its early growth stages, similar to many agronomic crops. Notably, the SMS treatment used approximately 80% of the irrigation water applied to the

NDVI-2 treatment, resulting in a statistically greater IWUE (Table 3.2). This suggests that a RZSWD greater than 40% could be used in the SWB model during the reproductive stage. This also shows that increased irrigation in sweet corn does not necessarily result in higher yield or better quality (Table 3.2, Table 3.3). Overall, when combining precipitation and irrigation, the highest-yielding treatment for Autumn 2024 (SMS) received a total of 405 mm (16 in) of water, which exceeds the overall water requirements for sweet corn throughout its growing season (ranging from 203-356 mm; 8-14 in) (Westerfield and Eason, 2024).

Figure 3.8 illustrates line graphs depicting soil water tension (the absolute value of matric potential) for the NDVI-1, NDVI-2, SMS, and Rainfed treatments during the Autumn 2024 growing season. An upward trend in soil water tension signals a reduction in soil moisture. Following Hurricane Helene's passage on 29 September, the Rainfed treatment demonstrated an increase in soil water tension as the soil moisture levels decreased. Conversely, all irrigated treatments maintained a wetter soil profile, with the NDVI-1 and NDVI-2 consistently exhibiting wetter conditions than the SMS treatment.

Although no statistically significant differences were identified in ear quality parameters across irrigation scheduling treatments within the same growing seasons, some observable trends were noted. Treatments with reduced irrigation generally produced smaller ears. For instance, during the Spring 2024 season, the treatments that received the most irrigation resulted in ears with the highest mean ear length and ear diameter. This trend is also present in the Autumn 2024 season. Similarly, mean no-tip fill values tended to be greater in treatments that received less irrigation. Furthermore, seasonal variations were evident, as the Autumn 2024 season yielded smaller ear sizes and increased no-tip fill values, even with a lower seeding rate. This phenomenon was

attributed to the cooler temperatures experienced in Autumn, which prolonged the growth and development periods for plants and ears.

3.4.2. Further Improvements to the NDVI-Based Kc Curve

In all 12 fields for which NDVI values were calculated, peak Kc values were observed around effective canopy closure. This is a crucial phase for sweet corn growth as it indicates the beginning of the reproductive stages. At this point in the growing season, $NDVI \geq 0.75$ at around 1000 GDD. Post-canopy closure, NDVI values fluctuated within the 0.75 to 0.85 range until harvest, indicating that the index was saturated (Figure 3.2). Because sweet corn is harvested while at peak crop water use, NDVI saturation does not affect irrigation scheduling in this crop as it does for agronomic crops like cotton, where the Kc-NDVI relationship must be modified to take NDVI saturation into account (Hunsaker et al., 2003).

In this study, the field perimeter was used to crop satellite images, and the area within the field perimeter was used to calculate a mean NDVI value for the date of the image. Noise in the NDVI data (Figure 3.2) may have been reduced if small in-field anomalies (wet areas, limestone outcroppings, etc.) were cropped from the images. Nevertheless, the mean NDVI values for each field were successfully used to develop a Kc curve that compared well to a sweet corn Kc curve developed by Bedwell et al. (2025a) using a different methodology.

In their study, Bedwell et al. (2025a) developed an ETc-based Kc curve derived empirically from soil moisture data. Their ETc-based Kc curve closely matches the NDVI-based Kc curve, indicating that the NDVI-based method can likely be used to develop Kc curves for other crops if the relationship between Kc and NDVI is well understood for each crop. Developing NDVI-based Kc curves is more complicated for annual agronomic crops that exhibit senescence prior to harvest as NDVI does not decrease in parallel to crop water use, and multiple regression methods like the

one developed by Hunsaker et al. (2003) may be needed. For agronomic crops, other vegetation indices like the ratio vegetation index, which are more responsive to crop changes later in the growing season, may be better suited than NDVI to estimate K_c . While the NDVI-derived K_c curve developed in this study may not apply to all sweet corn varieties, Vellidis et al. (2022) found that K_c curves customized to a region tend to represent most cultivars developed for the region quite well.

The NDVI-2 model showed improved performance compared to the original NDVI-1 model in both yield, irrigation water applied, and IWUE during the Autumn 2024 season, but it still resulted in more irrigation than the SMS treatment. This was particularly the case as the crop approached the reproductive stages ($\sim 800 - 1100$ GDD) (Figure 3.3). To address this issue, further refinements to the K_c curve are needed.

While both maize and sweet corn canopies look similar as they are varieties of the same plant, the sweet corn canopy is less dense, and overall, the sweet corn plant contains less biomass at harvest than maize (Revilla et al., 2021). Modifying Eq. 3.4, as shown in Eq. 3.6 (changing the slope from 1.5 to 1.45) to account for the lower biomass may be a reasonable approach to improving the performance of the NDVI-derived K_c curve for sweet corn.

$$K_c = 1.45 \times NDVI \quad (3.6)$$

This modification can potentially reduce over-irrigation and better reflect the crop's actual water needs. Figure 3.9 shows the K_c values resulting from applying Eq. 3.6 to the 195 NDVI field values derived from the 12 grower fields. Also shown on the graph is a polynomial fitted to the revised data, the K_c curve used in the NDVI-2 model for comparison, and a new tetra-linear model (NDVI-3) matching the polynomial curve that will be incorporated into SI CropFit and evaluated with irrigation scheduling trials during the Spring 2025 growing season. The NDVI-3 model will

result in lower Kc values in the late pre-reproductive and during the reproductive stages, thus resulting in lower daily ETc values and fewer irrigation events.

The Kc curves developed in this study and those used for cotton, maize, peanut, and soybean in SI CropFit are generic for well-managed crops and do not consider the actual growth stage of the crop in individual fields. Using the generic Kc curve for fields in which the crop is not developing at the expected rate may result in over-irrigating. For example, the NDVI-derived Kc values for Field 3 (circled in Figure 3.2) between 250-600 GDD indicate a Kc value of approximately 0.4. In contrast, the revised Kc curve-derived value for 600 GDD is approximately 0.8, which would result in doubling the daily ETc estimate. The relationship shown in Eq. 3.6 offers the potential of using the Kc-NDVI relationship to customize Kc curves for individual fields by using near-real-time remotely sensed data to ground-truth the Kc curves for individual fields. Project team members are pursuing this approach with the goal of adding this type of functionality to SI CropFit in the future.

3.5. Conclusion

The NDVI-based methodology used in this study to develop a Kc curve for sweet corn appears to be a simpler but reliable approach to developing Kc curves when compared to traditional approaches of estimating daily ETc using soil moisture sensors or weighing lysimeters. With the availability of public domain and for-pay satellite platforms with ideal spatial and temporal resolution, collecting field-scale reflectance data for many fields throughout multiple growing seasons is no longer a limiting factor and can be done retroactively for past growing seasons. The NDVI-derived Kc curve that was incorporated into the SWB model resulted in high yields and good quality but applied more irrigation water than the sensor-based method and the Grower Standard treatment, indicating that further refinement is needed. It is

important to remember that the Grower Standard treatment was based on the irrigation scheduling abilities of an experienced grower who has extensive experience using soil moisture sensors for irrigation scheduling. This indicates that incorporating the NDVI-derived Kc curve into SI CropFit would likely provide useful irrigation scheduling to the many sweet corn growers in the southeastern U.S.

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3.7. References

- Abioye, E., Abidin, M., Mahmud, M., Buyamin, S., Ishakj, M., Rahman, M., Otuoze, A., Onotu, P., and Ramli, M. 2020. A Review on Monitoring and Advanced Control Strategies for Precision Irrigation. *J. Computers and Electronics in Agriculture*. 173:105441. <https://doi.org/10.1016/j.compag.2020.105441>.
- Ainsworth, E. Yendrek, C., Skoneczka, J., Long, P. 2012. Accelerating Yield Potential in Soybean: Potential Targets for Biotechnological Improvement: Targets to Improve Soybean Yields. *J. Plant, Cell & Environment*. 35(1), 38-52. <https://doi.org/10.1111/j.1365-3040.2011.02378.x>.
- Allen, R.G., Pereira, L.S., Raes, D., Smith, M. 1998. Crop evapotranspiration: Guidelines for computing crop water requirements. Irrigation and Drainage Paper No. 56. Food and Agricultural Organization, United Nations, Rome, Italy. https://edisciplinas.usp.br/pluginfile.php/3887570/mod_folder/content/0/Boletim_FAO56.pdf. Accessed August 2021.
- Allen, R.G., Pereira, L.S., Smith, M., Raes, D., Wright, J.L. 2005. FAO-56 dual crop coefficient method for estimating evaporation from soil and application extensions. *J. Irrigation and Drainage Engineering*. 131(1), 2-13. [https://ascelibrary.org/doi/abs/10.1061/\(ASCE\)0733-9437\(2005\)131:1\(2\)](https://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9437(2005)131:1(2)). Accessed August 2021.
- Barros-Rios, J., Romani, A., Garrote, G., Ordas, B. 2015. Biomass, sugar and bioethanol potential of sweet corn. *J. Global Change Biology Bioenergy*. 7(1), 153-160. <https://doi.org/10.1111/gcbb.12136>.
- Bausch, W., Neale, C. 1987. Crop coefficients derived from reflected canopy radiation: A concept. *Trans. American Society of Agricultural and Biological Engineering*. 30(3), 703-709. <https://doi.org/10.13031/2013.30463>.
- Bednarz, C.W., Ritchie, G., Hook, G.E., Yager, R., Cromer, S., Cook, D., Griner, I. 2002. Cotton crop water use and irrigation scheduling. Georgia Cotton Research-Extension Report. Univ. of Georgia, Athens, GA. 61-64. <http://ugacottonnews.org/vault/rer/2003/p72.pdf>. Accessed January 2022.
- Bedwell, E. da Silva, A., Hayes, B., McAvoy, T., Vargas, A., Yu, Z., Washington, B., Vellidis, G. 2025a. An irrigation scheduling model for sweet corn based on FAO-56. *J. Agricultural Water Management* (in preparation).
- Bedwell, E., McAvoy, T., da Silva, A., Hayes, B., McAvoy, T., Vargas, A., Yu, Z., Washington, B.J., Vellidis, G. 2025b. Evaluating the impact of irrigation scheduling on quality parameters of sweet corn. *J. Horticulture Technology*. (in preparation).
- Benli, B., Kodal, S., Ilbeyi, A., Ustun, H. 2006. Determination of evapotranspiration and basal crop coefficient of alfalfa with a weighing lysimeter. *J. Agricultural Water Management*. 81(3). 358-370. <https://doi.org/10.1016/j.agwat.2005.05.003>.
- Bongiovanni, R., Lowenberg-Deboer, J. 2004. Precision Agriculture and Sustainability. *J. Precision Agriculture*. 5(4), 359–87. <https://doi.org/10.1023/B:PRAG.0000040806.39604.aa>.
- Braunworth, W., Mack, H. 1987. Evaluation of Irrigation Scheduling Methods for Sweet Corn. *J. American Society of Horticultural Science*. 112(1), 29-32. <https://pdfs.semanticscholar.org/6f05/d22d1910c71268dc90bbb1aa9c1b5d50a0a0.pdf>. Accessed January 2022.

- Broner, I. 2005. Irrigation Scheduling: Fact Sheet No. 4708. Colorado State University Extension, Crop Series 2. <https://extension.colostate.edu/docs/pubs/crops/04708.pdf>. Accessed 3 November 2021.
- Datta, D., Chandra, S., Nath, C., Kar, G., Ghosh, S., Chaturvedi, S., Bhatnagar, A., Singh, G., Singh, V. 2022. Soil-plant water dynamics, yield, quality and profitability of spring sweet corn under variable irrigation scheduling, crop establishment and moisture conservation practices. *J. Field Crops Research*. 279. <https://doi.org/10.1016/j.fcr.2022.108450>.
- Dhaliwal, D., Williams, M., II. 2023. An Outlook on Processing Sweet Corn Production from the Last Three Decades (1990s–2010s). *J. Horticultural Science*. 58(7), 792-796. <https://doi.org/10.21273/HORTSCI17109-23>.
- Ertek, A., Kara, B. 2013. Yield and Quality of Sweet Corn under Deficit Irrigation. *Agricultural J. Water Management*. 129, 138–144. <https://doi.org/10.1016/j.agwat.2013.07.012>.
- Food and Agriculture Organization (FAO). 2017. The Future of Food and Agriculture- Trends And Challenges. Annual Report, 296. Rome.
- Gallios, I. 2023. Decision support tools for irrigation scheduling in peanut. University of Georgia. <https://esploro.libs.uga.edu/esploro/outputs/graduate/DECISION-SUPPORT-TOOLS-FOR-IRRIGATION-SCHEDULING/9949575227602959#file-0>
- García, I., Lecina, S., Ruiz-Sánchez, M., Vera, J., Conejero, W., Conesa, M., Domínguez, A., Pardo, J., Lélis, B., Montesinos, P. 2020. Trends and Challenges in Irrigation Scheduling in the Semi-Arid Area of Spain. *J. Water*. 12(3), 785. <https://doi.org/10.3390/w12030785>.
- Garcia y Garcia, A., Guerra, L., Hoogenboom, G. 2009. Water use and water use efficiency of sweet corn under different weather conditions and soil moisture regimes. *J. Agricultural Water Management*. 96(10), 1369-1376. <https://doi.org/10.1016/j.agwat.2009.04.022>.
- Gilmore, E., Rogers, J. 1958. Heat Units as a Method of Measuring Maturity in Corn. *Agronomy Journal*. 50(10), 611–615. <https://doi.org/10.2134/agronj1958.00021962005000100014x>.
- Hassanli, A., Ebrahimizadeh, M., Beecham, S. 2009. The Effects of Irrigation Methods with Effluent and Irrigation Scheduling on Water Use Efficiency and Corn Yields in an Arid Region. *J. Agricultural Water Management*. 96(1), 93–99. <https://doi.org/10.1016/j.agwat.2008.07.004>.
- Hayes, M., Porter, W., Snider, J., Reagin, K., Perry, C. 2024. Cotton Irrigation Scheduling: Which Approach is the Best Fit for Georgia? *J. Cotton Science*, 28, 136-144. <https://doi.org/10.3146/0095-3679-51-PS1607>.
- Howell, T. Irrigation Scheduling Research and Its Impact on Water Use. 1996. Evapotranspiration and Irrigation Scheduling, Proceedings of the International Conference, Nov. 3-6, 1996, San Antonio, TX, American Society of Agricultural Engineers, St. Joseph, MI. <https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=4216fcee2583f303cdf8cdf342c825a2c2fd7b1>.
- Hunsaker, D. Pinter Jr., P., Barnes, E., Kimball, B. 2003. Estimating cotton evapotranspiration crop coefficients with a multispectral vegetation index. *J. Irrigation Science*. 22:95-104. <https://doi.org/10.1007/s00271-003-0074-6>.
- Jha, K., Doshi, A., Patel, P., Shah, A. 2019. A Comprehensive Review on Automation in Agriculture Using Artificial Intelligence. *J. Artificial Intelligence in Agriculture*. 2:1-12. <https://doi.org/10.1016/j.aiia.2019.05.004>.
- Jones, H. 2004. Irrigation Scheduling: Advantages and Pitfalls of Plant-Based Methods. *J. Experimental Botany*. 55(407), 2427–2436. <https://doi.org/10.1093/jxb/erh213>.

- Kara, B. 2011. Fresh ear yield and growing degree days of sweet corn in different sowing dates in southwestern Anatolia region. *Turkish Journal of Field Crops*. 16(2), 166-171. <https://dergipark.org.tr/en/download/article-file/158720>.
- Lass, L., Callihan, R., Everson, D. 1993. Forecasting the Harvest Date and Yield of Sweet Corn by Complex Regression Models. *J. American Society for Horticultural Science*. 118(4), 450–455. https://www.researchgate.net/profile/Robert-Callihan/publication/265917092_Forecasting_the_Harvest_Date_and_Yield_of_Sweet_Corn_by_Complex_Regression_Models/links/54ff26510cf2eaf210b68484/Forecasting-the-Harvest-Date-and-Yield-of-Sweet-Corn-by-Complex-Regression-Models.pdf.
- Liakos, V., Porter, W., Liang, X., Tucker, M. A., McLendon, A., Vellidis, G. 2017. Dynamic variable rate irrigation tool for greatly improving water use efficiency. *J. Advances in Animal Biosciences*. 8(2), 557-563. <https://doi.org/10.1017/S2040470017000711>.
- Liu, C., Zhang, X., Zhang, Y. 2002. Determination of daily evaporation and evapotranspiration of winter wheat and maize by large-scale weighing lysimeter and micro-lysimeter. *J. Agricultural and Forest Meteorology*. 111(2), 109-120. [https://doi.org/10.1016/S0168-1923\(02\)00015-1](https://doi.org/10.1016/S0168-1923(02)00015-1).
- McAvoy, T., Coolong, T. 2023. Shipper Sweet Corn in Southern Georgia. University of Georgia Cooperative Extension Service. Bulletin 1549. <https://extension.uga.edu/publications/detail.html?number=B1549>. Accessed 5 January 2025.
- McMaster, G. Wilhelm, W. 1997. Growing degree-days: one equation, two interpretations. *J. Agricultural and Forest Meteorology*. 87(4), 391-300. [https://doi.org/10.1016/S0168-1923\(97\)00027-0](https://doi.org/10.1016/S0168-1923(97)00027-0).
- Myneni, R., Hall, F., Sellers, P., Marshak, A. 1995. The Interpretation of Spectral Vegetation Indexes. *IEEE Transactions on Geoscience and Remote Sensing*. 33(2), 481–86. <https://doi.org/10.1109/TGRS.1995.8746029>.
- Ozores-Hampton, S., Olson, S., Webb, S., Smith, S., Raid, R., McAvoy, E. 2012. Vegetable Production Handbook, Chapter 21 Sweet Corn Production in Florida. University of Florida IFAS Extension. 283-296. https://www.researchgate.net/profile/Monica-Ozores-Hampton/publication/265184286_Chapter_21_Sweet_Corn_Production_in_Florida/links/56fa9ec308ae8239f6dad110/Chapter-21-Sweet-Corn-Production-in-Florida.pdf.
- Paranhos, J., Foshee, W., Coolong, T., Hayes, B., Salazar-Gutierrez, M., Keshimer, K., Silva, A. 2023. Characterization of Sweet Corn Production in Subtropical Environmental Conditions. *J. Agriculture*. 13(6), 1156. <https://doi.org/10.3390/agriculture13061156>.
- Pettorelli, N., Vik, J., Myrsterud, A., Gaillard, J., Tucker, C., and Stenseth, N. 2005. Using the Satellite-Derived NDVI to Assess Ecological Responses to Environmental Change. *J. Trends in Ecology & Evolution*. 20(9), 503–510. <https://doi.org/10.1016/j.tree.2005.05.011>.
- Porter, W., Tostenson, M., Reagin, K., Tubbs, R., Smith, A. 2024. Evaluation of Soil Water Tension Trigger Levels for Optimizing Peanut (*Arachis hypogaea*) Yield and Water Use Efficiency. *J. Peanut Science*, 51(1), 100-1005. <https://doi.org/10.3146/0095-3679-51-PS1607>.
- Rao, N., Sarma, P., Chander, S. 1988. Irrigation Scheduling under a Limited Water Supply. *J. Agricultural Water Management*. 15(2), 165–75. [https://doi.org/10.1016/0378-3774\(88\)90109-6](https://doi.org/10.1016/0378-3774(88)90109-6).
- Revilla, P., Anibas, C. M., Tracy, W. F. 2021. Sweet Corn Research around the World 2015–2020. *J. Agronomy*. 11(3), 534. <https://doi.org/10.3390/agronomy11030534>.

- Savitha, M., UmaMaheswari, O. 2018. Smart Crop Field Irrigation in IoT Architecture Using Sensors. J. Advanced Research in Computer Science. 9(1), 302-306. <https://doi.org/10.26483/ijarcs.v9i1.5348>.
- Singh, R., Liu, S., Tieszen, L., Suyker, A., Verma, S. 2012. Estimating Seasonal Evapotranspiration from Temporal Satellite Images. J. Irrigation Science. 30(4), 303-13. <https://doi.org/10.1007/s00271-011-0287-z>.
- Steele, D., Stegman, E., Gregor, E. 1994. Field comparison of irrigation scheduling methods for corn. American Society of Agricultural Engineers. Transactions of the ASAE. 37(4), 1197-1203. <https://doi.org/10.13031/2013.28194>.
- Stone, K., Bauer, P., Sigua, G. 2016. Irrigation management using an expert system, soil water potentials, and vegetative indices for spatial applications. Transactions of the ASABE. 59(3), 941-948. <https://doi.org/10.13031/trans.59.11550>.
- Sui, R. 2017. Irrigation Scheduling Using Soil Moisture Sensors. J. Agricultural Science. 10(1), 1. <https://doi.org/10.5539/jas.v10n1p1>.
- Talaviya, T., Shah, D., Patel, D., Yagnik, H., Shah, M. 2020. Implementation of Artificial Intelligence in Agriculture for Optimization of Irrigation and Application of Pesticides and Herbicides. Artificial Intelligence in Agriculture, 4:58–73. <https://doi.org/10.1016/j.aiia.2020.04.002>.
- Umair, S., Usman, R. 2010. Automation of Irrigation System Using ANN Based Controller. International J. Electrical & Computer Sciences. 10(2), 45-51. https://www.researchgate.net/profile/Usman-Rauf-2/publication/261191835_Automation_of_Irrigation_System_Using_ANN_based_Controller/links/55882b9d08aead25f0ed05c5/Automation-of-Irrigation-System-Using-ANN-based-Controller.pdf.
- United States Department of Agriculture (USDA). 2024. Sweet Corn Grades and Standards. <https://www.ams.usda.gov/grades-standards/sweet-corn-grades-and-standards>. Accessed 20 August 2024.
- Vellidis, G., Tucker, M., Perry, C., Kevin, C., Bednarz, C. 2008. A real-time wireless smart sensor array for scheduling irrigation. J. Emerging Technologies for Real-Time and Integrated Agriculture Decisions. 61(1), 44-50. <https://doi.org/10.1016/j.compag.2007.05.009>
- Vellidis, G., Liakos, V., Andreis, J., Perry, C., Porter, W., Barnes, E., Morgan, K., Fraisse, C., Migliaccio, K. 2016. Development and Assessment of a Smartphone Application for Irrigation Scheduling in Cotton. J. Computers and Electronics in Agriculture. 127, 249–259. <https://doi.org/10.1016/j.compag.2016.06.021>.
- Vellidis, G. 2022. BMPs & precision ag tools in GA: reducing inputs while maintaining yields [Informational flyer].
- Viswanatha, G., Ramachandrappa, B., Nanjappa, H. 2002. Soil plant Water Status and Yield of Sweet Corn (*Zea Mays L. Cv. Saccharata*) as Influenced by Drip Irrigation and Planting Methods. J. Agricultural Water Management. 55(2), 85-91. [https://doi.org/10.1016/S0378-3774\(01\)00189-5](https://doi.org/10.1016/S0378-3774(01)00189-5).
- Wang, D., Cai, X. 2009. Irrigation Scheduling—Role of Weather Forecasting and Farmers' Behavior. J. Water Resources Planning and Management. 135(5), 364–372. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2009\)135:5\(364\)](https://doi.org/10.1061/(ASCE)0733-9496(2009)135:5(364)).
- Westerfield, R., Eason, N. 2024. Growing Home Garden Sweet Corn. University of Georgia Cooperative Extension Service.

<https://woodstock.recdesk.com/RecDeskPortal/Portals/770/Sweet%20Corn.PDF>. Accessed 27 December 2024.

Wu, G., Miller, N., De Leon, N., Kaeppler, S., Spalding, E. Predicting *Zea Mays* Flowering Time, Yield, and Kernel Dimensions by Analyzing Aerial Images. 2019. J. Frontiers in Plant Science. 10:1251. <https://doi.org/10.3389/fpls.2019.01251>.

Yang, J., Li, B., Shiping, L. 2000. A large weighing lysimeter for evapotranspiration and soil-water-groundwater exchange studies. J. Hydrological Processes. 14(10), 1887-1897. [https://doi.org/10.1002/1099-1085\(200007\)14:10<1887::AID-HYP69>3.0.CO;2-B](https://doi.org/10.1002/1099-1085(200007)14:10<1887::AID-HYP69>3.0.CO;2-B).

3.8. Tables and Figures

Table 3.1. Weighting factors used for sensor depths. Factors were based on growing degree days (GDDs) which were indicative of rooting depth.

Root Depth Weighting			
GDD	UGA SSA		
	15 cm	31 cm	46 cm
0-300	80%	20%	0%
301-800	50%	30%	20%
801-1000	50%	25%	25%
1001-Harvest	40%	30%	30%

Table 3.2. Yield, irrigation amounts, and irrigation water use efficiency (IWUE) of Spring 2024 and Autumn 2024 treatments. There was no statistical significance at $\alpha = 0.05$.

Treatment	Yield ² (bx ha ⁻¹)		Irrigation Applied ⁵ (mm)		IWUE ⁴ (bx ha ⁻¹ mm ⁻¹)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	1214	1059	127	169	2.00	3.67
SWB NDVI-1	1113	1016	162	192	0.33	2.87
SWB NDVI-2 ¹	-	1102	-	192	-	3.67
SMS	1164	1186	124	154	1.33	5.67
Rainfed	1062	636	37 ³	59 ³	-	-

¹SWB NDVI-2 was evaluated only in Autumn 2024.

²Spring 2024 and Autumn 2024 seeding rates were 12,550 and 10,526 ha⁻¹, respectively.

³ Indicates irrigation applied to promote emergence (Spring: one event; Autumn: two events), activate herbicide (Spring: 0, due to precipitation; Autumn: one event), and fertigate (Spring: six events; Autumn: six events).

⁴Does not include irrigation related to emergence, herbicide activation, or fertigation.

⁵Includes amounts related to treatment irrigation, emergence, herbicide activation, and fertigation.

Table 3.3. Mean length, diameter, and no-tip fill of Spring and Autumn 2024 growing seasons. There was no statistical significance at $\alpha = 0.05$ during either the Spring or Autumn 2024 growing season.

Treatment	Ear Length (cm)		Ear Diameter (mm)		No-Tip Fill (mm)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	18.4	16.8	46.80	43.69	8.73	14.33
NDVI-1	18.7	16.7	46.90	44.54	7.19	15.05
NDVI-2 ¹	-	16.3	-	43.66	-	17.49
SMS	18.3	15.8	47.77	43.31	6.71	16.41
Rainfed	17.7	15.4	46.90	41.68	12.37	23.65

¹SWB NDVI-2 was evaluated only in Autumn 2024.

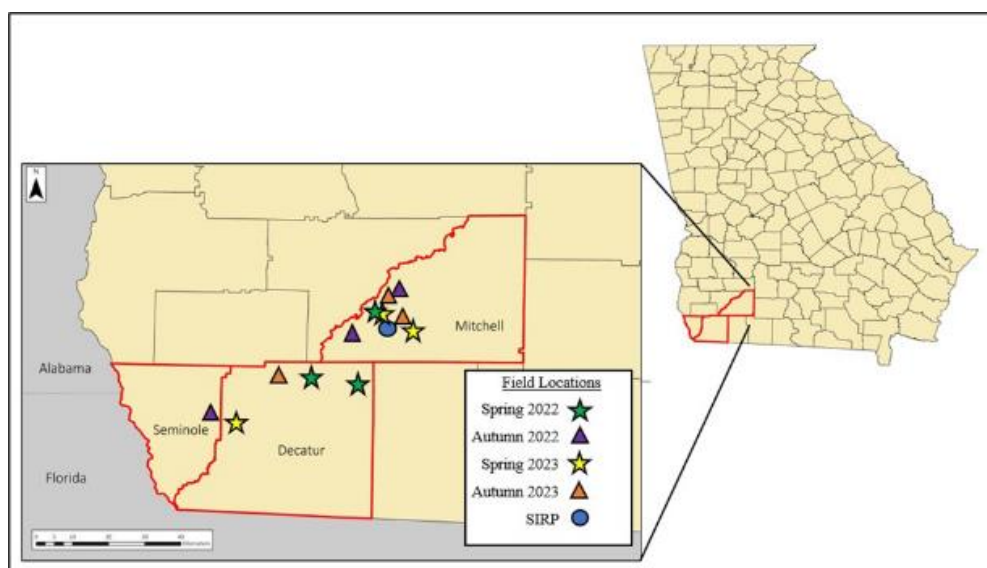


Figure 3.1. Map indicating approximate locations of 12 grower managed sweet corn fields and University of Georgia's Stripling Irrigation Research Park (SIRR).

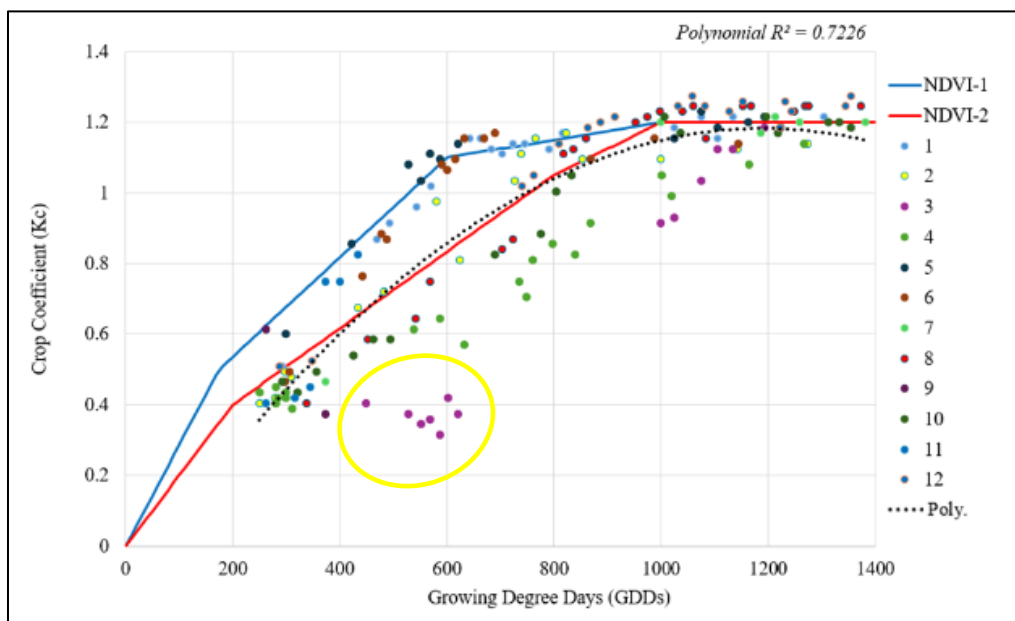


Figure 3.2. Line chart and scatter plot indicating original (blue line) and revised (red line) crop coefficient (Kc) curve derived from PlanetScope sourced NDVI values from 12 individual grower-managed sweet corn fields in southwestern Georgia, U.S. (location-specific daily NDVI indicated by points of various colors and shapes). The yellow oval indicates Kc values for Field 3 which are much lower than those of other fields.

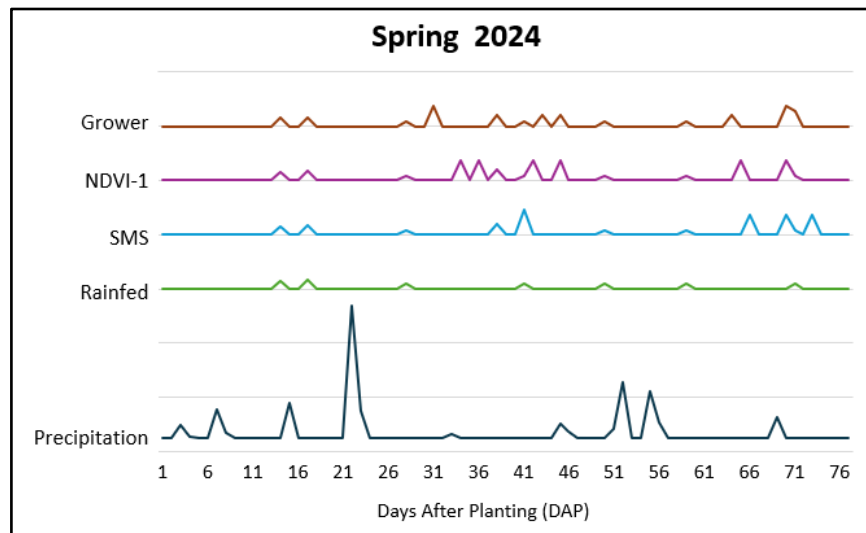


Figure 3.3. Combined line charts indicating frequency and magnitude of Spring 2024 irrigation events for each treatment and precipitation event. There were 16 days with precipitation events totaling 441 mm (17 in).

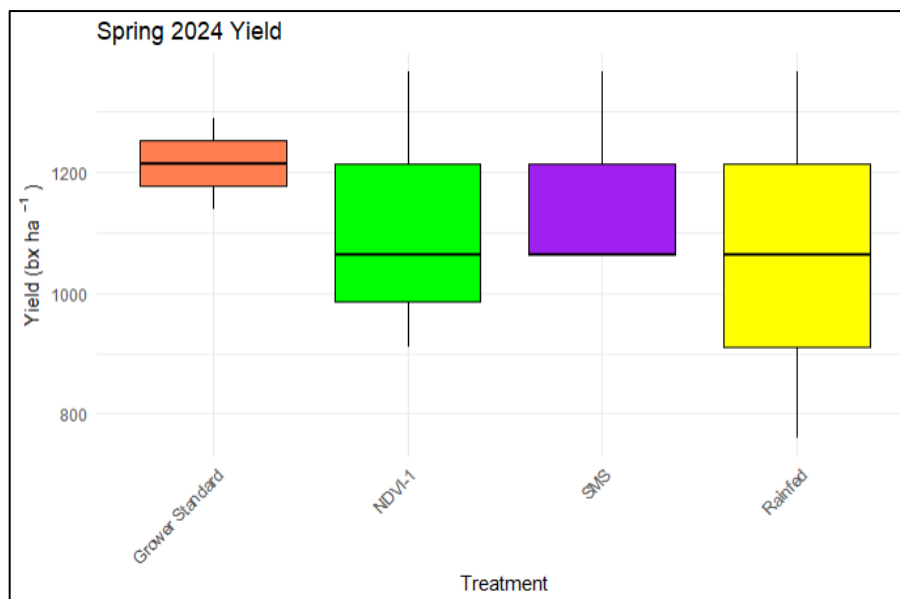


Figure 3.4. Box and whisker plot of Spring 2024 yield per treatment (in bx ha^{-1}) (no statistical significance between treatments at $\alpha = 0.05$).

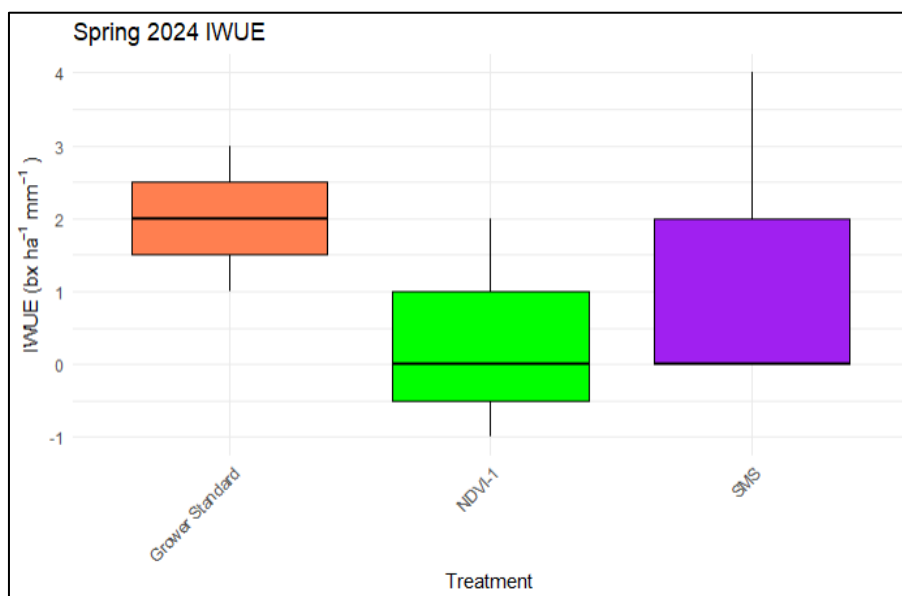


Figure 3.5. Box and whisker plot of Spring 2024 irrigation water use efficiency (IWUE) per irrigated treatment (in bx ha⁻¹ mm⁻¹) (no statistical significance between treatments at $\alpha = 0.05$).

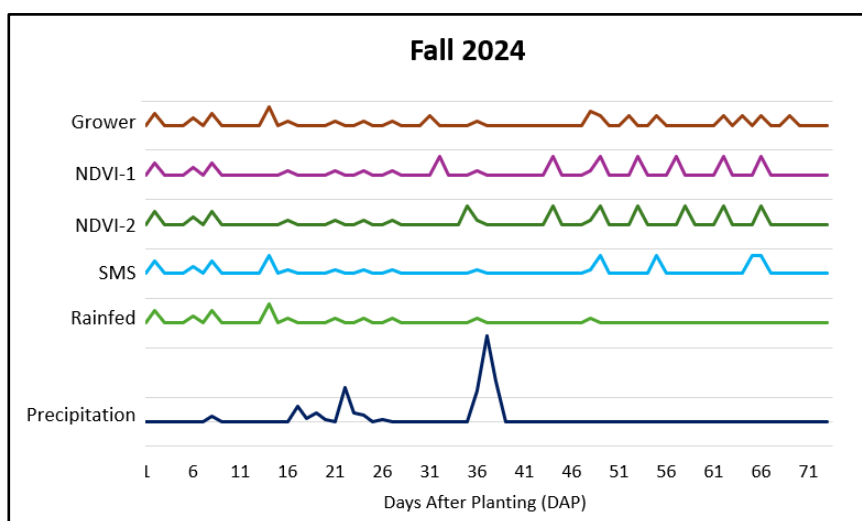


Figure 3.6. Combined line charts indicating frequency and magnitude of Autumn 2024 irrigation events for each treatment and precipitation event. There were 13 days with precipitation events totaling 251 mm (10 in). Most of the precipitation (162 mm; 6.4 in) was received between 35-37 DAP and was associated with Hurricane Helene.

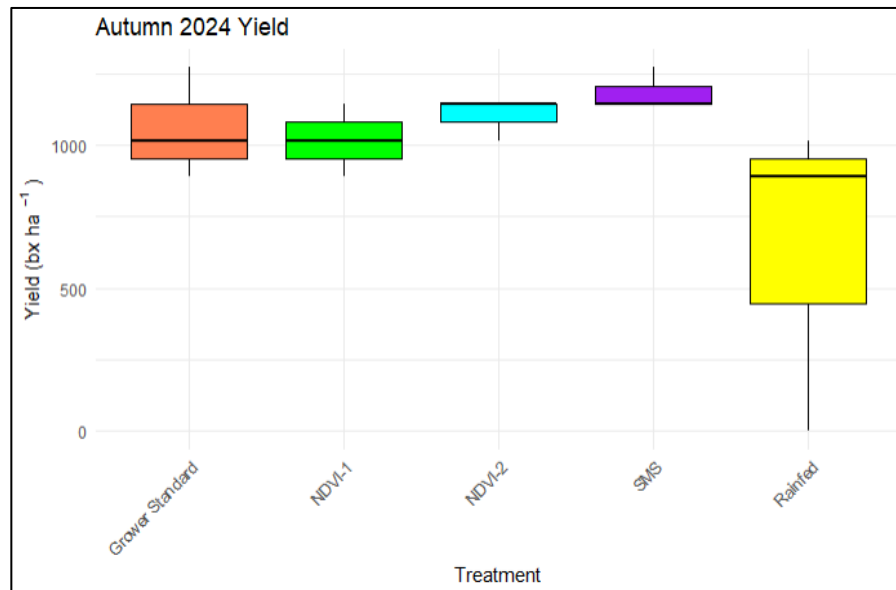


Figure 3.7. Box and whisker plot of Autumn 2024 yield per treatment (in bx ha⁻¹) (no statistical significance between treatments at $\alpha = 0.05$).

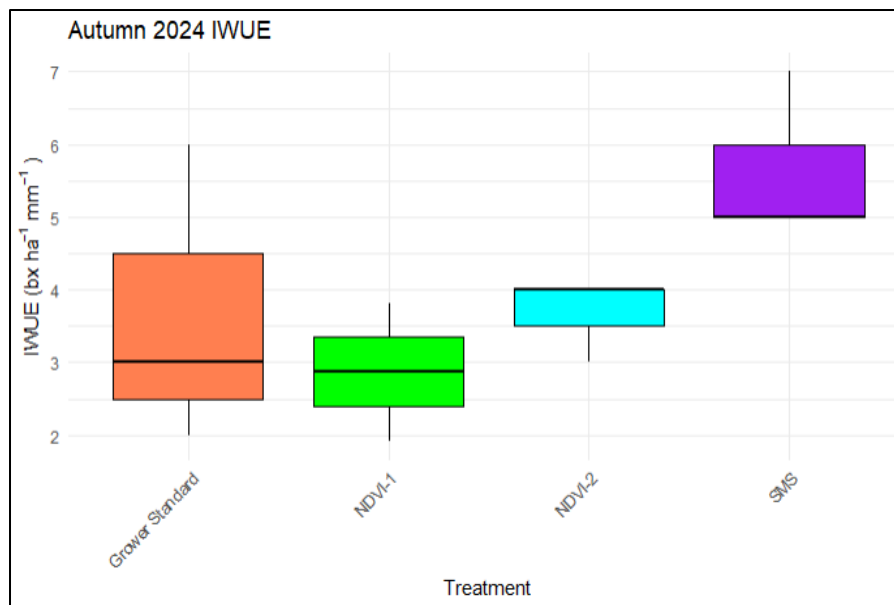


Figure 3.8. Box and whisker plot of Autumn 2024 irrigation water use efficiency (IWUE) per irrigated treatment (in bx ha⁻¹ mm⁻¹) (no statistical significance between treatments at $\alpha = 0.05$).

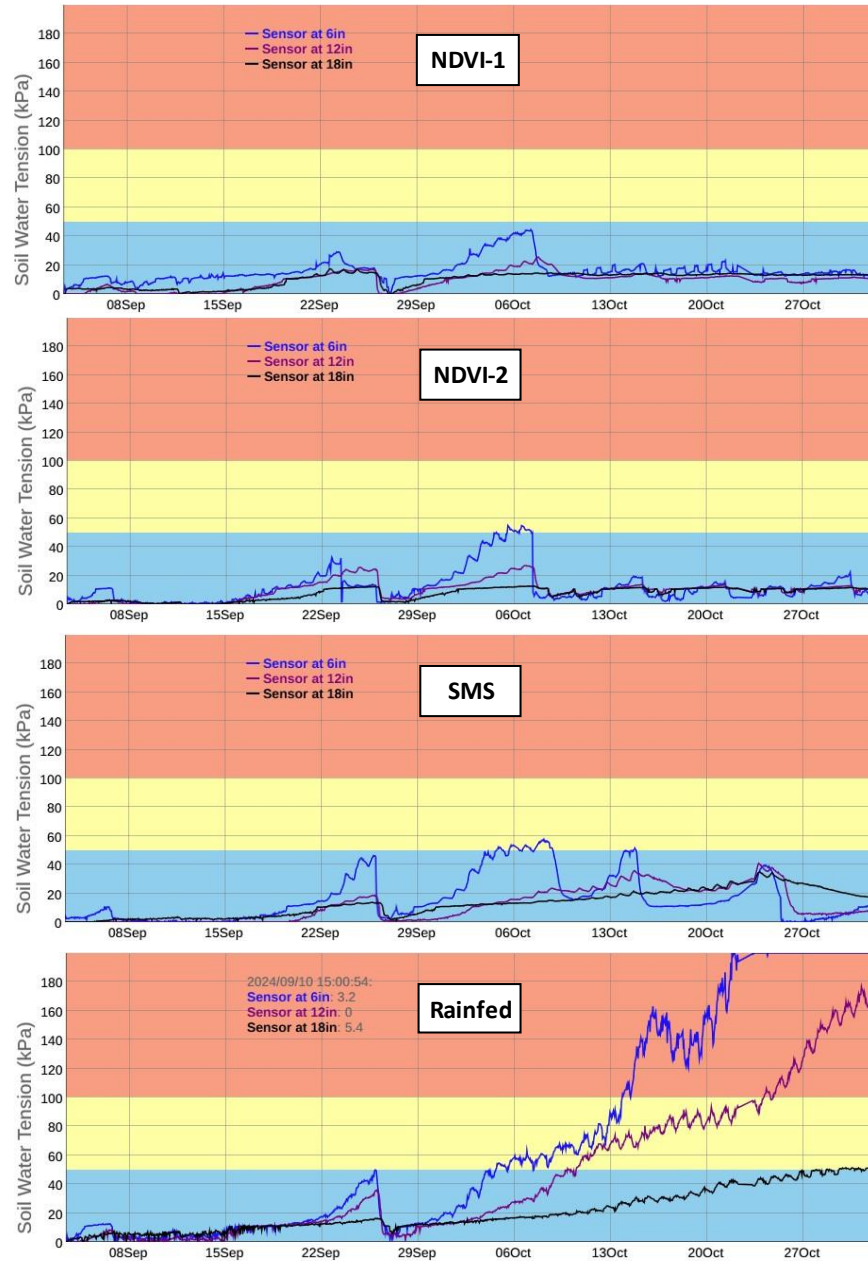


Figure 3.9. Line graphs of soil water tension (the absolute value of matric potential) for four treatments from the Autumn 2024 growing season. The maximum soil water tension recorded by the Watermark sensors used in the UGA SSA probes is 200 kPa. Each curve on the graph indicates soil water tension at the depth shown in the legend. The sensors were centered at depths of 15.2 cm (6 in), 30.5 cm (12 in), and 45.7 cm (18 in).

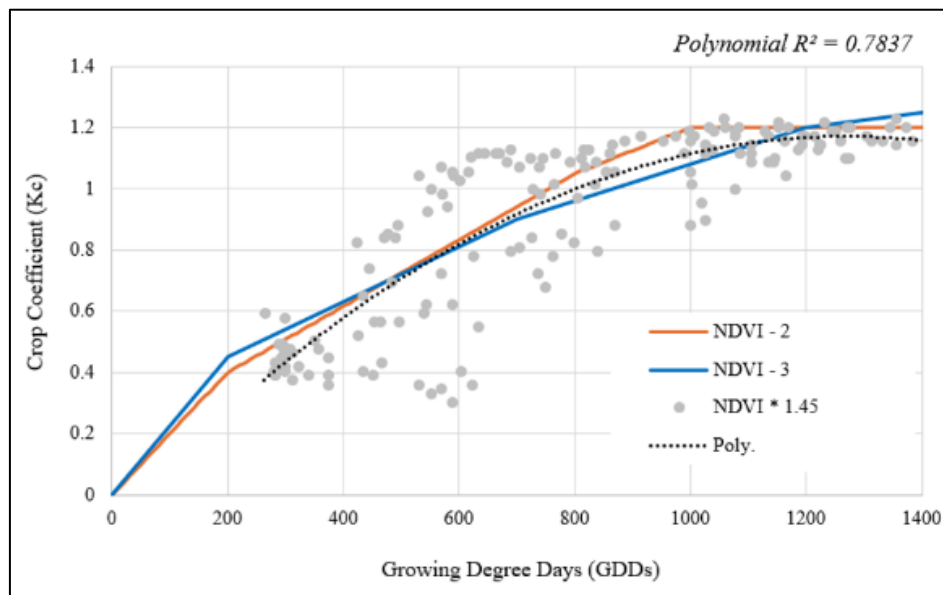


Figure 3.10. Line chart of NDVI-2 (Autumn 2024) Kc model and the proposed modified model (NDVI-3 Spring 2025) based on Eq. 3.6.

³CHAPTER 4

IRRIGATION SCHEDULING EFFECTS ON SWEET CORN PHYSICAL ATTRIBUTES AND FRESH MARKET QUALITY³

³Bedwell, E., McAvoy, T., Hayes, B., Vargas, A., Yu, Z., Washington, B.J., Vellidis, G. To be submitted to the *Journal of Horticulture Technology*.

4. Abstract

The United States (U.S.) is the leading producer of fresh market sweet corn (*Zea mays* subsp. *Mayes* L.), with Georgia being a top contributor, harvesting over 9,000 ha (23,000 ac) annually with an economic value exceeding USD 106 million in 2023. Failure to meet sweet corn water requirements can adversely affect quality and marketability. To mitigate the risk of yield and quality losses, growers often over-irrigate this valuable crop. However, excessive irrigation can cause problems such as deteriorating soil health, declining water tables, nutrient runoff, and inefficient water use. Therefore, assessing optimal irrigation management practices for sweet corn is vital for improving sustainability and water use efficiency while maintaining crop quality.

This study aimed to evaluate how different soil moisture regimes affected the physical qualities related to the marketability of U.S. Fancy Grade sweet corn through replicated plot trials conducted in southwestern Georgia during two growing seasons (Spring and Autumn 2024). There were no statistically significant differences in yield between irrigation treatments within either season. However, yields were notably lower in Autumn than Spring, primarily due to reduced planting density and cooler temperatures during the Autumn. The least irrigated treatment during Autumn 2024 produced the highest yield, indicating that sweet corn can tolerate drier soils during the vegetative stages. Increased irrigation was associated with larger ear sizes and lower no-tip fill, while a slight increase in no-tip fill was observed as irrigation approached 250 mm (9.8 in). Rainfed treatments resulted in ears with the largest no-tip fill. Treatments with increased irrigation produced taller plants with a lower harvest index (HI), whereas those with less irrigation resulted in shorter plants with a higher HI. Seasonal differences were present, with higher ear weight, ear length, ear diameter, plant height, and ear set height values in Spring than Autumn. No-tip fill values were significantly lower in Spring than Autumn.

An ear quality index (EQI) was developed to quantify quality parameters. Spring ears met or exceeded market standards, receiving “above average” to “excellent” EQI ratings. Autumn ears met market standards but trended lower than Spring ratings, receiving “average” or slightly “below average” EQI ratings. The Rainfed treatment received the lowest EQI ratings during both seasons, underscoring the importance of supplemental irrigation for sweet corn quality. These insights highlight the critical role of irrigation management in fresh market quality across varying seasonal conditions.

Keywords: smart irrigation; quality index; irrigation scheduling; soil moisture; U.S. Fancy Grade.

4.1. Introduction

4.1.1. Sweet Corn in Georgia, U.S.

Sweet corn (*Zea mays* subsp. *mays* L.) is one of the most widely grown and consumed crops globally, with the United States (U.S.) ranking first in worldwide production. The state of Georgia plays a significant role in this global contribution by ranking third in national sweet corn production. In 2023, the state's sweet corn production was valued at over USD 106 million and spanned over 9,000 ha (23,000 ac) (McAvoy and Coolong, 2023). The U.S. Department of Agriculture (USDA) has specific quality guidelines for fresh market sweet corn, highlighting the importance of effective management. Quality is often closely tied to sufficient water supply, as water is vital to sweet corn growth and development (Hassanli et al., 2009). By adopting optimal irrigation practices, growers can substantially boost sweet corn market quality and overall yields while also improving water use efficiency (Viswandatha, 2002; Braunworth and Mack, 1987; Hassanli et al., 2009; Ertek and Kara, 2013; Datta et al., 2022).

4.1.2. U.S. Fancy Grade Sweet Corn Quality Standards

Sweet corn grown within the U.S. is targeted for three markets: fresh, canning, and freezing. The fresh market accounts for over 30% of the national production and contributes to more than 65% of the economic production value (Lizaso et al., 2007; USDA-NASS, 2023). Because sweet corn produced for the fresh market is harvested at near maximum moisture and soluble sugar content, it is highly susceptible to perishability (Becerra-Sanchez and Taylor, 2021; Bayer, 2025). As a result, the U.S. established quality standards for fresh market sweet corn that also include factors associated with appearance and size. U.S. Fancy Grade is the premium grade for sweet corn and brings the highest market price (USDA, 1992).

The basic requirements of U.S. Fancy Grade sweet corn are that ears must have similar varietal characteristics, be well trimmed, and be well developed. "Similar varietal characteristics" refers to ears that have similar kernel color and character of growth, i.e., varieties of sweet corn having white kernels shall not bear characteristics of varieties that have yellow kernels. Well-trimmed describes ears that have intact husks and a shank no more than 15.2 cm (6 in), and well-developed can be defined as ears that are "fairly straight and not stunted" with no more than 38.1 mm (1.5 in) of poor-/no-tip fill (USDA, 1992). Similarly, ears must be free from smut (*Mycosarcoma maydis*), corn earworm (*Helicoverpa zea*), insect, bird and mechanical injury, decay, rust, and disease. U.S. Fancy Grade ears are also required to have kernels that are "plump and milky" and that are well covered with fresh husks. Lastly, ears shall not be clipped or be less than 15.2 cm (6 in) in length (USDA, 1992). When sweet corn faces water stress, specifically during reproductive stages, ear quality can be negatively affected (Ertek and Kara, 2013).

4.1.3. Sweet Corn Growth and Development

4.1.3.1. Accumulated Heat Units

The phenological stage of a crop is a crucial factor that affects its water requirements. Accumulated heat units, commonly known as growing degree days (GDD), are vital for determining these developmental stages. GDDs forecast the timing of a plant's biological processes, which can improve the prediction of phenological events. This, in turn, helps enhance the efficiency of irrigation management (McMaster and Wilhelm, 1997). GDDs are calculated using the following equation:

$$GDD = \left[\frac{T_{max} + T_{min}}{2} \right] - T_{base} \quad (4.1)$$

where,

T_{max} is the maximum daily temperature,

T_{min} is the minimum daily temperature, and

T_{base} is the base temperature of the crop.

The base temperature, or the minimum temperature necessary for sweet corn to grow effectively, is 10°C (50°F) (Gilmore and Rodgers, 1958; Lass et al., 1993; Kara, 2011). However, when temperatures rise above 30°C (86°F), it adversely affects growth, causing a decline in yields by 0.5% every day above this threshold (Dhaliwal and Williams II, 2022). Phenological predictions based on GDDs tend to be more accurate than those that rely only on days after planting (DAP), as the temperatures during the growing season significantly affect how quickly a crop moves through its developmental stages (Vellidis et al., 2016).

4.1.3.2. Germination and Emergence

Sweet corn's growth begins with the germination stage. For seeds to germinate, they need adequate soil moisture and temperatures between 10°C to 35°C (50°F and 95°F). If temperatures drop below 10°C (50°F), it can cause chilling injury, which damages plant cells and aborts root growth. This results in poor germination or stunted growth. Germination typically occurs within 7 to 10 days after planting, depending on environmental conditions, particularly temperature and soil moisture. After germination, sweet corn emerges, and seedlings start to develop their root and shoot systems. Irrigation and pest and disease management are crucial during this stage to ensure healthy growth (McAvoy and Coolong, 2023; McAvoy et al., 2025).

4.1.3.3. Vegetative Stages

During the vegetative stages, sweet corn primarily focuses on leaf development. At this time, the plant grows rapidly, producing one to two new leaves each week, depending on environmental factors such as temperature. This vigorous growth necessitates adequate soil fertility and effective weed control to minimize competition for nutrients and sunlight. Proper irrigation is also crucial

to support this accelerated growth and development throughout the vegetative stages (McAvoy et al., 2025).

4.1.3.4. Tasseling, Silking, and Pollination

Tasseling is a crucial phase in the development of sweet corn, as it marks the transition from vegetative to reproductive growth. During this stage, sweet corn plants produce tassels containing pollen. Wind disperses these pollen grains from tassels onto the silks emerging from the ears, which results in pollination. As sweet corn is primarily wind-pollinated, successful, and efficient pollination relies on adequate spacing between plants and uniform planting. Environmental factors such as temperature and humidity also significantly affect pollination success. Temperatures exceeding 35°C (95°F) terminate pollen grains and desiccate silks, which can lead to poor pollination and yield loss. Irrigation is most critical during the reproductive stages, as this is when sweet corn water needs are the greatest and when the crop is most sensitive to water stress (McAvoy et al., 2025).

4.1.3.5. Ear Development

After successful pollination, the fertilized silks turn brown, indicating that pollination has been successful, and that embryo (kernel) development is occurring. The kernels then begin to swell and fill out the ears. Providing optimal irrigation during this period is crucial, as under-irrigation can cause poor tip fill, resulting in yield losses, while over-irrigation may lead to split kernels when temperatures exceed 35°C (95°F), which may result in disease or fungus (McAvoy and Coolong, 2023). Ear development is also a growth stage in which sweet corn is highly susceptible to water stress (McAvoy et al., 2025).

4.1.3.6. Maturation and Harvest

As sweet corn reaches maturity, kernels undergo physiological changes, transitioning from milky and full of moisture to doughy and firm. Sweet corn is typically harvested when the kernels are in the milk stage, also known as R3, which is characterized by a milky white liquid that can be squeezed from the kernels. If the ears are not harvested promptly during R3, the sugars in the kernels will begin to convert to starch, lowering the sweetness and tenderness of the kernels. Therefore, harvesting sweet corn during the ideal window (approximately three days) is critical to ensure optimal flavor and sweetness (Szymanek, 2009; McAvoy and Coolong, 2023; McAvoy et al., 2005). In contrast, if ears are harvested prior to R3, underripe ears will have small, underdeveloped kernels, negatively impacting quality (McAvoy and Coolong, 2023; McAvoy et al., 2025). Additionally, harvesting should occur during the cooler early morning hours to help preserve the corn's sweetness and mitigate excessive moisture loss (McAvoy et al., 2025).

4.1.4. Sweet Corn Water Needs

As mentioned previously, sweet corn's response to water stress varies depending on its growth stage (Rao, 1988). Thus, accurately determining the phenological stage of this crop is essential for efficient irrigation management, as its water requirements shift notably from the early and mid-growth to the reproductive stages. The maturity of sweet corn varieties commonly grown in the southeastern U.S. can range from 60 to 100 days, depending on the growing season (Spring versus Autumn) and geographical area (Allen et al., 1998), with water requirements differing by region and potentially increasing by as much as 70% during peak growth periods (Ozorez-Hampton et al., 2012).

In the southeastern U.S., the sweet corn varieties typically require between 203 and 356 mm (8-14 in) of water during the growing season, depending on the specific variety (Westerfield and

Eason, 2024). Although the annual rainfall in this region averages between 1200-1500 mm (47-60 in), the unpredictability of precipitation timing and amounts, along with sandy soils with low water holding capacity, contributes to significant variability in yields from rainfed crops (Kwabiah, 2004). To mitigate this risk of high yield variability in the southeastern U.S., many growers utilize irrigation systems to alleviate crop water stress, particularly for crops that are increasingly sensitive to water stress as the season progresses (Bednarz et al., 2002; Stone et al., 2016; Sui, 2017).

4.1.5. *Irrigation Scheduling*

Irrigation scheduling improves water use efficiency by maintaining plant available soil water within an optimal range and avoiding over-and/or under-irrigation (Jones, 2004; Howell, 1996). Plant available soil water is defined as the water held by the soil matrix between field capacity (the point at which water no longer moves through the soil due to gravity) and the wilting point (the point at which the plants can no longer effectively extract water from the soil). In irrigation scheduling, the amount of water that must be applied to return the soil profile to field capacity is frequently described as the root zone soil water deficit (RZSWD). A 50% RZSWD or depletion of 50% of plant available soil water is a commonly accepted irrigation threshold for agronomic crops (Vellidis et al., 2016). In sandy soils, the RZSWD deficit can increase rapidly as the plant available soil water is limited. Because sweet corn is more sensitive to water stress than most agronomic crops, many sweet corn growers choose to maintain the soil profile near field capacity, which requires frequent irrigation in areas like the southeastern Coastal Plain, which has sandy soils.

4.1.6. *Objectives*

The goal of this study was to evaluate how different soil moisture regimes affect the physical qualities related to the marketability of U.S. Fancy Grade sweet corn. The goal was achieved by

conducting replicated field trials with the specific objectives of assessing the effect of various irrigation methods on 1) the fresh market quality of sweet corn ears and 2) the physical characteristics of sweet corn.

4.2. Materials and Methods

The project was conducted in conjunction with a larger study to develop evapotranspiration (ET) -based irrigation scheduling models for sweet corn described in detail by Bedwell et al. (2025a). Within this study, seven irrigation scheduling treatments that maintained the soil profile at different moisture levels were evaluated. The general comparisons were to 1) maintain the soil profile at near field capacity (less than 30% RZSWD) throughout the growing season and 2) maintain the soil profile at between 30% and 50% RZSWD soil water prior to the reproductive stage (tasseling) and near field capacity from tasseling to harvest.

The study was conducted at the University of Georgia's (UGA) Stripling Irrigation Research Park (SIRP) in Camilla, Georgia, U.S., on a four-ha research field called the Newton Lateral Field (31°16'46.24" N, 84°17'59.59" W) at SIRP. The field was divided into three blocks – North, Middle, and South—each containing 27 plots. Each plot measured 14.5 m × 14.5 m (48 ft × 48 ft), with the central eight rows used for data collection while the outer rows serve as buffers (Figure 4.1). The soil type in this field is categorized as Lucy Loamy Sand, with an available water holding capacity of 2 mm mm⁻¹ (0.08 in in⁻¹) and a slope ranging from 0 to 5%. The North block was used for this study. The soil texture of the North block is 86% sand, 8% silt, and 6% clay. The study was conducted over the spring and autumn growing seasons of the 2024 calendar year.

The Bayer Crop Science Obsession hybrid bicolor cultivar was planted at a density of 12,550 seeds ha⁻¹ (31,000 seeds ac⁻¹) on 30 March and harvested on 3 June during the Spring 2024 season. The Autumn 2024 crop was planted at 10,526 seeds ha⁻¹ (26,000 seeds ac⁻¹) on 21 August and

harvested on 31 October. These planting densities reflect typical practices for sweet corn production in southwestern Georgia and are adjusted seasonally to maximize yields and ear size while minimizing defects related to variations in daylight (McAvoy and Coolong, 2023). The Obsession cultivar was chosen for its popularity in commercial production within this region of the U.S. The seed had a germination rating of 95%, as indicated on the label. The actual estimates were 11,943 seeds ha⁻¹ (29,500 seeds ac⁻¹) in Spring 2024 and 10,000 ha⁻¹ (24,700 seeds ac⁻¹) in Autumn 2024.

4.2.1. Irrigation Treatments

For the Spring and Autumn 2024 seasons, the study used a randomized complete block design with seven treatments and three replicates of each treatment, totaling 21 plots (Figure 4.1). The remaining plots were cultivated but not included in this study. The treatments included six irrigation scheduling treatments and a rainfed treatment.

UGA Smart Sensor Array (UGA SSA) soil moisture sensor probes (Liakos et al., 2017; Vellidis et al., 2008) were installed in each plot shortly after emergence. Each UGA SSA probe consisted of three Irrometer Watermark sensors (The Irrometer Company—Riverside, California, U.S.) that measure soil moisture in terms of matric potential and report values in kilopascals (kPa). The sensors were centered at depths of 15 cm (6 in), 30 cm (12 in), and 45 cm (18 in). Data were transmitted to a cloud server at hourly intervals. The UGA SSA probes were used to provide a continuous measure of soil moisture in all treatments and were also used for irrigation scheduling in some of the plots.

Sentek Drill and Drop 60 cm (24 in) soil moisture probes (Sentek Sensor Technologies, Stepney SA, Australia) were installed in nine plots (three treatments). The probes measured soil moisture as VWC and soil temperature at depths of 10, 20, 30, 40, 50, and 60 cm (4, 8, 12, 16, 20,

and 24 in). The probes were connected to AgSense data loggers (AgSense Solutions, South Dakota, U.S.) that transmitted data to a cloud server at 30-minute intervals. The probes were installed in two treatments in which irrigation was scheduled using VWC thresholds and the Rainfed treatment.

During irrigation scheduling, sensor data from both the UGA SSA and Sentek probes were weighted by depth based on GDD to indicate root water uptake at various depths (Table 4.1). For example, from 0-300 GDD, the data from the Watermark sensor at 15 cm (6 in) in a UGA SSA probe was assigned a weight of 0.8 (80%), data from the sensor at 30 cm (12 in) assigned a weight of 0.2 (20%), and data from the sensor at 45 cm (18 in) a weight of 0.

Irrigation scheduling treatments were selected based on existing literature and the authors' experiences with similar studies on other crops, including several years of maize research. The seven treatments used during the Spring 2024 growing season are described below and included a Grower Standard. The Grower Standard treatment followed the irrigation scheduling practices of one of the top sweet corn producers in Georgia, which has a history of using soil moisture sensors for irrigation scheduling and consistently produces high yields. However, soil moisture sensors were not installed in the grower's field during this study. In essence, the Grower Standard treatment was the benchmark against which the other irrigation treatments were compared. All other management practices, including fertilization, were applied uniformly across all treatments. Table 4.2 presents the management practices used during each growing season. Most fertilizer was applied with in-season fertigation events.

1. Grower Standard – Irrigation timing and amounts mimicked a commercial grower's field located within 2 km (1.2 mi) of SIRP. This field was planted on the same date as the plots,

using the same sweet corn variety. The amount of water applied at each irrigation event ranged from 8-19 mm (0.3-0.75 in) and was determined by the grower.

2. VWC Wet – Daily VWC was measured at 7:00 AM by averaging the sensor readings from each depth across the three replicates. These average values were then used to calculate a weighted average by depth, using the values presented in Table 4.1. If the weighted average approached or fell below a VWC of 14.8%, the treatment was irrigated with 19 mm (0.75 in) of water. For the soils of the field site, a VWC of 14.8% was expected to maintain the soil profile between 30% RZSWD and field capacity.
3. VWC Dry/Wet – Daily VWC at 7:00 AM was calculated as described above, but irrigation was triggered at 14% VWC prior to the reproductive stage (tasseling) and at 14.4% from the reproductive stage until harvest. This treatment was also irrigated with 19 mm (0.75 in). For the soils of the field site, a VWC of 14% was expected to maintain the soil profile above 30% RZSWD. The 14.4% VWC threshold was selected to maintain the soil profile below RZSWD of 30% but slightly drier than field capacity.
4. MP Wet – Daily matric potential was calculated at 7:00 AM, as described above. When the weighted average approached or exceeded a matric potential of -30 kPa, the treatment was irrigated with 19 mm (0.75 in). For the soils of the field site, a matric potential of -30 kPa was expected to maintain the soil profile between 30% RZSWD and field capacity.
5. MP Dry/Wet – For this treatment, matric potential was calculated as described earlier. Irrigation was triggered at -40 kPa before tasseling and at -30 kPa from tasseling until harvest. This treatment received 19 mm (0.75 in) of irrigation. For the soils of the field site, a matric potential of -40 kPa was expected to maintain the soil profile above 30% RZSWD.

The -30 kPa threshold was selected to maintain the soil profile below RZSWD of 30% but slightly drier than field capacity.

6. SWB – In this treatment, an ET-based soil water balance (SWB) model that operated in spreadsheet mode was used for irrigation scheduling. At the time of planting, the soil profile was set to 0% RZSWD (field capacity). Daily crop evapotranspiration (ET_c) was estimated using the method developed by Bedwell et al. (2025a) and was subtracted from the previous day's RZSWD to calculate the current RZSWD. Precipitation and irrigation inputs were added to the soil water balance. If the daily RZSWD approached or exceeded 30%, irrigation was applied. This treatment was irrigated with 19 mm (0.75 in).
7. Rainfed – In this treatment, irrigation was used only for management, i.e., to promote emergence, activate herbicides, and for fertigation. These amounts applied are described in more detail immediately below.

During the Spring 2024 season, management events included one 8 mm (0.3 in) irrigation event to promote emergence, five 4 mm (0.17 in) fertigation events, and one 9 mm (0.34 in) fertigation event) that were applied to all treatments and totaled approximately 37 mm (1.5 in). On Friday, 26 April 2024, a 10 mm (0.4 in) irrigation event was applied to all irrigated treatments to avoid crop water stress over a hot, dry weekend.

During the Autumn 2024 season, management events included six 4 mm (0.17 in) fertigation events, 8 mm (0.3 in) and 13 mm (0.5 in) irrigation events to promote emergence, and one 13 mm (0.5 in) event for herbicide activation, totaling approximately 59 mm (2.32 in).

The total irrigation amount reported for each treatment includes irrigation used to promote emergence, activate herbicides, and fertigate. However, the number of irrigation events reported

for each treatment is indicative only of treatment irrigation and does not include those related to promoting emergence, activating herbicides, or fertigation.

Because scheduling with the SWB ET model during Spring 2024 resulted in more frequent irrigation than anticipated during the first half of the growing season, the SWB model was revised to reduce the number of irrigation events as described by Bedwell et al. (2025). The updated SWB model (SWB Updated) replaced the SWB treatment during the Autumn 2024 season. The other six treatments remained the same.

4.2.2. *Phenology, Harvest, and Data Collection*

To increase the data available for quantifying phenology, prior to the study reported here, sweet corn phenology was monitored weekly in 12 growers' fields over four growing seasons (two Spring and two autumn seasons in 2022 and 2023). Phenology was also monitored weekly in each of the 21 plots during the Spring 2024 and Autumn 2024 growing seasons. Phenology was determined by assessing the current phenological stage of ten plants in the field or plot. To determine the vegetative stage, true leaves with collars were counted. When the plants began to tassel, this indicated that the crop was preparing to enter its reproductive phase. Following tasseling, silks begin to emerge from the developing ear at leaf nodes, indicating the R1 (silking) stage. As the silks were pollinated by the pollen grains, the silks turned brown (R2/blister stage). Lastly, the kernels continued to fill with moisture until they reached R3 (milk stage). These data from 14 fields over six growing seasons in three years (2022-2024) were correlated with the accumulated GDDs on the observation dates and were used to establish the relationship between phenological stage development and estimated GDDs for sweet corn in southwestern Georgia (Table 4.3).

Harvest in the grower fields was managed entirely by the growers, and field average yield was reported to the authors. For the plot studies, a USDA-certified fresh market sweet corn grader determined the crop's optimal harvest date and the grading of the harvested ears. The plot harvest was designed to closely resemble commercial sweet corn harvesting practices. In commercial harvesting, the upper ear (the largest ear on the plant) is the one that is harvested by hand. Therefore, for the ear data collection in this study, the upper ears of ten consecutive plants in the middle row of each plot (the fourth row) were harvested by hand. Plot harvest took place in the morning to ensure cooler temperatures, and ears were kept in an air-conditioned space until measured to mitigate moisture loss. Ten consecutive plants from the fifth row of each plot were cut at the soil surface and used for whole plant measurements.

Ears were classified as marketable or unmarketable based on the USDA's U.S. Fancy Grade sweet corn market standards (USDA, 2024). Ears that were less than 15.2 cm (6 in) in total length had more than 38.1 mm (1.5 in) of poor or no tip fill or displayed any signs of smut, mechanical damage, or insect or bird damage were deemed unmarketable. The standard metric for sweet corn yield is boxes per unit area harvested (bx ha^{-1} ; bx ac^{-1}), as this is how fresh market sweet corn is harvested and sold. In the southeastern U.S., standard boxes measure 28 cm $\times$ 28 cm (11 in $\times$ 11 in) and contain 48 ears of marketable sweet corn. An ear is considered "marketable" if it complies with the U.S. Fancy Grade standards (McAvoy and Coolong, 2023; USDA, 2024). Yield was calculated based on the grade of the harvested ears. For instance, if six out of ten ears were marketable, the treatment grade would be 60%. To calculate yield, the treatment grade was multiplied by the observed germination rate. This method follows the common assumption among sweet corn growers that each plant produces at least one marketable ear (McAvoy and Coolong, 2023). Only marketable ears were included in yield calculations.

Plant height was measured from the point at which the plant was cut to the tassel tip. Ear set height was measured from the point at which the plant was cut to the base of the lowest ear. Total ear length was measured from the top of the shank, or base of the ear, to the tip of the ear (out of husk). Shank length was measured from the end of the shank to the base of the ear. Flag length was measured from the longest flag on the ear (Figure 4.2). Ear diameter (out of husk) and no-tip fill were measured immediately after harvest to the nearest 0.01 mm using a caliper. Ear and plant weights were also measured directly after harvest with a scale with an accuracy of 0.01 kg. Kernel count was calculated following harvest by multiplying the number of rows per ear by kernels per row. Wet harvest index (HI) was calculated immediately following harvest (to maintain moisture) using Eq. 4.2.

$$HI = \frac{\text{ear weight (kg)}}{\text{total plant weight (kg)}} \quad (4.2)$$

During the fresh weight measurement process, all samples were kept at 20°C (68°F) to prevent excessive moisture loss from the kernels. Following the fresh weight measurements, the ears and plants were dried in an oven at 70°C (158°F) until their weight stabilized, indicating that all moisture had been removed from the samples. Dry HI was calculated in the lab using dry weights and Eq. 4.2.

4.2.3. Ear Quality Index

In addition to individual quality metrics, sweet corn ear quality was evaluated using an ear quality index (EQI) that was based on three critical parameters that are key to marketability: ear length, no-tip fill, and ear diameter. These parameters are indicative of marketability due to specific U.S. Fancy Grade standards (ear length and no-tip fill) as well as whether the ears will fit in the boxes at harvest (ear length and ear diameter) (USDA, 2024; McAvoy and Coolong, 2023). Each parameter was rated on a scale from 1 to 5, where 5 represented “excellent” quality, 4

indicated “above average” quality, 3 signified “average” quality, 2 denoted “below average” quality, and 1 was considered “unacceptable” (Table 4.4). These ratings were assigned according to how well the harvested ears met established U.S. Fancy Grade standards. EQI, as shown in Eq. 4.3, was developed, and used to quantify the overall ear quality of each treatment,

$$EQI = (0.33 \times EL_r) + (0.33 \times NTF_r) + (0.33 \times ED_r) \quad (4.3)$$

where,

EL_r is the mean ear length rating per treatment,

NTF_r is the mean no-tip fill rating per treatment, and

ED_r is the mean ear diameter rating per treatment.

EQI was calculated by first assigning a rating (1-5) for each of the three critical parameters to the ears harvested from each plot based on visual inspection and measurement and then averaging the ratings to derive a final quality score (EQI) for the plot. The EQI provided a comprehensive assessment of sweet corn ear quality, with higher values indicating superior quality and lower values reflecting poorer quality. The EQI allowed for an overall quality comparison across treatments.

4.2.4. Statistical Analyses

An analysis of variance (ANOVA) was conducted on the parameters described above via R Studio (version 2024.04.2 + 764) (Boston, Massachusetts, U.S.) to evaluate the impact of irrigation treatment on ear quality and physical attributes. The ANOVA was performed using Type III sum of squares, and residual diagnostics were performed to ensure that the assumptions of the ANOVA were met.

Following the ANOVA, a Tukey posthoc test was applied to assess pairwise differences between treatment groups. The results from the posthoc analysis were then visualized using a

compact letter display, which indicated statistically significant differences at $\alpha = 0.05$ between the irrigation treatments if any were present. This comprehensive statistical approach provided insights into how irrigation treatments influenced fresh market quality and physical sweet corn parameters.

4.3. Results and Discussion

4.3.1. Irrigation and Yield

Table 4.5 presents yield, irrigation amounts, and number of irrigation events per treatment. During the Spring 2024 season, the SWB and VWC Wet treatments, which also resulted in the highest amount of irrigation, resulted in the highest yields (Figure 4.3). The MP Dry/Wet treatment had the lowest yield of the irrigated treatments. The Grower Standard treatment resulted in the second highest yield (1214 bx ha^{-1}) while irrigating 42% less than the SWB treatment, making it comparable to the other irrigated treatments. There were no statistically significant differences in yield across treatments during the Spring 2024 season (Table 4.5; Figure 4.3), including the Rainfed treatment. There also were no statistically significant differences in yield when Rainfed yields were omitted from the analysis. Two main factors likely contributed to this. Firstly, 389 mm (15.3 in) of precipitation was received during the growing season, which is more than the estimated seasonal sweet corn water requirements. Moreover, most of this precipitation occurred during the reproductive stage when crop water needs were the highest. While it is common for growing season precipitation to meet or exceed sweet corn water demands in southwestern Georgia, evenly distributed precipitation is rare. This typical uneven distribution of precipitation highlights the need for irrigation in the region's sandy soils. Secondly, the lack of statistically significant differences in treatment yields can be attributed to the high variability observed among replicate

plots in specific treatments, particularly VWC Dry/Wet and MP Dry/Wet (Figure 4.3). The reason for this variability remains uncertain.

In Autumn 2024, although there were larger numerical differences between mean treatment yields than in Spring 2024 (1186 vs. 636 bx ha⁻¹; 480 vs. 257 bx ac⁻¹), these differences were not statistically significant (Table 4.5; Figure 4.4), even when Rainfed was excluded from the analysis. This was likely due to the high variability within the replicates of the treatments. In contrast, there was considerably less variation in the irrigated treatments in Autumn 2024 compared to Spring 2024, mainly because most water was applied through irrigation events that were timed similarly across treatments.

The MP Dry/Wet treatment resulted in the highest yield during the Autumn 2024 season despite applying the least amount of irrigation throughout the season (Table 4.5; Figure 4.4). The SWB Updated treatment resulted in the second-highest yield despite irrigating approximately 23% less than the treatment that received the highest amount of irrigation (VWC Dry/Wet). This suggests that sweet corn, similar to many agronomic crops, can withstand drier soil conditions, especially during the vegetative stages. Conversely, the MP Wet treatment resulted in the lowest yield during the Autumn 2024 season (Table 4.5; Figure 4.4). These yield differences are likely due to the uneven distribution of irrigation events.

The yield from the Grower Standard in Autumn 2024 was within the range of the highest-yielding irrigated treatments during the Autumn 2024 season, as it resulted in the third highest yield (Table 4.5; Figure 4.4). However, the amount of irrigation applied to the Grower Standard treatment at each irrigation event varied between 8 mm (0.3 in) and 19 mm (0.75 in) based on the grower's assessment of crop needs, while the amount applied for all the other treatments was fixed at 19 mm (0.75 in), with the exception of when irrigation was applied to promote emergence or

activate herbicide and fertilizer. This discrepancy between the amount applied for the Grower Standard treatment and the other treatments explains why the total irrigation amounts applied by most irrigated treatments were larger than the Grower Standard, even though the number of events was similar (Table 4.5).

Autumn 2024 yields were significantly lower than those in Spring 2024 (Figure 4.5). For instance, the Grower Standard treatment resulted in a seasonal yield difference of -13% when comparing Spring yields to Autumn yields. This is partially due to the 16% lower planting density in the Autumn season. Despite the lower planting density, ears in the Autumn 2024 season resulted in significantly lower mean ear length and mean ear diameter values with significantly higher mean no-tip fill values. These differences likely contributed to the lower yields in the Autumn season, as well. These differences are discussed in more detail further below.

4.3.2. Ear Weight, Length, Diameter, and No-Tip Fill

Table 4.6 and Figures 4.6, 4.7, and 4.8 show the results of the ear quality attributes (mean ear weight, ear length, ear diameter, and no-tip fill) of all treatments. As with yield, there were no statistically significant differences in ear quality parameters between the irrigation scheduling treatments within each growing season. As described earlier, this is likely the result of high variability of replicates within some treatments as shown by the box and whisker plots (Figures 4.6-4.8) and more clearly with the graphs showing trends in quality metrics (Figures 4.9-4.11). Nevertheless, some interesting trends were observed that merit discussion and further investigation with future studies.

During the Spring 2024 season, treatments that received between 125 mm and 150 mm (4-6 in) of irrigation mostly resulted in larger ear length and ear diameter values (Figures 4.9 and 4.10). Interestingly, ears from one Rainfed plot were both long and had large diameters (Figures 4.9 and

4.10), but a large portion of the ears was not filled (Figure 4.11). More irrigation generally resulted in smaller no-tip fill values (Figure 4.11). Again, likely because of the increased precipitation during the Spring growing season, even the Rainfed treatment resulted in ears with mean values that met the U.S. Fancy Grade standards (Table 4.6). The Grower Standard treatment resulted in ear weight, length, diameter, and no-tip fill that were in the range of all irrigated treatments during the Spring 2024 season.

During the Autumn 2024 season, interesting trends were observed, as well. Although the Rainfed treatment resulted in a substantially drier soil profile as the season progressed when compared to the irrigated treatments (Figure 4.12), Rainfed mean ear length and mean diameter values were comparable to those of the irrigated treatments (Table 4.6; Figures 4.13 and 4.14). Conversely, Rainfed no-tip fill values were affected by the drier soil, resulting in higher mean no-tip fill values than irrigated treatments (Table 4.6; Figure 4.15). There was a slight upward trend in ear length and diameter as irrigation increased (Figures 4.16 and 4.17). While no-tip fill tended to decrease with increased irrigation, there was a slight upward trend in no-tip fill values as irrigation amounts approached 250 mm (9.8 in) (Figure 4.18). This indicates that the treatments that irrigated between 150 mm and 200 mm (6 in and 8 in) (MP Dry/Wet, SWB Updated, and Grower Standard) maintained optimal soil moisture levels, especially during late reproductive stages, as this is the key time for kernel fill. This also supports the fact that these three treatments resulted in the highest yields in the Autumn 2024 season. The Grower Standard treatment resulted in the highest mean ear weight, ear length, ear diameter, and the lowest no-tip fill values of all the treatments during the Autumn 2024 season (Table 4.6) demonstrating the smaller, more regular irrigation events may be more effective than the larger events used by the other scheduling treatments.

When comparing the Spring and Autumn 2024 growing seasons, there are also some trends related to quality parameters. For instance, during the Spring 2024 season, mean ear weight (Figure 4.19) values were significantly higher than those in the Autumn 2024 season. Similarly, mean ear length (Figure 4.20) values trended lower in the Autumn 2024 season than the Spring 2024 season, and mean no-tip fill values (Figure 4.21) trended lower in the Spring 2024 season than the Autumn 2024 season. The Grower Standard treatment resulted in a 25% decrease in ear weight, a 9% decrease in ear length, a 7% decrease in ear diameter, and a 61% increase in no-tip fill from the Spring 2024 season to Autumn 2024, likely due to cooler temperatures (Table 4.6). This difference further supports the difference in yield of all treatments between seasons.

4.3.3. Flag Length, Shank Length, and Kernel Count

Table 4.7 shows the mean kernel count per ear, flag length, and shank length per treatment. The statistically significant differences observed in flag length during the Spring 2024 season may relate to soil moisture levels. The treatments that had the highest cumulative irrigation applied resulted in the highest mean flag lengths, whereas treatments that received less irrigation and allowed the soil profile to dry exhibited the lowest mean flag length (Table 4.7). While flag length does not technically impact U.S. Fancy Grade market standards, it remains an important attribute, as buyers tend to prefer ears with longer flags, often associating them with a healthier, more appealing product. Similarly, while shank length is not directly measured when determining marketability, little variation in shank length is ideal because if shanks are excessively long or short, it can affect whether the ears will fit in a harvest box and, therefore, whether they are marketable. When comparing the Spring and Autumn 2024 season results, mean flag and shank length values were higher during the Spring 2024 season (Figures 4.22 and 4.23). While there were no significant differences between treatments for kernel count, it is interesting to note that kernel

counts were approximately 16-23% lower in the Autumn 2024 season than in the Spring 2024 season, corresponding to smaller ears. The Grower Standard treatment resulted in mean kernel count, flag length, and shank length that were within the range of all irrigated treatments during both the Spring and Autumn 2024 seasons.

4.3.4. *Plant Parameters and Harvest Index*

Table 4.8 depicts mean plant height, ear set height, and wet and dry HI values. During the Spring 2024 season, statistically significant differences were observed in two plant attributes: mean plant height and wet HI (Table 4.8; Figures 4.24 and 4.25). Treatments that resulted in higher cumulative irrigation generally produced taller plants and resulted in a lower wet HI. In contrast, treatments with less irrigation led to shorter plants that had a higher wet HI. Additionally, there were notable differences in plant attributes between the two seasons. Both mean plant height and ear set height were significantly lower in the Autumn 2024 season compared to Spring 2024 (Table 4.8; Figures 4.26 and 4.27). This is, again, likely due to the cooler temperatures and fewer hours of daylight during the Autumn growing season. There was also a significant difference in mean dry HI values between the two seasons (Table 4.8; Figure 4.28). The HI values increased in the Autumn 2024 season because the plants were substantially smaller than in the Spring 2024 season. Despite the smaller plant size, the plants still produced ears that were marketable, which contributed more to the total plant weight and resulted in higher wet and dry HI values. Also, the relationship between higher irrigation amounts and lower wet HI indicates that, at a certain point, additional irrigation may not necessarily suppress yield, but the additional water is not being used in ear development and kernel production but instead is held in vegetative tissue.

4.3.5. Ear Quality Ratings and Ear Quality Index

Table 4.9 presents each treatment's individual parameter ratings—ear length, no-tip fill, and the overall EQI per treatment. These ratings provide a detailed comparison of sweet corn ear quality across the Spring and Autumn 2024 seasons. In the Spring 2024 season, all individual ratings, as well as the overall EQI rating, were above average, with most parameters falling between the "above average" (4) or "excellent" (5) categories (Table 4.9). The MP Wet treatment, which irrigated the least, resulted in the lowest, yet still near “above average”, overall EQI rating during the Spring. However, the consistent above average ratings across *ELr*, *NTFr*, and *EDr* for the irrigated treatments indicate that the sweet corn grown during the Spring 2024 season generally met or exceeded market standards and with less variation than the Autumn season. The increased and evenly distributed rainfall throughout the Spring 2024 growing season likely contributed to this outcome, as it provided adequate moisture for optimal ear development and growth for all treatments, even Rainfed. The Grower Standard treatment resulted in the highest ratings for *ELr*, *NTFr*, *EDr*, and overall EQI of all treatments during the Spring 2024 season, with irrigated treatments resulting in comparable ratings.

In contrast, during the Autumn 2024 season, individual parameter ratings and overall EQI scores were lower than in the Spring season, with many parameters falling within the "average" (3) or near "below average" (2) categories. Although all irrigated treatments resulted in marketable ratings, the decrease in quality ratings during the Autumn 2024 season is evident across all parameters, indicating suboptimal ear development. For instance, the VWC Wet treatment resulted in a “below average” rating for *EDr*. Interestingly, this rating is lower than that of the Rainfed treatment. The cooler temperatures during the Autumn 2024 season likely slowed the growth and development of the ears and contributed to smaller ears and poorer tip fill. These seasonal-related

stresses negatively affected ear growth and development, resulting in a higher proportion of no-tip fill, shorter ear lengths, and smaller ear diameters, even in irrigated treatments. Like the Spring 2024 season, during the Autumn 2024 season, the Grower Standard treatment also resulted in the highest ratings for *ELr*, *NTFr*, *EDr*, and overall EQI of all treatments.

During the Autumn 2024 season, the Rainfed and MP Wet treatments resulted in the lowest *ELr*. Conversely, the MP Wet, VWC Dry/Wet, and VWC Wet treatments resulted in the lowest *NTFr* of the irrigated treatments despite maintaining a wet soil profile. This indicates that a saturated soil profile may discourage late-stage ear development and kernel fill, especially during the Autumn season when paired with cooler temperatures. This is also apparent in Figure 4.18, as no-tip fill values increase slightly as irrigation amounts exceed 200 mm (8 in). As a result, the overall EQI rating for all treatments for the Autumn 2024 season was notably lower than the Spring 2024 season (Figure 4.29).

The variation in EQI ratings between the Spring 2024 and Autumn 2024 seasons (Figures 4.30, 4.31, 4.32) highlights the impact of adequate soil moisture levels and seasonal weather conditions on sweet corn production. The above average ratings and lower variability during the Spring of 2024 suggest that optimal rainfall and temperatures supported healthy growth, while the cooler and drier conditions of the Autumn 2024 season hindered ear and kernel development, which resulted in lower ratings and increased variability in quality parameters. During both the Spring 2024 and Autumn 2024 seasons, the Rainfed treatment resulted in the lowest EQI ratings, indicating the importance of supplemental irrigation in sweet corn production.

4.4. Conclusion

The results of this study emphasized the importance of effective irrigation management in enhancing both the yields and quality of sweet corn, particularly in regions with sandy soils and

irregular precipitation patterns. Fewer irrigation events were required in Spring 2024 due to regular precipitation in contrast to the Autumn 2024 season, which had extended periods without precipitation. The Autumn precipitation pattern underscores the need for supplemental irrigation and the need to maintain optimal soil moisture conditions throughout the growing season to achieve high sweet corn fresh market quality. The irrigation management strategy used in the Grower Standard treatment that is based on years of experience of a top sweet corn grower resulted in high yields and good quality and at least matched the best performing of the other scheduling treatments. The sensor and ET -based scheduling treatments used in the study can be improved by reducing the amount of irrigation applied at each event which may result in more frequent irrigation events.

The EQI results from the Spring 2024 and Autumn 2024 seasons highlight how environmental factors, such as temperature, variation in daylight hours, and rainfall, influence sweet corn fresh market ear quality. In the Spring 2024 season, most irrigated treatments resulted in “above average” ratings across all quality parameters—*ELr*, *NTFr*, *EDr*, as well as EQI —indicating that optimal soil moisture levels support increased ear fresh market quality. In contrast, the Autumn 2024 season showed a downward shift in quality, with individual parameter ratings and the overall EQI scores being “average” or slightly “below average”. This is likely due to cooler temperatures impacting ear and kernel development. It is also important to iterate that the Grower Standard treatment was used as a benchmark in this study as it was based on the management and irrigation practices of one of the top sweet corn growers in Georgia that has consistently high yields. Both the SWB Updated and MP Dry/Wet treatments produced comparable results to the Grower Standard, with similar results in ear length, no-tip fill, ear diameter, and overall EQI during the Spring and Autumn 2024 growing seasons.

Statistically significant results were not found for most variables evaluated during the study. This was likely the result of high variability within the replicates of some treatments which may have been affected by the sampling size used to determine yield and quality. In future studies, it may be prudent to significantly increase the number of ears and plants collected during harvest although this requires a significant increase in the labor required for quantifying yield and quality parameters after the ears and plants are collected.

4.5. Acknowledgments

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4.6. References

- Allen, R.G., Pereira, L.S., Raes, D., Smith, M. 1998. Crop evapotranspiration: Guidelines for computing crop water requirements. Irrigation and Drainage Paper No. 56. Food and Agricultural Organization, United Nations, Rome, Italy.
https://edisciplinas.usp.br/pluginfile.php/3887570/mod_folder/content/0/Boletim_FAO56.pdf. Accessed August 2021.
- Allen, R.G., Pereira, L.S., Smith, M., Raes, D., Wright, J.L. 2005. FAO-56 dual crop coefficient method for estimating evaporation from soil and application extensions. *J. Irrigation and Drainage Engineering*. 131(1), 2-13. [https://ascelibrary.org/doi/abs/10.1061/\(ASCE\)0733-9437\(2005\)131:1\(2\)](https://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9437(2005)131:1(2)). Accessed August 2021.
- Bayer Crop Science. 2025. Sweet Corn Harvest: Quality and Safety.
https://seminisus.s3.amazonaws.com/app/uploads/2016/11/16_Sweet-Corn-Harvest-Quality-and-Safety-Seminis.pdf.
- Bednarz, C.W., Ritchie, G., Hook, G.E., Yager, R., Cromer, S., Cook, D., Griner, I. 2002. Cotton crop water use and irrigation scheduling. Georgia Cotton Research-Extension Report. Univ. of Georgia, Athens, GA. 61-64.
<http://ugacottonnews.org/vault/rer/2003/p72.pdf>. Accessed January 2022.
- Bedwell, E., McAvoy, T., da Silva, A., Hayes, B., McAvoy, T., Vargas, A., Yu, Z., Washington, B.J., Snider, J., Ortiz, B., Vellidis, G. 2025a. An irrigation scheduling model for sweet corn based on FAO-56. *J. Agricultural Water Management*. (in preparation).
- Becerra-Sanchez, F., Taylor, G. 2021. Reducing Post-Harvest Losses and Improving Quality in Sweet Corn (*Zea mays* L.): Challenges and Solutions for Less Food Waste and Improved Food Security. *J. Food and Energy Security*. 10(3). <https://doi.org/10.1002/fes3.277>.
- Braunworth, W., Mack, H. 1987. Evaluation of Irrigation Scheduling Methods for Sweet Corn. *J. American Society of Horticultural Science*. 112(1), 29-32.
<https://pdfs.semanticscholar.org/6f05/d22d1910c71268dc90bbb1aa9c1b5d50a0a0.pdf>. Accessed January 2022.
- Datta, D., Chandra, S., Nath, C., Kar, G., Ghosh, S., Chaturvedi, S., Bhatnagar, A., Singh, G., Singh, V. 2022. Soil-plant water dynamics, yield, quality and profitability of spring sweet corn under variable irrigation scheduling, crop establishment and moisture conservation practices. *J. Field Crops Research*. 279. <https://doi.org/10.1016/j.fcr.2022.108450>.
- Dhaliwal, D., Williams, M., II. 2023. An Outlook on Processing Sweet Corn Production from the Last Three Decades (1990s–2010s). *J. Horticultural Science*. 58(7), 792-796.
<https://doi.org/10.21273/HORTSCI17109-23>.
- Ertek, A., Kara, B. 2013. Yield and Quality of Sweet Corn under Deficit Irrigation. *Agricultural J. Water Management*. 129, 138–144. <https://doi.org/10.1016/j.agwat.2013.07.012>.
- Gilmore, E., Rodgers, J. 1958. Heat Units as a Method of Measuring Maturity in Corn. *Agronomy Journal*. 50(10), 611–615.
<https://doi.org/10.2134/agronj1958.00021962005000100014x>.
- Hassanli, A., Ebrahimizadeh, M., Beecham, S. 2009. The Effects of Irrigation Methods with Effluent and Irrigation Scheduling on Water Use Efficiency and Corn Yields in an Arid Region. *J. Agricultural Water Management*. 96(1), 93–99.
<https://doi.org/10.1016/j.agwat.2008.07.004>.
- Howell, T. Irrigation Scheduling Research and Its Impact on Water Use. 1996. Evapotranspiration and Irrigation Scheduling, Proceedings of the International Conference,

- Nov. 3-6, 1996, San Antonio, TX, American Society of Agricultural Engineers, St. Joseph, MI.
<https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=4216fcee2583f303cdf8cdf342c825a2c2fd7b1>.
- Hunsaker, D. Pinter Jr., P., Barnes, E., Kimball, B. 2003. Estimating cotton evapotranspiration crop coefficients with a multispectral vegetation index. *J. Irrigation Science*. 22:95-104.
<https://doi.org/10.1007/s00271-003-0074-6>.
- Jones, H. 2004. Irrigation Scheduling: Advantages and Pitfalls of Plant-Based Methods. *J. Experimental Botany*. 55(407), 2427–2436. <https://doi.org/10.1093/jxb/erh213>.
- Kara, B. 2011. Fresh ear yield and growing degree days of sweet corn in different sowing dates in southwestern Anatolia region. *Turkish Journal of Field Crops*. 16(2), 166-171.
<https://dergipark.org.tr/en/download/article-file/158720>.
- Kwabiah, A. 2004. Growth and yield of sweet corn cultivars in response to planting date and plastic mulch in a short-season environment. *Scientia Horticulturae*. 102 (2), 147-166.
<https://doi.org/10.1016/j.scienta.2004.01.007>.
- Lass, L., Callihan, R., Everson, D. 1993. Forecasting the Harvest Date and Yield of Sweet Corn by Complex Regression Models. *J. American Society for Horticultural Science*. 118(4), 450–455. https://www.researchgate.net/profile/Robert-Callihan/publication/265917092_Forecasting_the_Harvest_Date_and_Yield_of_Sweet_Corn_by_Complex_Regression_Models/links/54ff26510cf2eaf210b68484/Forecasting-the-Harvest-Date-and-Yield-of-Sweet-Corn-by-Complex-Regression-Models.pdf.
- Liakos, V., Porter, W., Liang, X., Tucker, M. A., McLendon, A., Vellidis, G. 2017. Dynamic variable rate irrigation tool for greatly improving water use efficiency. *J. Advances in Animal Biosciences*. 8(2), 557-563. <https://doi.org/10.1017/S2040470017000711>.
- Lizaso, J., Boote, K., Cherr, C., Scholberg, J., Casanova, J., Judge, J., Jones, J., Hoogenboom, G. 2007. Developing a Sweet Corn Simulation Model to Predict Fresh Market Yield and Quality of Ears. *J. American Society for Horticultural Science*. 132(3), 415-422.
<https://doi.org/10.21273/JASHS.132.3.415>.
- McAvoy, T., Bedwell, E., Vellidis, G. 2025. Growing Degree Days and Why They Matter: How Temperature Affects Sweet Corn Growth in Southern Georgia. University of Georgia Cooperative Extension Service. Circular 1320. (in press).
- McAvoy, T., Coolong, T. 2023. Shipper Sweet Corn in Southern Georgia. University of Georgia Cooperative Extension Service. Bulletin 1549.
<https://extension.uga.edu/publications/detail.html?number=B1549>. Accessed 5 January 2025.
- McMaster, G. Wilhelm, W. 1997. Growing degree-days: one equation, two interpretations. *J. Agricultural and Forest Meteorology*. 87(4), 391-300. [https://doi.org/10.1016/S0168-1923\(97\)00027-0](https://doi.org/10.1016/S0168-1923(97)00027-0).
- Ozores-Hampton, S., Olson, S., Webb, S., Smith, S., Raid, R., McAvoy, E. 2012. Vegetable Production Handbook, Chapter 21 Sweet Corn Production in Florida. University of Florida IFAS Extension. 283-296. https://www.researchgate.net/profile/Monica-Ozores-Hampton/publication/265184286_Chapter_21_Sweet_Corn_Production_in_Florida/links/56fa9ec308ae8239f6dad110/Chapter-21-Sweet-Corn-Production-in-Florida.pdf.
- Rao, N., Sarma, P., Chander, S. 1988. Irrigation Scheduling under a Limited Water Supply. *J. Agricultural Water Management*. 15(2), 165–75. [https://doi.org/10.1016/0378-3774\(88\)90109-6](https://doi.org/10.1016/0378-3774(88)90109-6).

- Stone, K., Bauer, P., Sigua, G. 2016. Irrigation management using an expert system, soil water potentials, and vegetative indices for spatial applications. *Transactions of the ASABE*. 59(3), 941-948. <https://doi.org/10.13031/trans.59.11550>.
- Sui, R. 2017. Irrigation Scheduling Using Soil Moisture Sensors. *J. Agricultural Science*. 10(1), 1. <https://doi.org/10.5539/jas.v10n1p1>.
- Szymanek, M. 2009. Influence of sweet corn harvest date on kernels quality. *J. Research in Agricultural Engineering*. 55(1), 10-17. DOI: 10.17221/13/2008-RAE.
- United States Department of Agriculture (USDA) Agricultural Marketing Service (AMS). 1992. United States Standards for Grades of Sweet Corn. https://www.ams.usda.gov/sites/default/files/media/Corn%2C_Sweet_Standard%5B1%5D.pdf.
- United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS). 2023. *Vegetables 2022 Summary*. USDA-NASS, Washington, DC. <https://downloads.usda.library.cornell.edu/usda-esmis/files/02870v86p/hq37x121v/4b29ck28c/vegean23.pdf>
- United States Department of Agriculture (USDA). 2024. Sweet Corn Grades and Standards. <https://www.ams.usda.gov/grades-standards/sweet-corn-grades-and-standards>. Accessed 20 August 2024.
- Vellidis, G., Tucker, M., Perry, C., Kevin, C., Bednarz, C. 2008. A real-time wireless smart sensor array for scheduling irrigation. *J. Emerging Technologies for Real-Time and Integrated Agriculture Decisions*. 61(1), 44-50. <https://doi.org/10.1016/j.compag.2007.05.009>
- Vellidis, G., Liakos, V., Andreis, J., Perry, C., Porter, W., Barnes, E., Morgan, K., Fraisse, C., Migliaccio, K. 2016. Development and Assessment of a Smartphone Application for Irrigation Scheduling in Cotton. *J. Computers and Electronics in Agriculture*. 127, 249–259. <https://doi.org/10.1016/j.compag.2016.06.021>.
- Viswanatha, G., Ramachandrappa, B., Nanjappa, H. 2002. Soil plant Water Status and Yield of Sweet Corn (*Zea mays L. cv. saccharata*) as Influenced by Drip Irrigation and Planting Methods. *J. Agricultural Water Management*, 7. [https://doi.org/10.1016/S0378-3774\(01\)00189-5](https://doi.org/10.1016/S0378-3774(01)00189-5).
- Westerfield, R., Eason, N. 2024. Growing Home Garden Sweet Corn. University of Georgia Cooperative Extension Service. <https://woodstock.recdesk.com/RecDeskPortal/Portals/770/Sweet%20Corn.PDF>. Accessed 27 December 2024.

4.7. Tables and Figures

Table 4.1. Weighting factors used for sensor depths. Factors were based on growing degree days (GDDs) which were indicative of rooting depth.

Root Depth Weighting									
GDD	UGA SSA			Sentek					
	15 cm	31 cm	46 cm	10 cm	20 cm	30 cm	40 cm	50 cm	60 cm
0-300	80%	20%	0%	40%	40%	10%	10%	0%	0%
301-800	50%	30%	20%	25%	25%	15%	15%	10%	10%
801-1000	50%	25%	25%	25%	25%	12.5%	12.5%	12.5%	12.5%
1001-Harvest	40%	30%	30%	20%	20%	15%	15%	15%	15%

Table 4.2. Fertilizer (Nitrogen-Phosphorus-Potassium (N-P-K)) and herbicide applications during the Spring and Autumn 2024 seasons.

Growing Degree Days (GDD)		Days After Planting (DAP)		Management Type	Application Method
Spring	Autumn	Spring	Autumn		
-	-	-	-	Fertilizer ² (34-31-224 units ¹)	Broadcast (dry blend)
0	0	0	0	Fertilizer (48-44-0 units ¹)	Pop-Up (liquid blend)
4	0	1	0	Herbicide	Sprayer
200	448	16	15	Fertilizer (18-0-0)	Irrigation System
362	565	27	20	Fertilizer (18-0-0)	Irrigation System
403	589	29	21	Fertilizer (90-20-136 units ¹)	Top-Dress (dry Blend)
610 ³	634 ³	40	23	Fertilizer (18-0-0)	Irrigation System
832	713	49	26	Fertilizer (18-0-0)	Irrigation System
1040	956	58	35	Fertilizer (10-0-10)	Irrigation System
1346	1256	70	47	Fertilizer (18-0-0)	Irrigation System

¹Indicates units of nitrogen, phosphorus, and potassium (N-P-K), respectively, applied at kg ha⁻¹.

²Indicates pre-planting fertilizer applied one day before planting.

³Beginning at approximately 600 GDD, pesticide was applied via sprayer every day, to every other day.

Table 4.3. Estimated phenological stages for sweet corn based on growing degree days (GDD). Based on data collected over two spring and two autumn seasons of Bayer Crop Science (Leverkusen, Germany) Obsession hybrid bicolor cultivar grown in southwestern Georgia, U.S.

GDDs	Phenology
0 - 70	Planting to Emergence
71 - 140	Emergence to V1
141 - 195	V1 to V2
196 - 255	V2 to V3
256 - 300	V3 to V4
301 - 355	V4 to V5
356 - 415	V5 to V6
416 - 490	V6 to V7
491 - 565	V7 to V8
566 - 645	V8 to V9
646 - 695	V9 to V10
696 - 770	V10 to V11
771 - 840	V11 to V12
841 - 890	V12 to V13
891 - 935	V13 to Tasseling
936 - 1050	Tasseling to Silking (R1)
1051 - 1190	Silking to Blister (R1 to R2)
1191 - 1345	Blister to Milk (R2 to R3)
1346 – 1400 +	Milk to Harvest

Table 4.4. Rating scale for individual ear quality parameters (ear length, no-tip fill, and diameter).

Rating	Ear Length (cm)	No-Tip Fill (mm)	Ear Diameter (mm)
5: Excellent	19.2 - 20.3	12.53 - 0	48.27 - 50.80
4: Above-Average	17.9 - 19.1	12.69 - 12.54	45.73 - 48.26
3: Average	16.6 - 17.8	25.39 - 12.7	43.19 - 45.72
2: Below-Average	15.2 - 16.5	38.10 - 25.40	40.65 - 43.18
1: Unacceptable	< 15.2	> 38.10	< 40.64

Table 4.5. Yield, irrigation amounts, and number of irrigation events of Spring 2024 and Autumn 2024 treatments. There were no statistically significant differences at $\alpha = 0.05$ during the Spring 2024 or Autumn 2024 growing seasons.

Treatment	Yield ² (bx ha ⁻¹)		Irrigation Applied (mm) ⁵		No. of Irrigation Events ⁴	
	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	1214	1059	127	169	7	10
VWC Wet	1315	1059	143	230	6	9
VWC Dry/Wet	1214	975	124	249	5	10
MP Wet	1265	932	105	211	4	8
MP Dry/Wet	1164	1186	124	154	5	5
SWB / Updated ¹	1315	1102	219	192	10	7
Rainfed	1062	636	37 ³	59 ³	7 ³	9 ³

¹SWB for Spring 2024 and SWB Updated for Autumn 2024.

²Spring 2024 and Autumn 2024 seeding rates were 12,550 and 10,526 ha⁻¹, respectively.

³Indicates irrigation applied to promote emergence (Spring: one event; Autumn: two events), activate herbicide (Spring: 0, due to precipitation; Autumn: one event), and fertigate (Spring: six events; Autumn: six events)

⁴Does not include events related to emergence, herbicide activation, or fertigation, except in Rainfed.

⁵Includes amounts related to treatment irrigation, emergence, herbicide activation, and fertigation.

Table 4.6. Mean ear weight, length, diameter, and no-tip fill of Spring and Autumn 2024 growing seasons. There were no statistically significant differences at $\alpha = 0.05$.

Treatment	Ear Weight (kg)		Ear Length (cm)		Ear Diameter (mm)		No-Tip Fill (mm)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	0.32	0.24	18.4	16.8	46.80	43.69	8.73	14.33
VWC Wet	0.34	0.22	18.6	15.7	47.75	41.35	5.43	19.53
VWC Dry/Wet	0.32	0.22	18.8	16.7	47.45	42.82	9.65	20.19
MP Wet	0.32	0.23	18.2	16.2	47.11	43.56	5.98	17.97
MP Dry/Wet	0.33	0.21	18.3	15.8	47.77	43.31	6.71	16.41
SWB / Updated ¹	0.34	0.23	18.4	16.3	47.68	43.66	5.23	17.49
Rainfed	0.29	0.20	17.7	15.4	46.90	41.68	12.37	23.65

¹SWB for Spring 2024 and SWB Updated for Autumn 2024.

Table 4.7. Mean kernel count, flag length, and shank length of Spring and Autumn 2024 growing seasons. There were statistically significant differences at $\alpha = 0.05$ for flag length during the Spring 2024 season, only.

Treatment	Kernel Count		Flag Length (cm)		Shank Length (cm)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	584	488	9.0 ^{ab}	4.7	6.4	3.8
VWC Wet	601	451	8.2 ^{ab}	3.9	6.4	3.4
VWC Dry/Wet	607	475	6.5 ^{ab}	5.1	5.9	3.9
MP Wet	595	504	7.1 ^{ab}	3.8	5.4	3.8
MP Dry/Wet	594	481	6.7 ^{ab}	3.8	6.1	3.5
SWB / Updated ¹	620	521	10.2 ^b	4.5	6.5	4.0
Rainfed	608	467	4.4 ^a	5.0	5.2	4.1

¹SWB for Spring 2024 and SWB Updated for Autumn 2024.

Table 4.8. Mean plant height, ear set height, wet harvest index and dry harvest index of Spring and Autumn 2024 growing seasons. There were statistically significant differences at $\alpha = 0.05$ during the Spring 2024 growing season for plant height and wet harvest index, as indicated by letter groups.

Treatment	Plant Height (m)		Ear Set Height (cm)		Harvest Index (wet)		Harvest Index (dry)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	2.05 ^b	1.58	66.1	22.9	0.40 ^{ab}	0.62	0.38	0.60
VWC Wet	1.99 ^b	1.58	62.9	20.8	0.40 ^{ab}	0.54	0.38	0.60
VWC Dry/Wet	1.94 ^{ab}	1.62	63.1	26.3	0.38 ^a	0.44	0.38	0.58
MP Wet	2.05 ^b	1.56	69.3	22.3	0.39 ^{ab}	0.54	0.37	0.58
MP Dry/Wet	1.99 ^b	1.48	64.1	22.4	0.40 ^{ab}	0.61	0.41	0.58
SWB / Updated ¹	2.07 ^b	1.54	68.1	21.8	0.37 ^a	0.54	0.37	0.60
Rainfed	1.81 ^a	1.52	52.7	22.6	0.44 ^b	0.54	0.41	0.55

¹SWB for Spring 2024 and SWB Updated for Autumn 2024.

Table 4.9. Rating values for critical ear quality parameters (ear length, no-tip fill, and ear diameter) and overall Ear Quality Index (EQI) per treatment during the Spring and Autumn 2024 seasons.

Treatment	Ear Length (ELr)		No-Tip Fill (NTFr)		Ear Diameter (EDr)		Ear Quality Index (EQI)	
	Spring	Autumn	Spring	Autumn	Spring	Autumn	Spring	Autumn
Grower Standard	5.0	5.0	5.0	3.7	4.0	2.7	4.7	3.8
VWC Wet	5.0	4.3	5.0	3.0	4.0	2.0	4.7	3.1
VWC Dry/Wet	5.0	5.0	4.3	3.0	4.0	2.3	4.5	3.4
MP Wet	5.0	5.0	5.0	3.0	3.7	2.7	4.6	3.6
MP Dry/Wet	5.0	4.7	5.0	3.7	4.3	2.7	4.8	3.7
SWB / Updated ¹	5.0	5.0	5.0	3.7	4.0	2.7	4.7	3.8
Rainfed	5.0	4.0	4.0	2.7	4.0	2.3	4.3	3.0

¹SWB for Spring 2024 and SWB Updated for Autumn 2024.

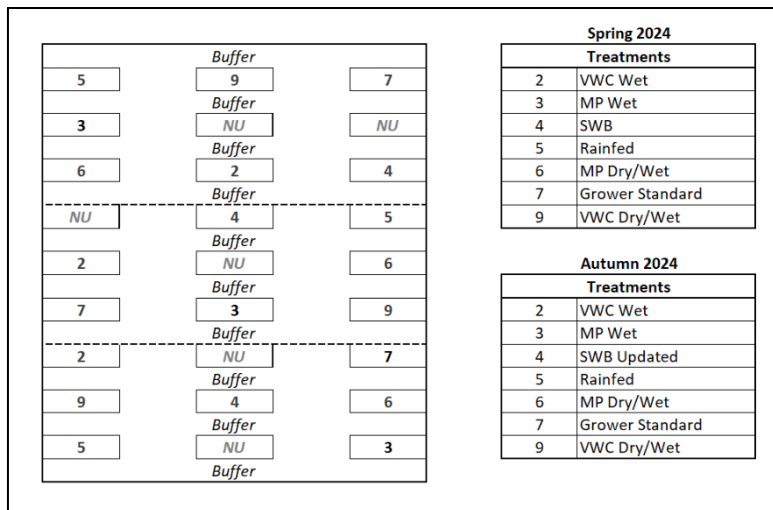


Figure 4.1. Spring and Autumn 2024 randomized complete block design experimental layout and treatments at University of Georgia’s Stripling Irrigation Research Park (SIRP). The rectangles indicate the eight data rows within each plot while *Buffer* indicates the 8 buffer rows between data rows. Numbers within the plots indicate treatment and the dashed lines separate the treatment blocks (replicate). Plots labeled “NU” were not used in the study.

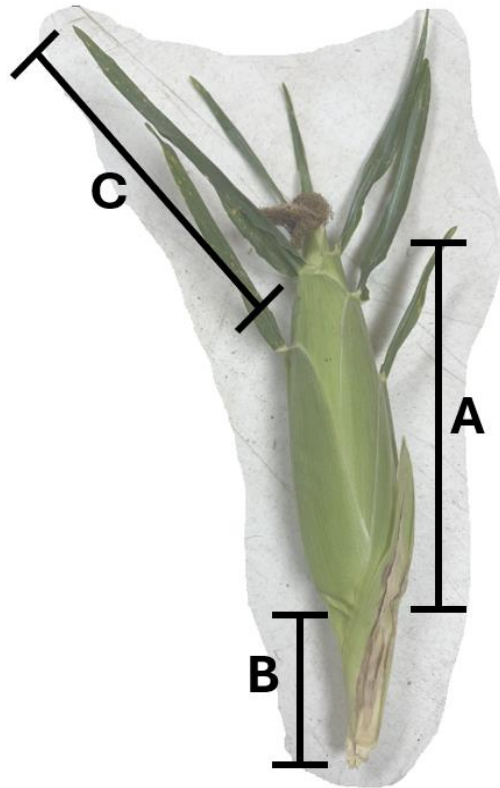


Figure 4.2. Schematic of ear length, shank length, and flag length measurements. “A” indicates ear length, “B” indicates shank length, and “C” indicates flag length.

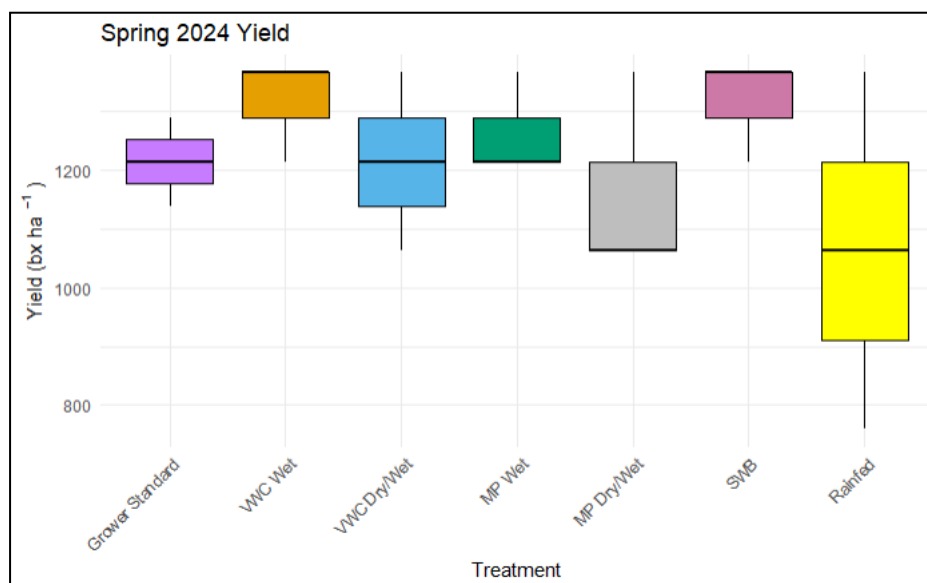


Figure 4.3. Box and whisker plot of Spring 2024 mean yield per treatment (in bx ha⁻¹) (no statistically significant differences between treatments at $\alpha = 0.05$).

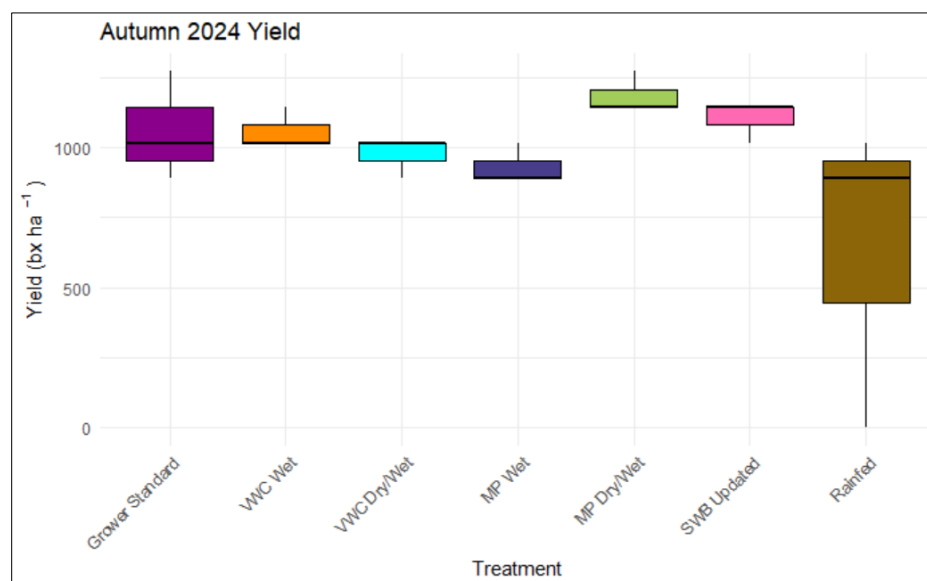


Figure 4.4. Box and whisker plot of Autumn 2024 mean yield per treatment (in bx ha⁻¹) (no statistically significant differences between treatments at $\alpha = 0.05$).

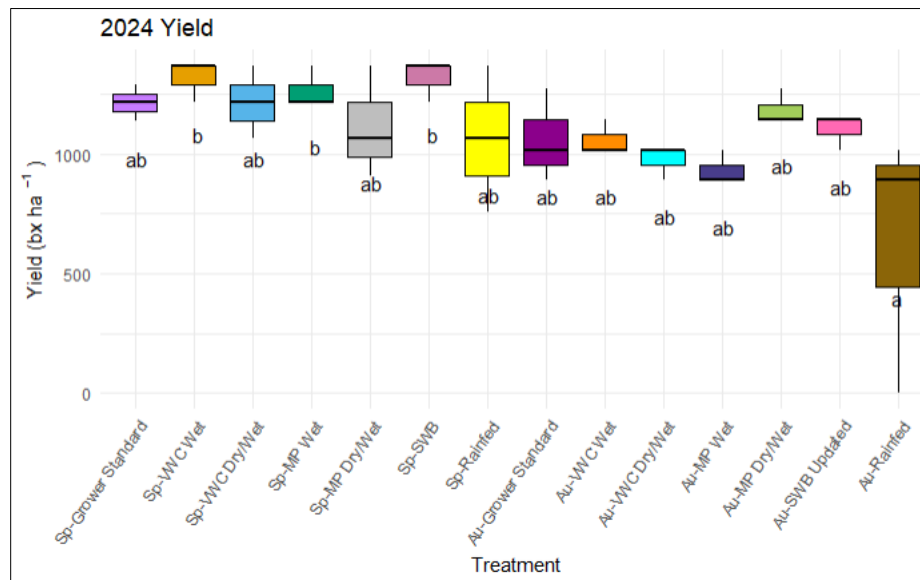


Figure 4.5. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean yield per treatment (in in bx ha⁻¹) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

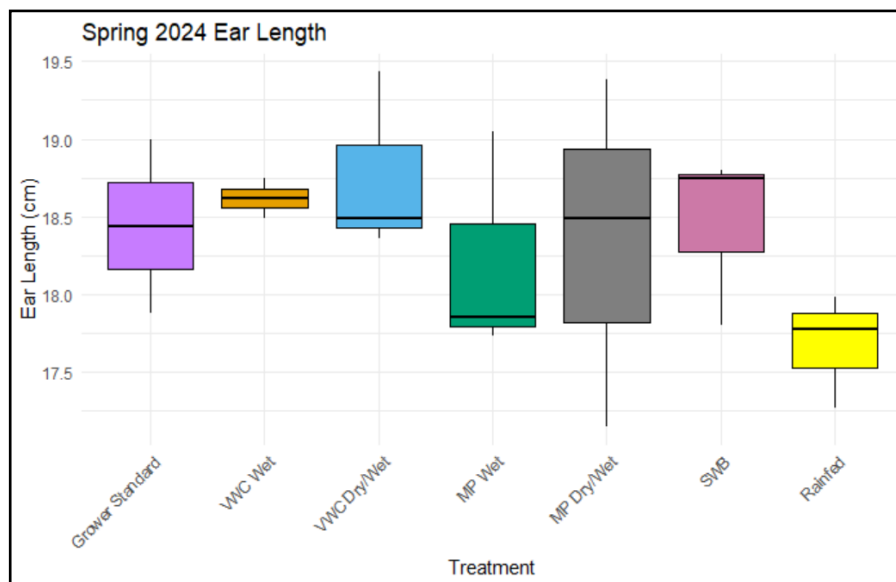


Figure 4.6. Box and whisker plot of Spring 2024 mean ear length per treatment (in cm) (no statistically significant differences between treatments at $\alpha = 0.05$).

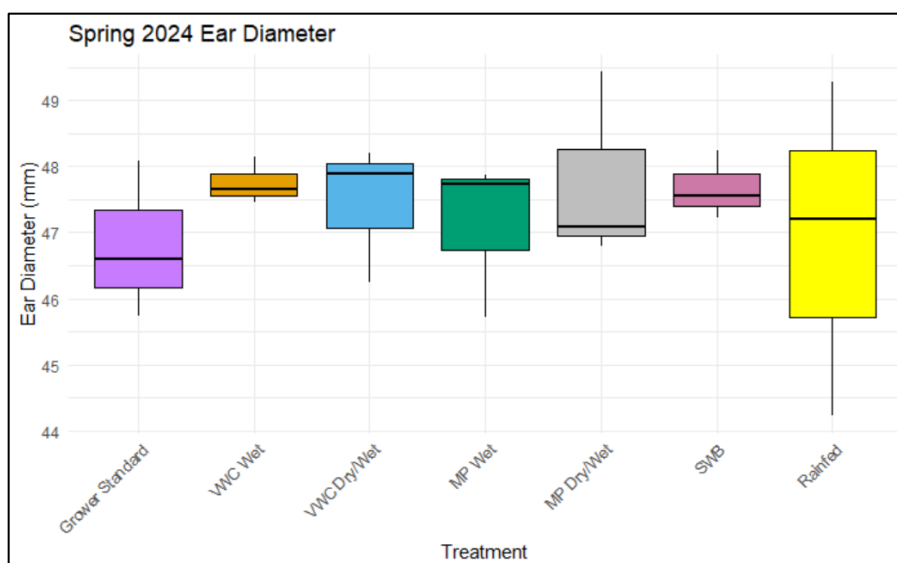


Figure 4.7. Box and whisker plot of Spring 2024 mean ear diameter per treatment (in mm) (no statistically significant differences between treatments at $\alpha = 0.05$).

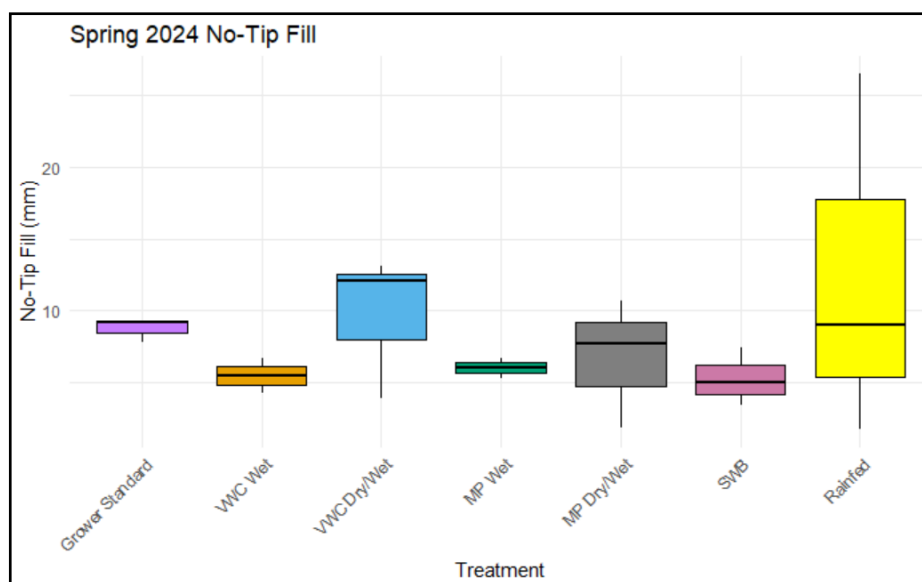


Figure 4.8. Box and whisker plot of Spring 2024 mean no-tip fill per treatment (in mm) (no statistically significant differences between treatments at $\alpha = 0.05$).

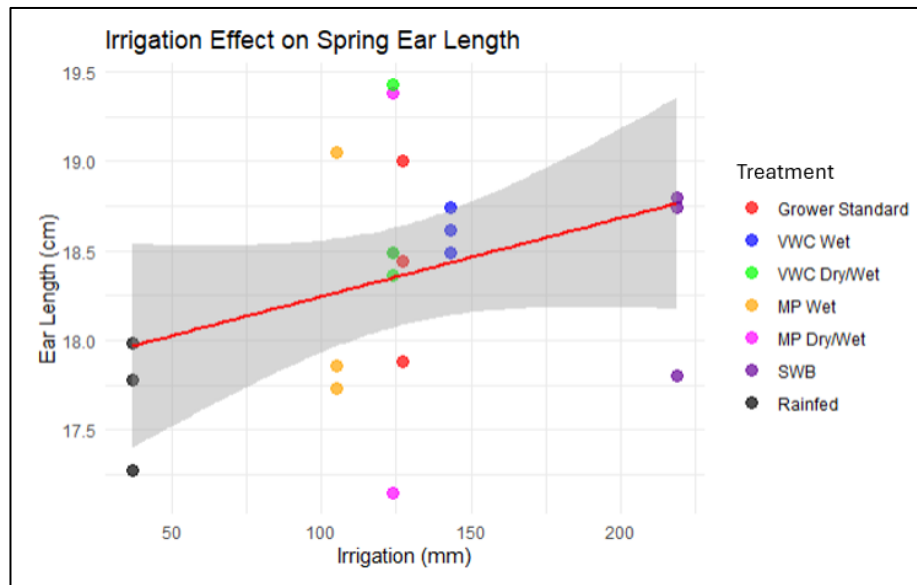


Figure 4.9. Scatter plot with linear regression line of irrigation effect on Spring 2024 ear length (in cm) per treatment.

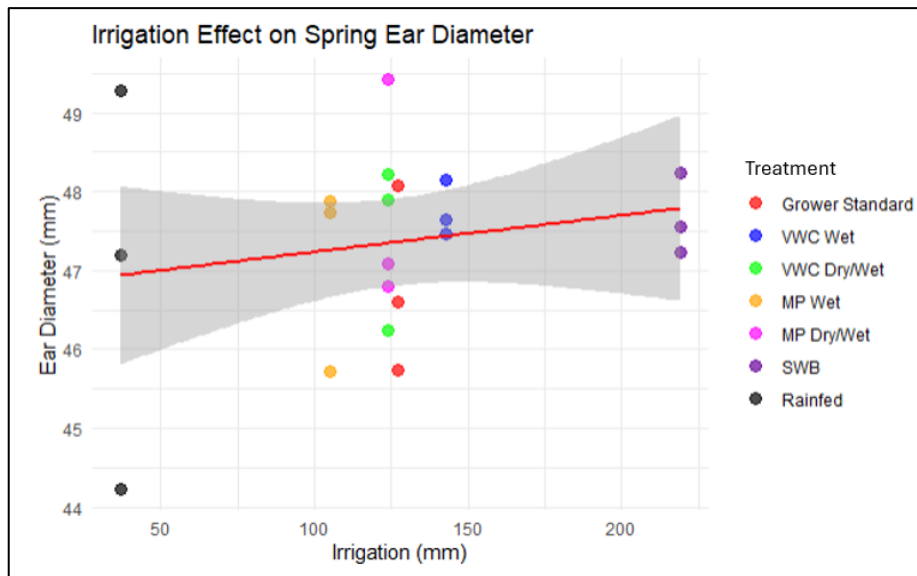


Figure 4.10. Scatter plot with linear regression line of irrigation effect on Spring 2024 ear diameter (in mm) per treatment.

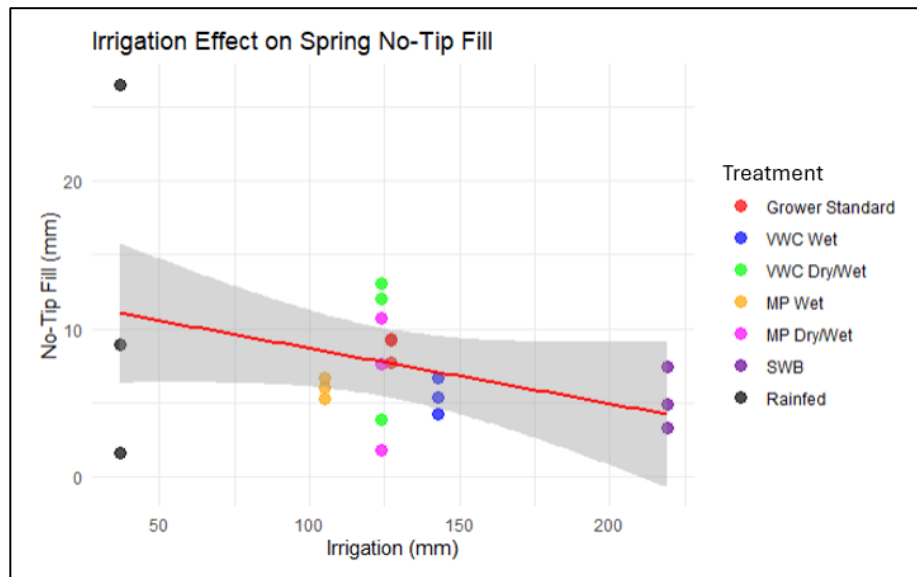


Figure 4.11. Scatter plot with linear regression line of irrigation effect on Spring 2024 no-tip fill (in mm) per treatment.

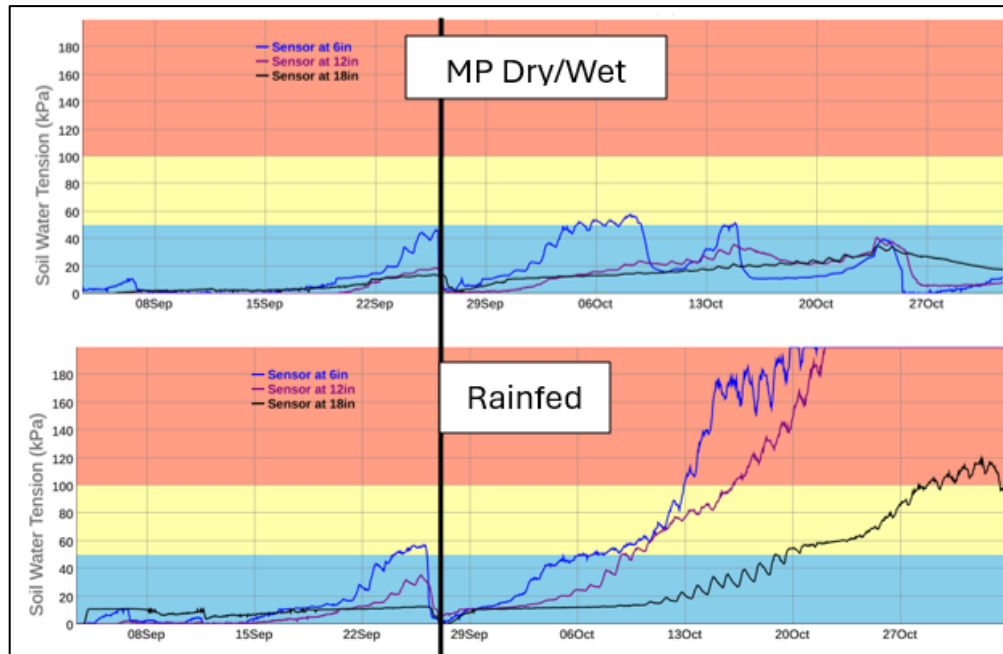


Figure 4.12. Line graphs of soil water tension (the absolute value of matric potential) for Rainfed and MP Dry/Wet treatments from the Autumn 2024 growing season. The maximum soil water tension recorded by the Watermark sensors used in the UGA SSA probes is 200 kPa. Each curve on the graph indicates soil water tension at the depth shown in the legend. The sensors were centered at depths of 15.2 cm (6 in), 30.5 cm (12 in), and 45.7 cm (18 in). The black vertical line indicates the estimated time of tasseling. The decrease in soil water tension immediately before the black line is the result of precipitation received during Hurricane Helene. No substantial precipitation was received from that time until harvest.

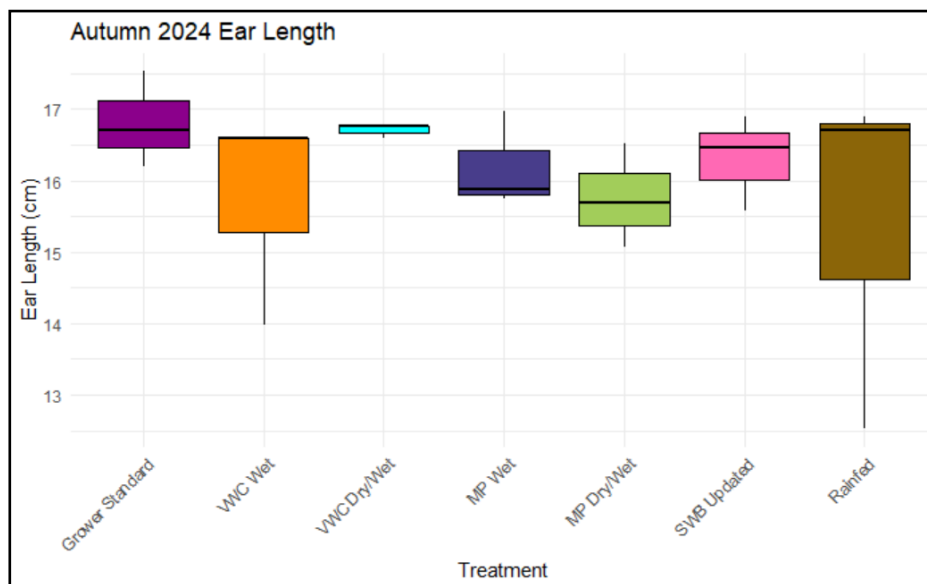


Figure 4.13. Box and whisker plot of Autumn 2024 mean ear length per treatment (in cm) (no statistically significant differences between treatments at $\alpha = 0.05$).

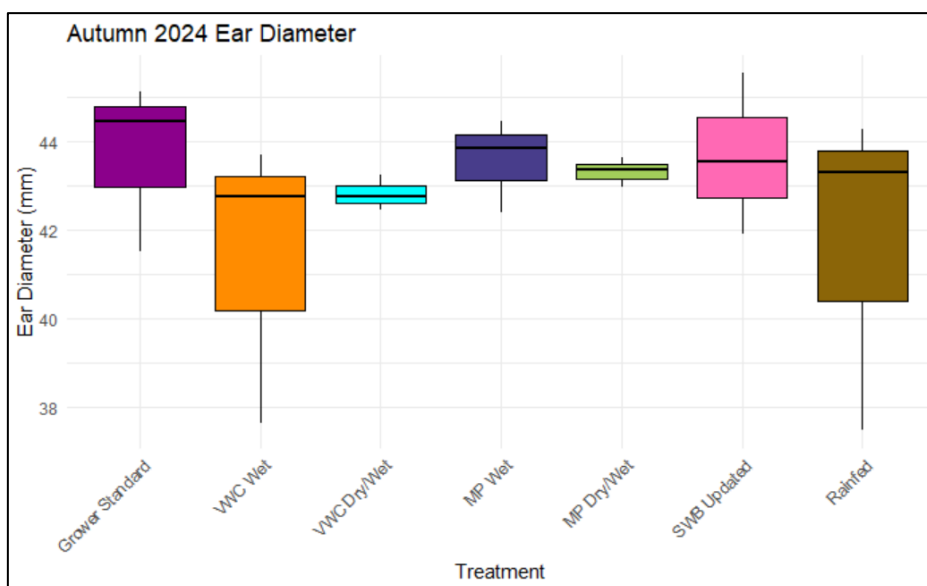


Figure 4.14. Box and whisker plot of Autumn 2024 mean ear diameter per treatment (in mm) (no statistically significant differences between treatments at $\alpha = 0.05$).

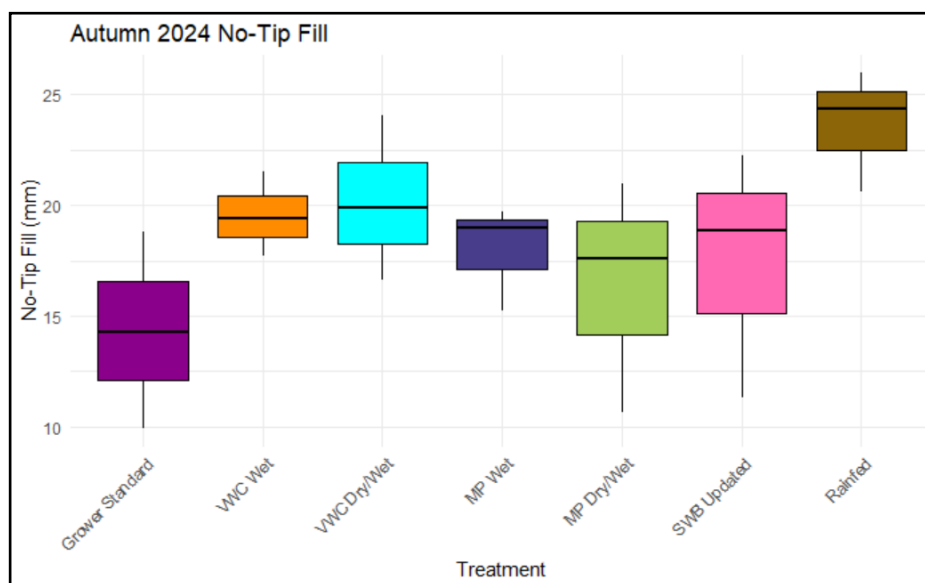


Figure 4.15. Box and whisker plot of Autumn 2024 mean no-tip fill per treatment (in mm) (no statistically significant differences between treatments at $\alpha = 0.05$).

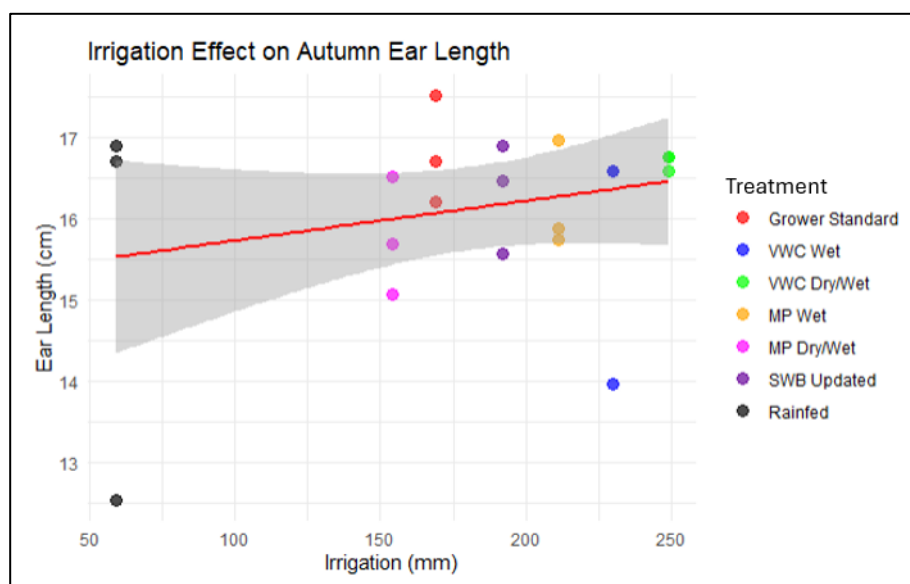


Figure 4.16. Scatter plot with linear regression line of irrigation effect on Autumn 2024 ear length (in cm) per treatment.

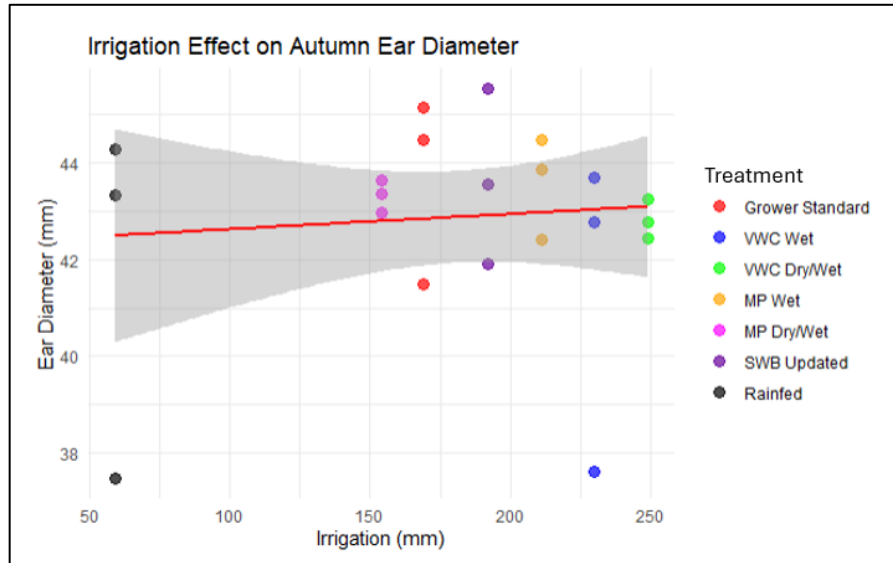


Figure 4.17. Scatter plot with linear regression line of irrigation effect on Autumn 2024 ear diameter (in mm) per treatment.

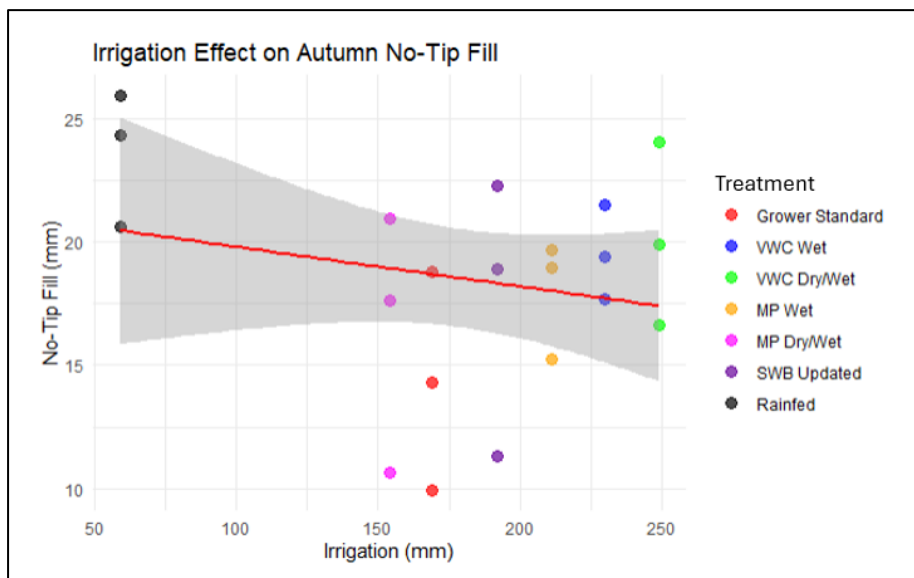


Figure 4.18. Scatter plot with linear regression line of irrigation effect on Autumn 2024 no-tip fill (in mm) per treatment.

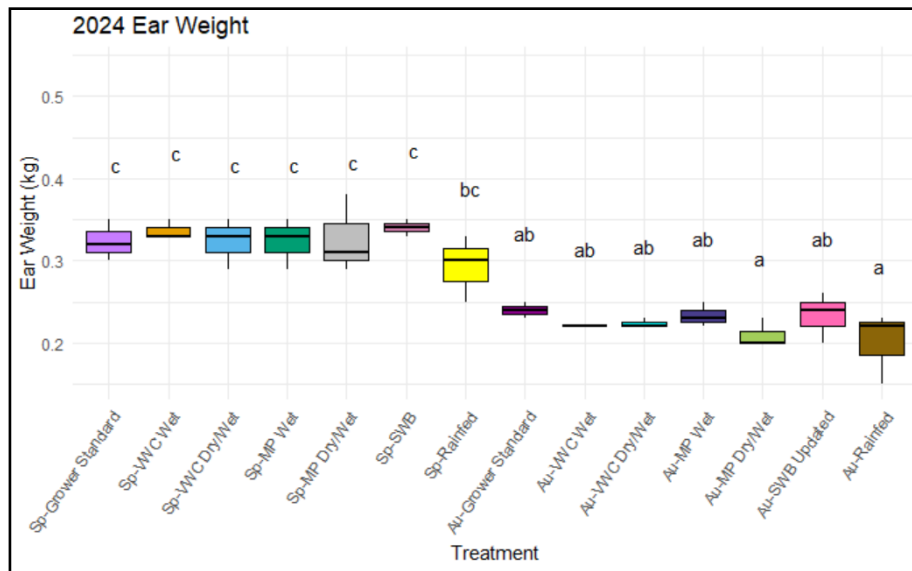


Figure 4.19. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-“) and Autumn 2024 (indicated by treatments beginning with “Au-“) mean ear weight per treatment (in kg) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

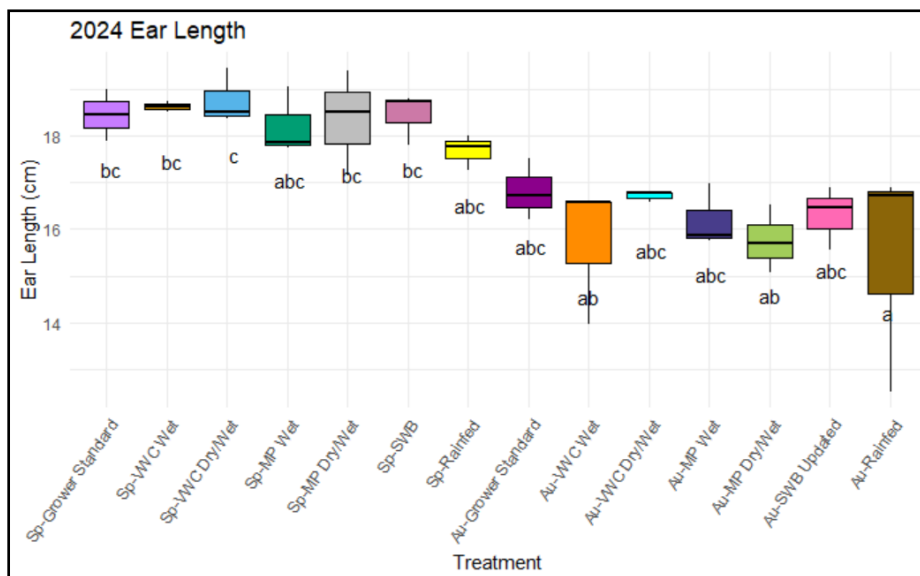


Figure 4.20. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-“) and Autumn 2024 (indicated by treatments beginning with “Au-“) mean ear length per treatment (in cm) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

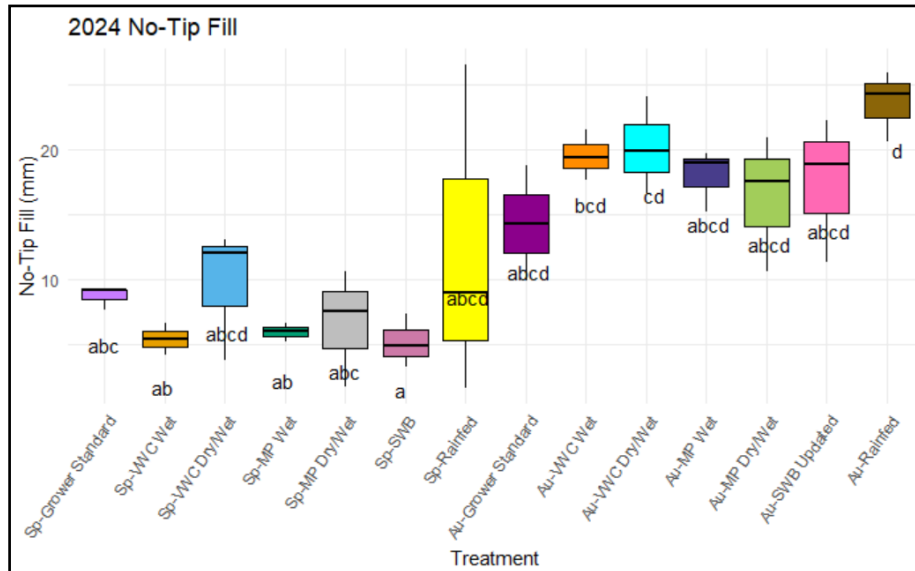


Figure 4.21. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean no-tip fill per treatment (in mm) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

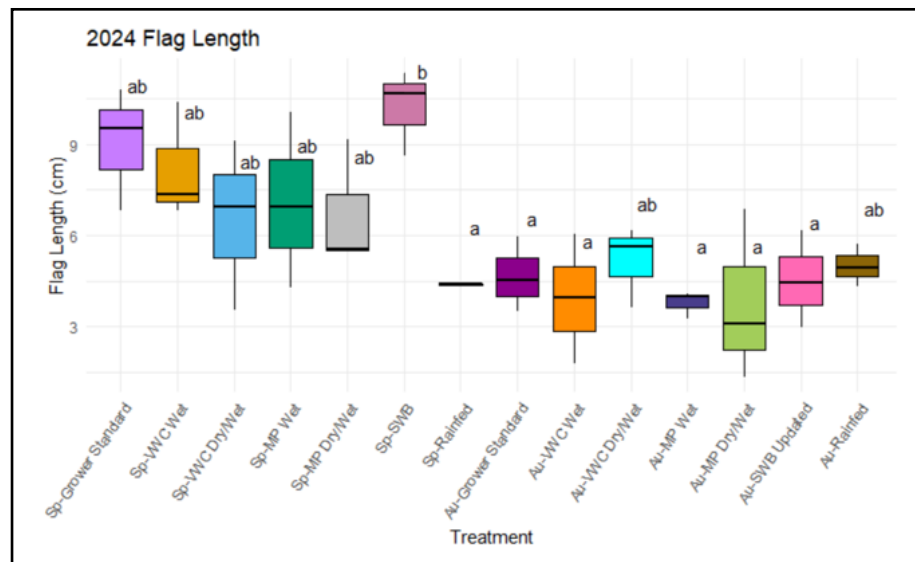


Figure 4.22. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean flag length per treatment (in cm) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

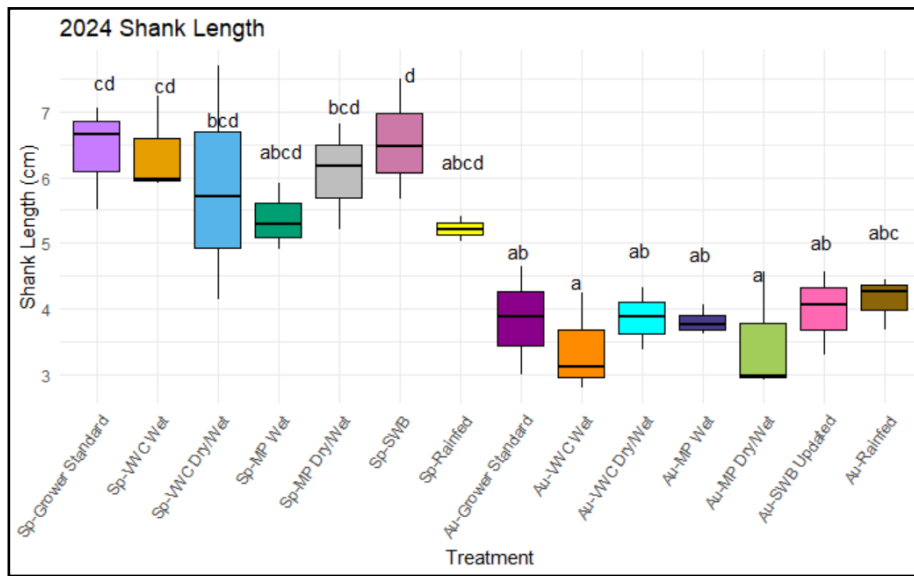


Figure 4.23. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean shank length per treatment (in cm) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

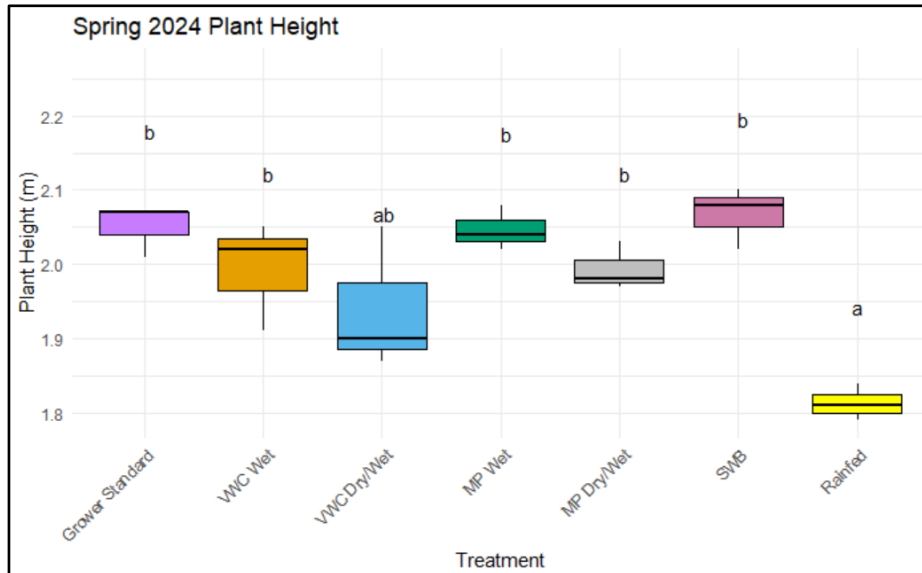


Figure 4.24. Box and whisker plot of Spring 2024 mean plant height per treatment (in m) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letters).

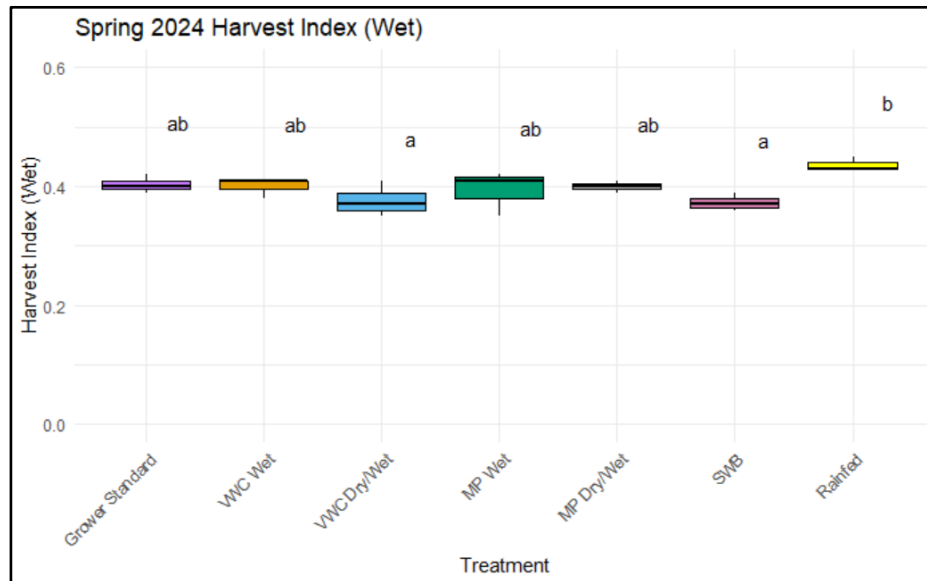


Figure 4.25. Box and whisker plot of Spring 2024 wet harvest index (HI) per treatment (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letters).

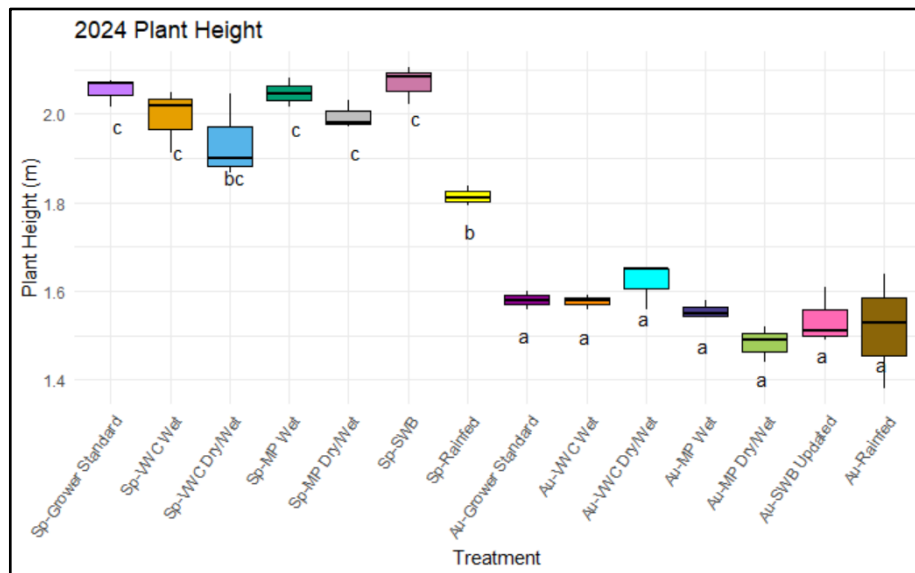


Figure 4.26. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean plant height per treatment (in m) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

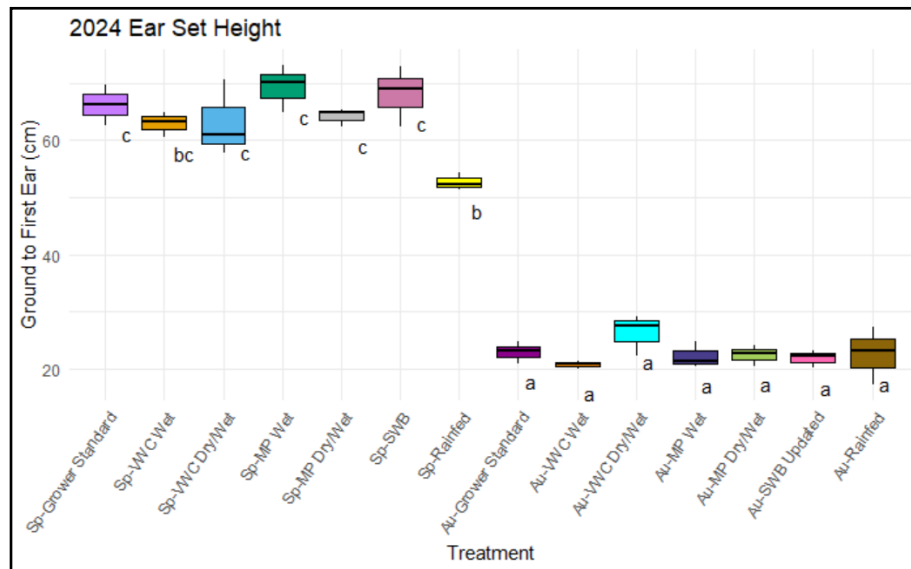


Figure 4.27. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean ear set height per treatment (in cm) (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

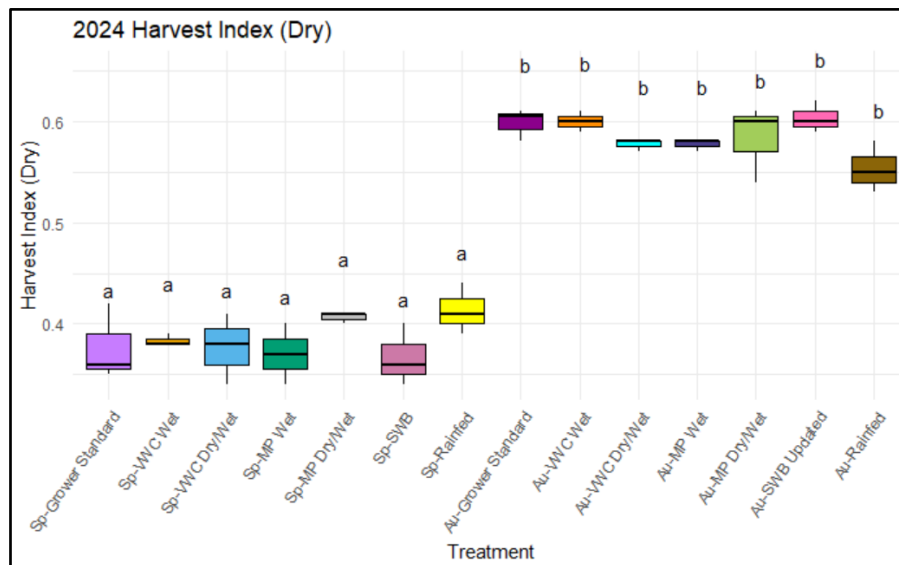


Figure 4.28. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) mean dry harvest index (HI) per treatment (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

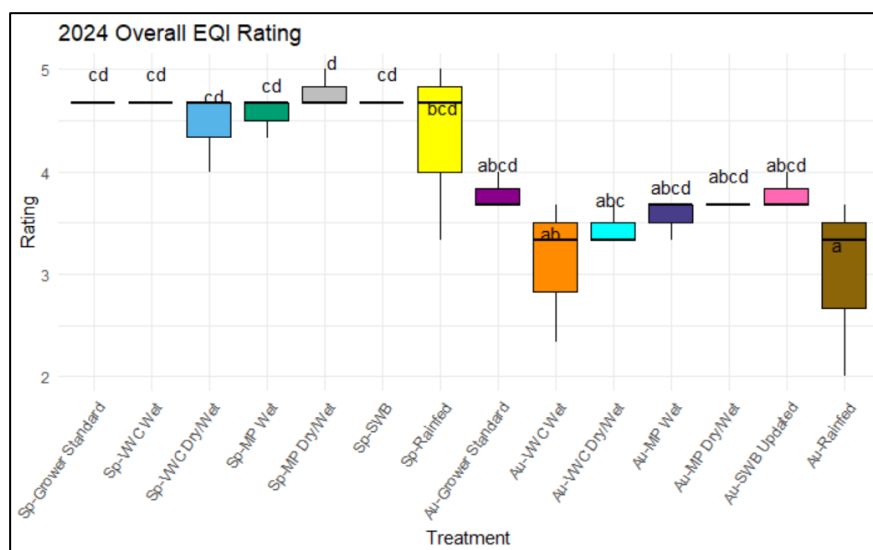


Figure 4.29. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) overall EQI Rating per treatment (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

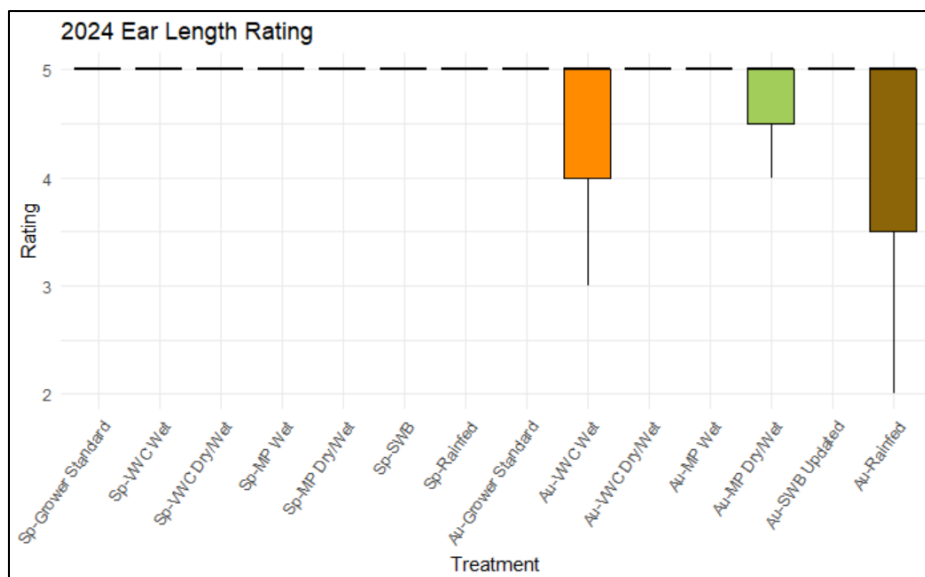


Figure 4.30. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) Ear Length Rating (*ELr*) per treatment (no statistically significant differences between treatments at $\alpha = 0.05$).

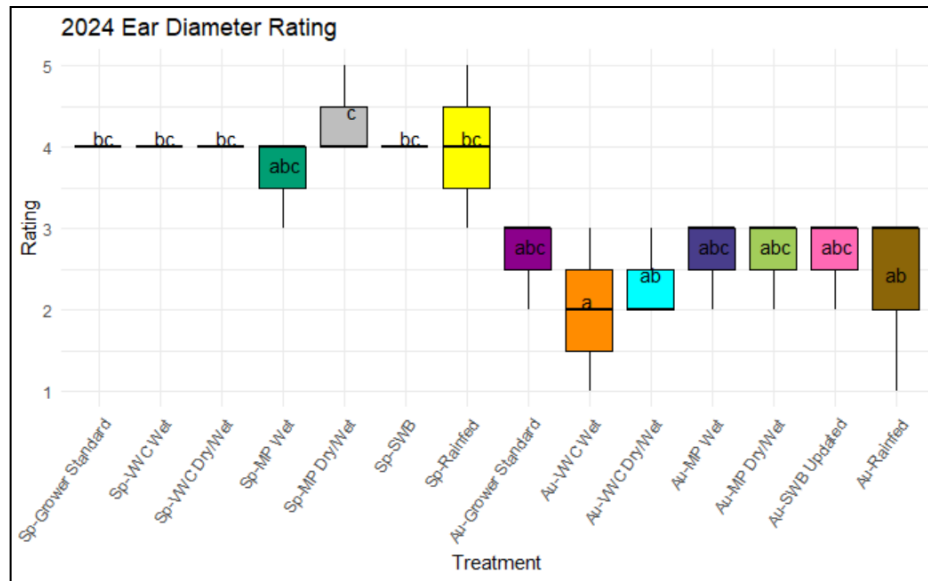


Figure 4.31. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) Ear Diameter Rating (*EDr*) per treatment (statistically significant differences between treatments at $\alpha = 0.05$ indicated by letter groups).

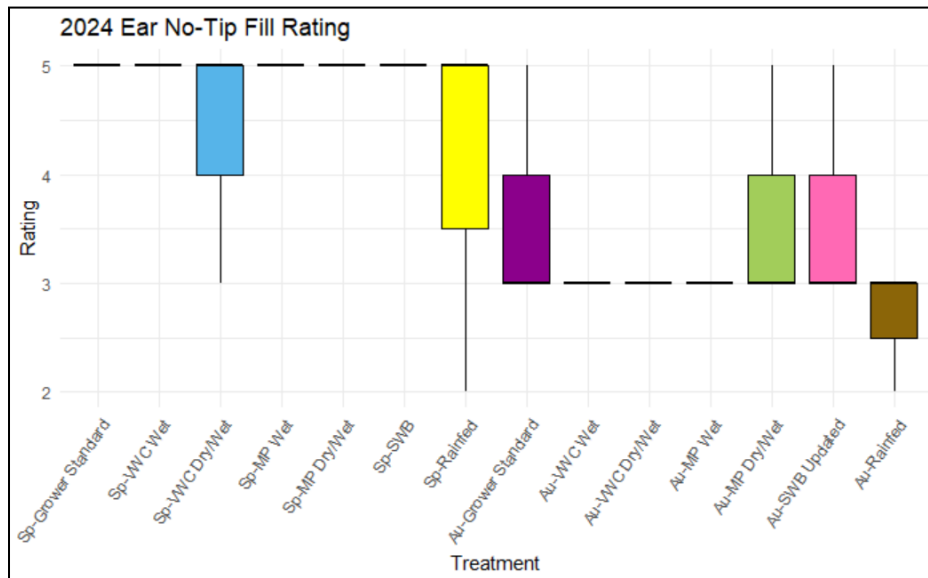


Figure 4.32. Box and whisker plot of Spring 2024 (indicated by treatments beginning with “Sp-”) and Autumn 2024 (indicated by treatments beginning with “Au-”) No-Tip Fill Rating (*NTFr*) per treatment (no statistically significant differences between treatments at $\alpha = 0.05$).

CHAPTER 5

CONCLUSION

5. Conclusion

5.1. Developing an Irrigation Scheduling Model for Sweet Corn Based on FAO-56

The results of this study iterate the impact of adequate irrigation on sweet corn yield and quality, specifically in regions with unpredictable precipitation. The science-based irrigation scheduling treatments evaluated during this study resulted in yields greater than or comparable to the average yields from the 12 field seasons for which data were collected in the participating grower fields. The volumetric water content (VWC) and matric potential (MP) approaches require the use of soil moisture sensors, which entails both the cost of purchasing the sensors and the labor for installation after planting and removal prior to harvest. In contrast, scheduling with SmartIrrigation CropFit (SI CropFit) requires only access to hyperlocal precipitation data for best performance, which may require purchasing and installing an automated rain gauge. There is no additional cost to using SI CropFit. In addition, SI CropFit provides the user with information on the accumulation of growing degree days (GDDs) and changes in crop phenology, which can be helpful in making crop management decisions – especially about scheduling harvest, which is typically done manually for fresh market sweet corn. SI CropFit offers the additional advantage of including irrigation scheduling models for maize, cotton, peanut, and soybean, which allows most growers in the southeastern U.S. to use a single tool for scheduling irrigation in most of the crops in their rotation.

Additional plot-scale on-farm testing is needed to assess the SI CropFit sweet corn model's performance and make additional improvements. For the 2025 growing seasons, the model will be made available to selected growers as a beta version for evaluation. Similarly, it will continue to be tested at the University of Georgia's Stripling Irrigation Research Park (SIRP) and compared to other scheduling tools, including the Grower Standard. The project's goal is to publicly release the model for the 2026 growing seasons.

5.2. *Using Remote Sensing to Develop a Crop Coefficient Curve for Sweet Corn*

Quantifying crop evapotranspiration (ET_c), or crop water use, is a complex process that traditionally utilizes instruments such as weighing lysimeters and soil moisture sensors. However, weighing lysimeters are not readily accessible, and soil moisture sensors are expensive and labor-intensive. The normalized difference vegetation index (NDVI)-based methodology used in this study to develop a crop coefficient (K_c) curve for sweet corn appears to be a simpler but reliable approach to developing K_c curves when compared to traditional approaches of estimating daily ET_c using soil moisture sensors or weighing lysimeters. With the availability of public domain and for-pay satellite platforms with ideal spatial and temporal resolution, collecting field-scale reflectance data for many fields throughout multiple growing seasons is no longer a limiting factor and can be done retroactively for past growing seasons.

The NDVI-derived K_c curve that was incorporated into the soil water balance (SWB) model in this study resulted in high yields and good quality but applied more irrigation water than the sensor-based method and the Grower Standard treatment, indicating that further refinement is needed. It is important to remember that the Grower Standard treatment was based on the irrigation scheduling abilities of an experienced grower who has extensive experience using soil moisture sensors for irrigation scheduling. This indicates that incorporating the NDVI-derived

Kc curve into SI CropFit would provide helpful irrigation scheduling to the many sweet corn growers in the southeastern U.S.

5.3. *Irrigation Scheduling Effects on Sweet Corn Physical Attributes and Fresh Market Quality*

Sweet corn quality is crucial in the fresh market, and the United States Department of Agriculture (USDA) has developed stringent standards to ensure fresh market quality. The results of this study emphasized the importance of effective irrigation management in enhancing both the yields and quality of United States (U.S.) Fancy Grade sweet corn, particularly in regions with sandy soils and irregular precipitation patterns. Fewer irrigation events were required in Spring 2024 due to regular precipitation in contrast to the Autumn 2024 season, which had extended periods without precipitation. The Autumn precipitation pattern underscores the need for supplemental irrigation and the need to maintain optimal soil moisture conditions throughout the growing season to achieve high sweet corn fresh market quality. The irrigation management strategy used in the Grower Standard treatment (that was based on years of experience of a leading sweet corn grower) resulted in high yields and good quality and at least matched the best performing of the other scheduling treatments. The sensor and evapotranspiration (ET) -based scheduling treatments used in the study can be improved by reducing the amount of irrigation applied at each event, which may result in more frequent irrigation events.

The ear quality index (EQI) results from the Spring 2024 and Autumn 2024 seasons highlight how environmental factors, such as temperature, variation in daylight hours, and rainfall, influence sweet corn fresh market ear quality. In the Spring 2024 season, most irrigated treatments resulted in “above average” ratings across all quality parameters—ear length rating (*ELr*), no-tip fill rating (*NTFr*), ear diameter rating (*EDr*), as well as EQI —indicating that optimal soil moisture levels

support increased ear fresh market quality. In contrast, the Autumn 2024 season showed a downward shift in quality, with individual parameter ratings and the overall EQI scores being “average” or slightly “below average”. This is likely due to cooler temperatures impacting ear and kernel development. It is also important to iterate that the Grower Standard treatment was used as a benchmark in this study as it was based on the management and irrigation practices of one of the top sweet corn growers in Georgia that has consistently high yields. Both the SWB Updated and MP Dry/Wet treatments produced comparable results to the Grower Standard, with similar results in ear length, no-tip fill, ear diameter, and overall EQI during the Spring and Autumn 2024 growing seasons.

Statistically significant results were not found for most variables evaluated during this study. This was likely the result of high variability within the replicates of some treatments, which may have been affected by the sampling size used to determine yield and quality. In future studies, it may be prudent to significantly increase the number of ears and plants collected during harvest, although this requires a significant increase in the labor required to quantify yield and quality parameters after the ears and plants are collected.

5.4. *Project Conclusion*

This research highlights the significance of increasing irrigation water use efficiency and the importance of meeting sweet corn water requirements with supplemental irrigation when targeting the U.S. Fancy Grade sweet corn market. These studies showed that optimal irrigation management positively impacted key quality parameters related to yield. While there are opportunities for further refinements, such as improving the NDVI-derived crop coefficient curve and increasing sample sizes in future replicated studies, the findings support the ongoing development and implementation of these irrigation models to provide growers in the southeastern

U.S. with practical tools to optimize their irrigation scheduling for better sweet corn yield and fresh market quality. Future field-scale testing will be completed, and resulting model improvements will ultimately be integrated into the SI CropFit sweet corn segment prior to its public release.