Effect of weather variability in sweet corn production under subtropical environment of the Southeastern U.S.

by

Jessica Giordano Paranhos

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Approved by

Andre da Silva, Chair, Associate Professor of Horticulture
Wheler Foshee, Associate Professor of Horticulture
Melba Gutierrez-Salazar, Assistant Professor of Horticulture
Katelyn Kesheimer, Assistant Professor of Entomology
Timothy Coolong, Associate Professor of Horticulture

Abstract

The main goals of this study were to evaluate the performance of commercial sweet corn cultivars in southeastern U.S. and to identify the effect weather variability on cultivar development; to find best practices for nitrogen (N) management and to identify the effect of weather in N management; lastly, to use the CSM-CERES-Sweetcorn model to analyze sweet corn production under different N fertilizer rates and application timing in different weather scenarios. Field trials for this study were conducted in three locations of the State of Georgia, and two locations of the State of Alabama, in 2020, 2021, and 2022. Heavy rainfall events, unpredictable heat and drought stresses, and frequent high-temperature fluctuation create challenges during crop growing seasons. Results indicated that cultivar performance was rather impacted by season rather location, and yields were higher in the spring compared to fall. Affection, GSS1170, Passion, and SCI336 had best performance for most locations in both season and showed high potential against environmental stresses. Higher total soil N was found in treatments with high N rate; however, it was not translated to yield. Moreover, yield did not show a significant difference among treatments, which may be explained by the same amount of N uptake by the plant in all treatments. Nitrogen use efficiency (NUE) was higher in lower N fertilizer treatments, and it was positively correlated to yield. Therefore, there is no need to increase N fertilization to achieve higher yields, instead it will increase N leaching and waste. The CSM-CERES-Sweetcorn model was able to simulate sweet corn growth and development under different N fertilizer rates across two years with different weather patterns. However, the model was not sensitive enough to detect differences in the N fertilizer rates applied, which require further research to improve the model and allow better predictions among the different N fertilizer rates.

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Chapter 1 (Introduction)

Horticulture crops, vegetables and fruits, cover most parts of U.S. agriculture (Johnson, 2014). Particularly, vegetable crops have important nutritional values being a source of vitamins, fibers, and minerals. These characteristics increase human health, reducing the risks of many diseases such as heart and gastrointestinal diseases or diabetes (Silva Dias, 2010).

Maize (*Zea mays* L.) is a cereal crop and one of the most important in the world, playing a significant role in human and animal foods (Adinurani et al., 2019; Budak & Aydemir, 2018). Sweet corn (*Zea mays* L.; Poaceae family), an annual grass and widely grown in temperate and tropical climates (Barros-Rios et al., 2015; Gross et al., 2016), considered one type of maize and only differ from the common maize due to its higher sugar content. Moreover, sweet corn has an important nutritional value, such as higher vitamins A and C compared to maize, low fat and low sodium contents (Adinurani et al., 2019). Particularly, sweet corn can be used for fresh consumption, canned, or frozen (USDA, 2020).

The U.S. is one of the main sweet corn-producing countries (Khan et al., 2017). Sweet corn is well-distributed crop inside the U.S., being produced in all 50 states, and is considered one of 25 main annual vegetable crops produced in the country. It is a commercial valuable crop valued at over U$1.2 billion. Upper Midwest and Pacific Northwest regions are the main regions for processing sweet corn production; and Georgia, Florida, and California are the most important states for fresh market production (Morton et al., 2017).

Sweet corn and maize are examples of grasses crops and those crops have advantages such as better water-use efficiency, better nitrogen use efficiency (NUE), and increased productivity (Leegood, 2016; Kar et al., 2017).

To achieve a higher commercial and nutritional value for this crop, it is necessary to update the current N fertilizer recommendation and provide best plant nutrient management strategies to ensure sweet corn quality, maximize crop yield, and decrease the negative impact of excess of fertilizer being leached to the environment (Calabi-Floody et al., 2018).

Thus, the main goal of this research is to develop a guideline to a better nitrogen recommendation for sweet corn crop as well as to evaluate the performance of 10 cultivars of sweet corn according to the weather variability of each region of the southeastern U.S.

Chapter 2 (Literature Review)

Sweet corn importance and characteristics

Horticulture crops, vegetables, and fruits cover most of U.S. agriculture (Johnson, 2014). Particularly, sweet corn is widely grown due to its economic and cultural importance, which place U.S. as one of the top production countries in the world. It is mainly produced for fresh and processed consumption (canned or frozen) and is a staple of summer picnics and barbecues (Khan et al., 2017; USDA, 2020). In U.S., sweet corn is in the top 25 vegetable crops grown and is one of the most important crops produced in the southeast. Upper Midwest and Pacific Northwest regions are the main regions for processing sweet corn production; Georgia, Florida, and California are the most important states for fresh market production (Morton et al., 2017; USDA-NASS, 2024). In 2023, the U.S. sweet corn production for fresh and processing marked had a value of U$1 billion with over U$330 million coming only from the southeastern U.S. (USDA-NASS, 2024).

Sweet corn (*Zea mays* L.; Poaceae family) is an annual grass crop and widely grown in temperate and tropical climates (Barros-Rios et al., 2015; Gross et al., 2016). It is considered one type of maize, differing from maize only by the higher sugar content, with a high nutritional value (Adinurani et al., 2019; Silva Dias, 2010). Sweetness is the main characteristic of sweet corn which most attracts consumers (Marinho et al., 2019). Another important difference between sweet corn and maize is found in the harvest period, in which maize is harvested when kernels are fully mature and hardened while sweet corn is harvested at “milk stage”, giving the sweet taste and unique texture to this vegetable (Marinho et al., 2019). In short, sweet corn is harvested before reaching physiological maturity, which can be an advantage over maize (Khan et al., 2017). According to Morton et al. (2017), the window to harvest sweet corn is from 65 to 90 days after planting day. However, differences in sweet corn genotype and environments may affect their harvest and storage time (Pairochteerakul et al., 2018).

To increase the sweetness and shelf life, breeding programs have been working on the manipulation of endosperm genes, which control the level of sugar found in the corn kernel (Lertrat & Pulan, 2017). The production of 'super sweet' varieties is increasing in the US, mainly in the most important sweet corn growing regions (Gross et al., 2016). However, super sweet varieties do not show a good performance in the field due to poor seed germination and vigor, more susceptibility to pests and diseases, and reduced yield (Pairochteerakul et al., 2018). Temperature and soil can also be a challenge for production due to their impact on seeding, tasseling, pollination and kernel development, and harvest (Morton et al., 2017).

Sweet corn varieties contain sugar levels greater than 25% during the milking stage when compared to field corn, and its sweet taste comes from a spontaneous mutation in the *su* ("sugary") gene of the field corn, which controls conversion of sugar to starch inside the endosperm of the corn kernel (Singh & Yadava, 2014). Regarding the sugar content in sweet corn, there are three main types of sweet corn including regular sweet corn (su), sugar enhanced sweet corn (se), and super sweet corn (sh2). They differ mainly on sugar content, storage and quality, and seed vigor. The type 'su' is more common among home gardeners and it contains 5-10% of sugar. The 'su' varieties are usually considered early varieties, which has the disadvantage of sugar being quickly turned into starchy after harvest even in a good storage condition. The type 'Se' is sweeter than 'su' as it contains 12-20% of sugar and holds it for a longer time post-harvest/shelf life. The heterozygous hybrids are composed of 25 % of 'se' genotype and 75 % of 'su' genotype; however, the homozygous hybrids have two 100 % of 'se' kernel. Ultimately, the 'Sh2' has a very slow conversion of sugar into starch, which increase storage time (10 to 14 days) but also a higher cost for growers with seeds, which are typically smaller in size (East & Kemble 2021; Singh et al., 2014). Synergistic and augmented shrunken are two other types of sweet corn related to the sweetness, but they are less common. Synergistic is a hybrid between su-1, sh2, and two copies of se, resulting in a very high sugar content and tender kernels. Augmented shrunken or augmented super sweet hybrid is a combination of Su-1, two copies of se, and two copied of sh2, resulting in 100% of tender super sweet varieties (Singh et al., 2014).

Besides the sweetness, sweet corn varieties can differ on kernel color, but the main types of sweet corn grown in the U.S. are yellow, white, and/or bicolor. White kernels have a creamy texture and mild flavor while yellow kernels, the most common in the U.S., are firm with a very sweet and juicy texture. The bicolor kernels are a combination of yellow and white characteristics and flavor (East & Kemble 2021). When growing sweet corn of different color types, isolation is required to avoid cross-pollination. Isolation can be done by distance (215-305 m) or by timing the maturity, ensuring that the tasseling and silking periods (when pollination occurs) of different types do not overlap, usually 10-14 days between varieties (Brandenberger et al., 2006; Hoeft et al., 2000). Regarding sweetness, cross-pollination can affect the taste (lost the sweetness and get starchy), texture, and color of the corn. For instance, supersweet (sh2) types cannot cross-pollinate with 'se' (Sugary Enhanced) or 'su' (normal sugary) types. If this happens, it will result in starchy kernels because 'sweet' genes are recessives, and field corn and popcorn carry dominant gene for starch. If one of them pollinates sweet corn, sweetness will be lost, and the starch will be expressed in the 'sweet' cultivars (Singh et al., 2014).

Most sweet corn breeding programs are focused on increased sugar content instead of yield (Dhaliwal & Williams, 2019) however, a proper agronomic management, good nutrition, and breeding strategies can improve their performance in the field (Pairochteerakul et al., 2018).

Therefore, (N) fertilizer management, one of the most important macronutrients, can be optimized to increase sweet corn yield (Khan et al., 2017 - 2).

Importance of Nitrogen fertilizer

Macronutrients are required in large amounts by the plants, and N is one of the most important macronutrients required by the plants (Khan et al., 2017 – 2; Kumar et al., 2002). The photosynthesis is the main process that allows plants growth, and its rate is directly related to N availability due to the presence of N in proteins, amino acid structures, and in chlorophyll pigments (Evans & Clarke, 2019).

N can be assimilated in different forms by the plants, such as nitrate, nitrite (present in low amounts), and ammonium (can be toxic) (Foyer & Noctor, 2002). Nitrate, the main form of N found in shoots and roots, acts as an important signal in plants, inducing gene expression of enzymes for its own metabolism and development (Campbell, 2002). When nitrate is the main source of N in plants, its conversion to ammonia happens obligatorily to allow the synthesis of amino acids (Rosenblueth et al., 2018). Therefore, the availability of soil N can be a limiting factor in sweet corn production (Rosenblueth et al., 2018) and proper N fertilization ensures increases in the plant's growth and development, increased photosynthetic rates, leaf area, biomass, yield, and helps in a better kernel development and quality (Evans & Clarke, 2019; Leghari et al., 2016; Morton et al., 2017; Sugiyama & Sabakibara, 2002).

Currently, there are challenges that may affect the N uptake by sweet corn plants, such as lack of nutrients in the soil, temperature, precipitation, and soil management, triggering reductions in sweet corn production (Leghari et al., 2016; Morton et al., 2017). The lack of a proper amount of soil N available to plants or the excess of N leads to a significant reduction in growth and development, presence of chlorosis, early senescence, reduced yield, and poor ear quality (Abkar et al., 2002; Capon et al., 2017; Cazetta et al., 1999; Chen et al., 2017; Leghari et al., 2016; Oketem & Oktem, 2005). A good understanding of nutritional requirements for each sweet corn growth stage is, thereby, essential to develop a good fertilization program.

Prior to any fertilizer application, soil testing is highly recommended to check the levels of N in the soil and all other macro and micronutrients available (Stephens & Liu, 2022). At planting or early vegetative stage, it is recommended to use a source of N fertilizer combined with phosphorus (P) and potassium (K) to enhance root development and allow a better initial growth (Jones et al.,1990). The recommended N rate for pre-plant application in sweet corn ranges from 33 to 56 kg N per hectare (Stephens & Liu, 2022). At vegetative growth stage (V6-V14), sweet corn has a rapid nutrient uptake, in this stage N promotes leaf and stem growth and K support continued growth and nutrient transport within the plant. The timing for its application will depend on soil fertility, weather conditions, and genotype/cultivar (Camberato et al., 2017). During tasseling and silking (VT and R1) nutritional needs peek, and adequate amounts of nutrients are crucial for ear development. However, it is also important remember micronutrients, such as zinc (Zn) and boron (B), are required in smaller quantities but critical for optimum yield (Ciampitti and Vyn, 2013). At grain filling (R2-R6) plants require adequate nutrient availability, mainly of N and K, to support kernel development and avoid limitation in yield, however, fertilizer applications are not recommended during this stage (Jones et al.,1990).

The soils in the southeastern U.S. are sandy soils, characterized by low water-holding capacity, high infiltration, low nutrient retention, and high soil surface temperature (Herawati et al., 2021; Kemble et al., 2023). Thus, the recommendation for N fertilization in this region is to apply a total of 140 to 196 kg ha^{-1}, where 45-68 kg ha^{-1} is applied before planting, 22 kg ha^{-1} band-place with planter, and 56-85 kg ha^{-1} at side-dress (12 to 18 inches tall) (Kemble et al., 2023).

However, growers are following the N recommendations for field corn production, and it is common to see N being applied at rates above 336 kg N ha^{-1} to ensure a good yield (Malik & Dechmi, 2019). The main impacts caused by higher amounts of N besides are yield losses, lodging, higher susceptibility to pest and diseases, and the negative impacts on groundwater quality (Calabi-Floody et al., 2018; Chivenge et. Al., 2021) in addition to can be the high cost for growers.

Nitrogen use efficiency (NUE) is a short-term measurement of the balance between N used for grain production and N lost to the environment, describing how effectively plants uptake N by the plants (Chivenge et al., 2021; Congreves et al., 2021; Kumar et al., 2002). However, it is hard to have full control over the NUE by the plants once it might be impacted by extreme weather, such as precipitation and temperatures fluctuations. As a result, the global NUE remains below 40%. One initiative, promoted to help growers with this, is called the 4Rs which focus on the Right source of fertilizer that matches the crop's need; Right rate of the fertilizer, Right time of application, and Right place of application to ensure optimal crop use (Omara et al., 2019; Tao et al., 2018).

The impact of the weather variability

The weather in the southeastern U.S., classified as a humid subtropical climate or warm temperate climate (Cfa), with heavy rainfall events during a hot summer and dry periods during the winter (Beck et al., 2018; Kalvová et al., 2003), makes this region the most important producer in the winter season for sweet corn fresh market (y Garcia et al., 2009). However, climate change and weather variability bring significant challenges to global food production, including to the southeastern U.S. (Rosenzweig et al., 2014), which have brought agricultural and economic consequences (Thornton et al., 2014) due to its direct and indirect impact on crop growth and development. Some of the challenges caused by weather variability may be related to the N availability to the plants and insect pressure on the field.

For instance, southeastern U.S. soils are more susceptible to weather variability (Herawati et al., 2021; Kemble et al., 2023) due to its characteristics. N is a very mobile and unstable nutrient in the soil increasing chances of getting lost (Panison et al., 2019). Heavy precipitation, drought events, or even heat waves may impact the N availability to the plants, leaching, denitrification, and volatilization (Congreves et al., 2016; Fowler et al., 2013; Galloway et al., 2008; Iqbal et al., 2017; Kay et al., 2006).

Besides nitrogen deficiency, the combination of excess water and N fertilizer (mainly nitrate form) in the soil may affect plant growth, furthermore, may increase the nitrate leaching rate through soil and drainage systems due to its mobility and cause negative impacts for both human and environmental healthy (He et al., 2011; Johnson et al., 2021; Silva et al., 2005).

The most common caterpillar pests that affects sweet corn production in the southeastern U.S. are corn earworm (*Helicoverpa zea*), fall armyworm (*Spodoptera frugiperda*), and european corn borer (*Ostrinia nubilalis*). Corn earworm and fall armyworm are predominantly ear feeding pests and European corn borer feeds on multiple parts of the plant. Caterpillar feeding may significantly decrease yield and quality (Kemble et al., 2023; Griffin & Williamson, 2021). Changes in temperature, precipitation, drought, and other weather patterns may cause fluctuations in insect populations, changing their key life cycle as emergence, reproduction, and hibernation (Steven et al., 2004; Prakash et al.2014). Understanding these impacts is crucial for developing effective strategies to mitigate potential threats to agriculture and ecosystems (Karp et al., 2018; Skendzic et al., 2021).

Warmer temperatures can advance insect development and cause earlier emergence, accelerating insect reproduction rates (more generations per year and potentially higher population densities), increase damage to crops, and reduced yields. Extended cold periods or late frosts can delay or disrupt life cycle events (Field et al., 2014; Prakash et al., 2014; Steven et al., 2004).

In sweet corn, the optimal temperature for a better development is around 20-30 °C. However, if higher or lower temperatures are present there may be damage to roots, leaves, grains and, consequently, yield losses. Temperature stress at seeding stage may affect sweet corn growth and yield. Besides temperature, changes in rainfall patterns can also reduce sweet corn production since drought (water stress) or flooding affect seeds germination, growth, biomass, and yield (Revilla et al., 2021).

According to Reilly et al. (2003), changes were observed in yield for different crops (i.e., maize, wheat, potatoes) due to the weather variability. Models predicted a warmer and drier climate, mainly in 2030, which may negatively affect crop production. For the southeastern U.S., the prediction shows a 70% of decrease in soybean, rice, and tomato production due to weather changes, however, may be beneficial for crops such as citrus. Some other studies also show an increase in temperatures, but also a decrease in the rainfall events in temperate regions. These changes may affect sweet corn production. A model prediction for sweet corn shows its season cycle will be decreased in about 20 days due to the higher temperatures, consequently, and yield and water requirements will also be reduced (Revilla et al., 2021).

Crop models can be a key in reducing the impacts caused by weather variability. The weather knowledge allows decision-making by the growers including choosing the best planting date, best fertilizer programs, best management practices and IPM strategies, best harvesting date to ensure better results to the growers and to the U.S. economy (Lazo et al., 2011; Ben-Asher et al., 2008).

Crop model and CSM-CERES-Sweetcorn

Crop models are mathematical equations used to simulate crop growth and development. This tool has been used as new approach in agriculture, making crop simulations and predictions which allows a better decision-making by the growers (Lykhovyd, 2020).

For instance, is it possible to simulate and predict the effects of weather variability on different crops yields over time (Karp et al., 2018). Moreover, crop models may provide insights into the complex relationships between climate, N fertilizer, insect populations, and crop performance, aiding the development of a better N fertilizer program, anticipating pest outbreaks and leading to the implementation of better management strategies (Kasampalis et al., 2018; Jin et al., 2018; Tonnang et al., 2022; Zhao et al., 2019).

Among several software available for crop modeling, the DSSAT (Decision Support System for Agrotechnology Transfer) is a free software available for crop modeling purposes (Zhao et al., 2019). It was designed to be an integrated platform of modeling and to be "self-explained" to users without experience be able to insert data sets and make simulations. However, DSSAT is only able to simulate crop models if the database has enough data. The database includes weather, soil, experiments, pests, genetics, and economics data, and for each one a minimum data set (MDS) is required. For example, a MDS for weather includes daily maximum and minimum temperature, rainfall, solar radiation; a MDS for soil includes color, slope, texture, permeability and more; a MDS of a crop management include the cultivars, planting date, population, row spacing, irrigation type and amount, fertilizer applications and its amounts. Those data are the required data to initiate the simulation of a model (Boote, 2019; Jones et al., 2003; Jin et al., 2018).

Inside the DSSAT software we can find the model CERES (Crop Estimation through Resource and Environment Synthesis) which is a powerful tool to simulate growth, biomass accumulation, yield under different environments and with different crop management (Geng et al., 2017; Zhao et al., 2019). The CERES-Maize is a very popular corn model that has been widely used for predictions on nitrate leaching, uptake, N stressed conditions, phenology and growth, growth response to N, leaf area, biomass, and yield (Adnan et al., 2017; He et al., 2011).

According to Reid (2017), there is still a lack of sweet corn models able to predict growth and development or its responses to environment and weather changes. As we know, sweet corn and maize differ in many aspects such as in the presence of sugar content, ear and kernel growth and development, susceptibility to water stress, root growth, leaf area growth, some nutrients response, and harvest time (Reid, 2017). The differences between maize and sweet corn lead us to understand that there is a need to well adapt maize models to sweet corn crop model. Therefore, Lizaso et al. (2007) were responsible to make the first adaptation of the CERES-Maize model to develop and release the sweet corn growth and development model, the CERES-Sweet Corn model.

CERES-Sweet Corn model had an adjustment in the description of ear and kernel growth and development characteristics. Now, the adjusted model can simulate sweet corn growth as well as simulate best N fertilization, ear growth, ear quality, marketable yield, under different weather conditions (Lizaso et al., 2007; Lone et al., 2020; Jones et al., 2003; Zhang et al., 2019).

Application of crop models can be found in the literature. Yuan et al (2017) used the AMaize model (daily-time-step decision-support system for optimizing N management) to calibrate to sweet corn and simulate the best N practices for sweet corn. The results showed the possibility to reduce around 30-48% of N fertilizer (typical N fertilizer rates described as 200 kg N ha^{-1}) at the same time to enhance crop yield by approximately 40%. Zhang et al. (2019) used three years of wheat data on DSSAT-CERES to identify the best N rates management to achieve a good yield on wheat. Moreover, Malik & Dechmi (2019) used DSSAT-CERES-Maize to improve N management practices got simulations showing growers can reduce the N fertilizer currently applied (390 kg ha^{-1}) to reduce N leaching and still have a good yield. These are examples of how crop models can be applied to agriculture aiming higher quality and profits.

Objectives

The main goal of this project is to promote a sustainable intensification of sweet corn production by minimizing the excessive N-fertilizer applied during growing seasons, mitigate environmental concerns, reduce cost of production, identify the effect of weather variability in different sweet corn varieties in the southeastern U.S., and increase crop yield.

The specific objectives are:

i) To evaluate the performance of commercial sweet corn cultivars in southeastern U.S. and to identify the effect weather variability on cultivar development and selection.

ii) To develop a guideline for optimum N-fertilizer strategies for sweet corn production in the southeastern U.S. and to identify the effects of weather variability on N fertilizer application on sweet corn.

iii) Use the CSM-CERES-Sweet Corn model to analyze sweet corn production under different N rates and timing in different weather scenarios and make future predictions.

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Chapter 3 (Characterization of sweet corn production in subtropical environmental conditions)

Abstract

Weather variability in subtropical environmental conditions of southeastern U.S. impact sweet corn production in the region, which is one of the most important in the country. Understanding sweet corn performance under these environmental conditions is important to help growers with decision making. Thus, the objectives of this study were to evaluate and characterize the performance of ten commercial sweet corn cultivars exposed to several environmental conditions of southeastern U.S. and to describe impacts of weather variability on cultivar development, yield, and ear quality. Field experiments were conducted in five locations of southeastern U.S. during the spring and fall of 2020 and 2021. Weather data, biomass accumulation, yield, and ear quality were measured for all cultivar within seasons and locations. Heavy rainfall events created waterlogging conditions for sweet corn development; however, it was daily air temperature of seasons that mostly impacted yield and ear quality. Daily air temperatures extended the growing season of spring but reduced crop development in the fall. Consequently, biomass accumulation was higher in the spring (4243 kg ha^{-1}) compared to fall (1987 kg ha^{-1}). Biomass accumulation translated into yield, which was, thereby, generally higher in the spring compared fall. Therefore, cultivars with great potential against environmental stresses and best performance for most locations were Affection, GSS1170, Passion, and SCI336 in the spring, and Affection, GSS1170, and SC1136 in the fall. Ultimately, sweet corn yield was strongly correlated to ear dimensions but poorly correlated with number of grains in a kernel, suggesting that breeding programs trying to increase potential yield should be focused on ear diameter and length.

Keywords: weather variability, yield, ear parameters, multivariate analysis.

Introduction

Sweet corn (*Zea mays* subsp. *Mays L.*) is an annual grass and a warm-weather vegetable crop widely grown in the U.S., where it ranks the third most grown vegetable crop [1-3]. Annually planted in approximately 150,178 ha, sweet corn is valued in $775 million with 44% of the national production relying on the environmental conditions of southeastern U.S. [4].

The southeastern U.S. is classified with a humid subtropical climate (Cfa), characterized by heavy rainfall events during summer and dry periods during winter [5,6]. This climate is considered optimal for sweet corn production; however, recent high spatial and temporal variability of regional weather conditions, also known as weather variability, has created challenges for sweet corn production in the southeastern U.S. [5,7,8]. Daily air temperatures have been impacting seed germination, roots and leaf development, tasseling, pollination, grain filling, and yield [9-11]. Particularly, sweet corn yield has been reported to drop in 23% due to heat stress in the southeastern U.S. [7]. Changes in rainfall patters also have been creating challenges [12]. Heat and drought events were reported to increase osmotic stress and reductions on seed germination, plant growth, leaf expansion, and ear development [13]. Whether heat stress is present during ear differentiation, there is decrease in ear length and number of kernel rows. Whether heat stress is present during tasseling, there is a significantly reduction in ear weight [14]. In the case of excessive rainfall events, saturated soils are reported to cause anaerobic conditions in the root zone, reducing water uptake, stomal conductance, photosynthesis rate, and chlorophyll content [13]; ultimately, excessive rainfall events reduce grain fill and ear weight [14].

Overall, the current weather variability of the subtropical climate in the southeastern U.S. requires a better understand of how weather is affecting the sweet corn growing seasons, plant development, yield, and ear quality. Information can help growers to ensure crop quality and potential yields. Thus, the objectives of this study were to evaluate and characterize the performance of ten commercial sweet corn cultivars exposed to several environmental conditions of the southeastern U.S. and to describe the impacts of weather variability on cultivar development, yield, and ear quality.

Materials and Methods

Sites description and experimental design

Field experiments were conducted in collaboration with sweet corn growers during the spring and fall growing seasons of 2020 at three sites in Georgia, U.S., and during the spring and fall growing season of 2021 at two sites in Alabama, U.S. (Table 3.1). All 5 locations were classified within the humid subtropical climate (Cfa), with heavy rainfall events during a hot summer and dry periods during the winter [5-6]. Soil characteristics of each location are shown in Table 3.1.

Table 3.1 Location, geographic coordinates, year, season, soil type, planting space (IRS), planting date (PD), Biomass sampling events (S) in days after planting (DAP), harvesting date, and growing degree days (GDD) accumulated for all field experiments.

							[3]DAP							
Location	Coordinates	Year	Season	Soil type	[1]IRS (cm)	[2]PD	[4]S0	[5]S1	[6]S2	[7]S3	[8]S4	[9]S5	Harvest	[10]GDD
Southwest GA	31.18269ºN	2020	Spring	Troup sand	15.24	April 15	1	43	55	69	-	-	69	898
	84.40958ºW	2020	Fall		17.78	Aug 26	1	14	28	47	66	-	66	928
Southeast GA	32.01807ºN	2020	Spring	Irvington	15.24	June 3	1	14	30	44	58	-	58	930
	82.22108ºW	2020	Fall	loamy sand	17.78	Aug 21	1	19	40	54	68	-	68	898
South GA	31.42378ºN	2020	Spring	Tifton loamy	15.24	April 2	1	47	60	68	-	-	68	877
	83.68807ºW	2020	Fall	sand	17.78	Aug 18	1	15	31	44	57	66	66	916
Southwest AL	31.14055ºN	2021	Spring	Benndale fine	15.24	March 23	1	52	65	85	-	-	85	930
	87.04885ºW	2021	Fall	sandy loam	15.24	Aug 6	1	19	40	63	73	-	73	992
Central AL		2021	Spring		15.24	April 14	1	30	43	64	78	-	78	991

32.50058ºN 85.89150ºW	2021	Fall	Kalmia loamy sand	15.24	Aug 12	1	29	48	64	78	-	78	965

In all locations, a factorial experimental design of sweet corn cultivar was arranged in a complete randomized block design with four replications in the Georgia sites and three replications in the Alabama sites. Sweet corn cultivars (n = 10) are described in Table 3.2. Experimental units were comprised of 80 sweet corn plants in all sites. Crop management practices associated with soil preparation, irrigation, and management of pests, weeds, and diseases followed recommendations of the Southeastern U.S. Vegetable Crop Handbook, for all locations [15].

Table 3.2 Overview of sweet corn commercial cultivars evaluated.

Cultivar	Color	Disease resistance
Passion	Yellow	Rust, HR: Rp1D, IR: Pst, Et
SCI336	Yellow	M: Ps, Et, Pst
Obsession	Bicolor	Ps, Et, Pst
Affection	Bicolor	-
EX08767143	Bicolor	Rust, IR: Et, Pst
Coastal	Bicolor	HR: Ps (Rp1-g)
Flagler	Bicolor	HR: Ps (Rp1-g)
BSS1075	Bicolor	HR: PS: Rp1-i
BSS8021	Bicolor	HR: PS: Rp1-i, Et
GSS1170	Yellow	HR: Et, Ps: Rsp1-i

*HR: high resistance; M: moderate resistance; IR: intermediate resistance; Rp1D, Rp1-g, Rsp1-i, and Rp1-i: genes that confer resistance to *Puccinia sorghi*, agent of common rust; Ps: fungus *Puccinia sorghi* (common rust); Pst: bacteria *Pantoea stewartii* (Stewart's wilt); Et: fungus *Exserohilum turcicum* (northern leaf blight).

Weather data and growing degree days (GDD)

During all growing seasons, daily maximum and minimum air temperature, and rainfall events in each location were monitored using the closest weather station from the Georgia Automated Weather Network or the Auburn University Mesonet.

Accumulated growing degree days (GDD) were determined using the following equation.

$$GDD = \frac{(T\max + T\min)}{2} - Tbase$$

where "Tmax" means average daily maximum temperature, "Tmin" means average daily minimum temperature, "Tbase" means the sweet corn base temperature, which was set at 10 ºC [7].

Biomass accumulation, yield, and ear quality

Sweet corn biomass was monitored with plant tissue samples collected at least 4 times during each growing season (Table 3.1). Samples were comprised of two representative plants of each plot, oven-dried at 65.5°C until a constant weight. Subsequently, sweet corn maximum crop biomass accumulation (NM), sweet corn biomass accumulation rate constant (k), and half maximum sweet corn biomass accumulation (l) of each variety within each season and location was simulated by fitting sweet corn biomass data into the Witty (1983) model [16] using the Sigma Plot Version 14.5 (Systat Software), as follows:

$$Crop\ biomass\ accumulation = \frac{\mathrm{NM}}{1 + e^{-k(t-l)}}$$

where "NM" is maximum crop biomass accumulation, "k" is crop biomass accumulation rate constant, "t" is time in days, and "l" is days to half maximum biomass accumulation.

At maturity, sweet corn ears were harvested in all locations (Table 3.1). During harvest, the number of ears and total weight were recorded. Additionally, five ears were randomly selected from each plot and ear length, ear diameter, number of kernel rows in an ear (KR), number of kernel grains in an ear row (KIR), and the total number of kernels in an ear (KTG) were measured.

Statistical analysis

Statistical analyses were performed using linear mixed techniques as implemented in the SAS PROC GLIMMIX (SAS/STAT 9.4; SAS Institute Inc., Cary, NC). All response variables were analyzed with location, year, and season as fixed effects. Blocks within location and season were considered a random effect. When the F value of the analysis of variance was significant, least-square means comparisons were performed using Tukey's Honest Significant Difference Test ($P<0.05$) and means were portioned using the slice command in SAS.

A multivariate analysis was also performed, using the R Studio software (version 4.0.2), RStudio Team, 2020. The dissimilarity among all response variables (biomass, yield, and ear quality parameters) was measured by the Euclidean distance and presented as a cluster analysis, which was built based on a hierarchical Unweighted Pair-Group Method Using Arithmetic Averages. In addition, all data were submitted to a Principal Component Analysis (PCA) to verify the contribution of biomass, yield, ear quality parameters, cultivars, location, and season to the construction of the principal components. A correlation-based network analysis was also performed using Pearson's method.

Results

Weather data and growing degree days (GDD)

Rainfall events and minimum and maximum daily air temperature of all locations are shown in Figure 3.1, while the total GDD accumulated within each season of all locations is shown in Table 3.1.

In southwest GA, average minimum and maximum daily air temperatures were 17 and 30 ºC during the spring growing season and averaged 19 and 30 ºC during the fall growing season of

2020, respectively. There were 280 and 233 mm of precipitation in spring and fall 2020, respectively.

In southeast GA, average minimum and maximum daily air temperatures were 22 and 33 ºC during the spring season and averaged 18 and 28 ºC during the fall growing season of 2020. There were 218 and 175 mm of precipitation in the spring and fall 2020, respectively.

In south GA, average minimum and maximum daily air temperatures were 15 and 28 ºC during the spring growing season and averaged 18 and 28 ºC in the fall growing season of 2020, respectively. There were 150 and 229 mm of precipitation at the study locations in spring and fall 2020, respectively.

In southwest AL, average minimum and maximum daily air temperatures were 15 and 27 ºC during spring 2021 and averaged 19 and 29 ºC in the fall 2021, respectively. There were 446 and 355 mm of precipitation at the study locations in spring and fall 2021, respectively.

In central AL, average minimum and maximum air daily temperatures were 17 and 29 ºC during the spring growing season and averaged 18 and 29 ºC in the fall growing season of 2021, respectively. There were 303 and 293 mm of precipitation at the study locations in spring and fall 2021, respectively.

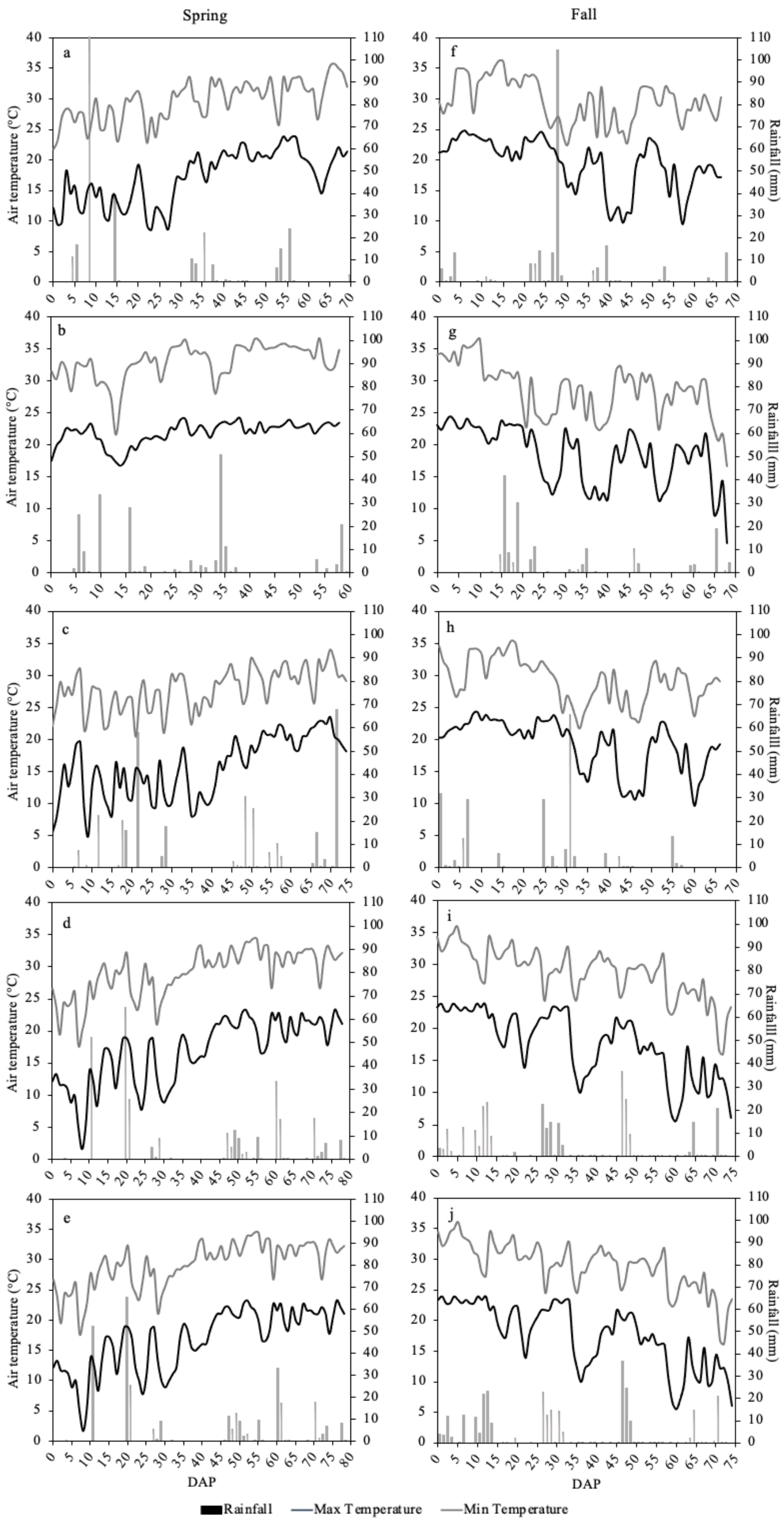
Spring
Fall
a
b
c
d
e
f
g
h
i
j
Air temperature (°C)
Rainfall (mm)
DAP
Rainfall
Max Temperature
Min Temperature

Figure 3.1 Rainfall and maximum and minimum daily air temperature in the spring (a, b, c, d, and e) and fall (f, g, h, i, and j) of southwest GA (a and f), southeast GA (b and g), south GA (c and h), southwest AL (d and i), and central AL (e and j).

Biomass accumulation

Biomass accumulation was not statistically compared among cultivars, locations, and seasons. Instead, biomass accumulation was fitted in the Witty (1983) model for characterization of the performance of sweet corn cultivars [16]. Table 3.3 has the NM, l, and k values for all cultivars within each season and location. In general, the NM of sweet corn cultivars were greater in the spring season compared to fall season within all locations. While l and k, which indicate sweet corn growth, were greater for the fall season compared to spring season.

Table 3.3. Effect of cultivar, location, and season on sweet corn maximum biomass accumulation (NM), days to reach half biomass (l), and crop biomass accumulation rate (k).

Cultivar	Southwest GA		Southeast GA		South GA		Southwest AL		Central AL	
	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall
	NM (kg ha^{-1})									
Affection	3505	1663	4030	2293	2819	1833	456	1418	9448	1754
BSS1075	3880	2127	5946	2638	2759	2137	1833	1678	8372	2671
BSS8021	3418	1947	4971	1777	2762	2209	486	1739	7056	1880
Coastal	3280	1749	3307	2460	3029	2010	604	1009	8731	2207
EX08767143	3475	1884	4641	2471	2726	2190	1237	1327	9568	2232
Flagler	3433	2084	4263	2474	3193	2266	1167	1610	9807	1798
GSS1170	3534	2191	4577	2221	2656	2219	506	1103	9149	1862
Obsession	3522	1784	5409	2546	2721	2073	1053	1731	10525	2107
Passion	3851	1959	5468	2546	2394	2189	879	1391	8731	2043
SCI336	3506	2262	5115	2456	2457	2179	1150	1338	10764	1618
	l (days)									
Affection	43.2	29.2	37.8	41.2	47.3	31.8	51.7	-	46.2	29.8
BSS1075	42.9	29.3	38.7	39.8	48.7	34.1	52.6	-	46.4	29.6

BSS8021	42.6	29.6	38.5	15.2	51.6	33.7	52.1	-	46.0	29.6
Coastal	42.7	29.0	35.9	34.0	47.1	34.5	52.1	-	46.0	30.0
EX08767143	42.7	29.0	36.2	36.8	45.7	37.0	52.3	-	46.4	29.9
Flagler	42.9	30.9	38.2	39.7	51.5	36.5	52.6	-	46.2	3.00
GSS1170	43.3	35.3	37.3	40.0	47.7	35.5	51.8	-	46.1	29.6
Obsession	42.9	32.2	39.0	39.7	49.3	33.6	52.6	-	46.3	30.1
Passion	41.7	29.1	38.5	38.2	51.0	34.6	52.0	-	46.3	29.6
SCI336	40.4	37.7	39.0	40.4	45.3	36.3	54.6	-	46.4	30.3
					k					
Affection	1.681	0.939	0.203	0.199	0.203	1.293	1.557	1.392	1.159	1.176
BSS1075	1.703	0.721	0.148	1.509	0.241	0.276	1.621	1.427	1.184	1.086
BSS8021	1.719	0.648	0.15	0.298	0.126	0.163	1.735	1.432	1.129	1.095
Coastal	1.622	0.808	0.187	0.079	0.133	0.227	1.612	0.429	1.173	1.111
EX08767143	1.325	0.6	0.202	0.117	0.167	0.141	2.604	1.423	1.172	1.193
Flagler	1.612	0.265	0.133	0.213	0.125	0.237	1.529	0.062	1.172	1.188
GSS1170	1.79	0.183	0.184	0.225	0.244	0.177	0.051	1.323	1.138	1.126
Obsession	1.817	0.227	0.173	1.437	0.134	0.35	1.661	1.413	1.247	1.088
Passion	0.209	0.682	0.152	0.203	0.138	0.236	-	1.356	1.192	2.069
SCI336	0.206	0.142	0.158	0.229	0.215	0.161	0.395	1.378	1.198	1.105

Sweet corn yield

Sweet corn yield was significantly impacted by the interaction among cultivar, location, and season (Table 3.4).

In southwest GA, cultivars Obsession (24.3 Mg ha^{-1}) and Passion (24.3 Mg ha^{-1}) had the highest yields in the spring, while cultivars GSS1170 (27.6 Mg ha^{-1}) and Affection (25 Mg ha^{-1}) had the highest yields in the fall. In southeast GA, cultivars EX08767143 (26.7 Mg ha^{-1}) and Coastal (23.7 Mg ha^{-1}) had the highest yield in the spring, while cultivars Affection (28.2 Mg ha^{-1}) and Coastal (27.8 Mgha^{-1}) had the highest yields in the fall. In south GA, cultivars Coastal (19.1 Mg ha^{-1}), Affection (17.7 Mg ha^{-1}) and GSS1170 (17.7 Mg ha^{-1}) had the highest yields in the spring, while cultivars Affection (32.1 Mg ha^{-1}) and SCI336 (30.5 Mg ha^{-1}) had the highest yields in the fall. In southwest AL, cultivars Coastal (35.8 Mg ha^{-1}) and BSS1075 (23.9 Mg ha^{-1}) had the highest yields in the spring, while cultivars SCI336 (15 Mg ha^{-1}) and GSS1170 (14.8 Mg ha^{-1}) had the highest yields in the fall. In central AL, cultivars EX08767143 (26.5 Mg ha^{-1}) and SCI336 (25.7 Mg ha^{-1}) had the highest yields in the spring, while cultivars EX08767143 (19.7 Mg ha^{-1}) and BSS1075 (16.7 Mg ha^{-1}).

For the yield comparison among cultivar in the spring and fall seasons within each location, cultivar Affection had the highest yield, which had no significant difference among location within the fall growing season. Cultivars BSS1075 and BSS8021 had the highest yield in the spring of southwest AL and central AL, and in the fall of southeast GA and south GA. Cultivar Coastal had the highest yields in the spring of central AL and southwest AL, and in the fall of southwest GA, southeast GA, and south GA. Cultivars EX08767143 and Flagler performed similarly and had the highest yields in the spring of southwest GA, southeast GA, southwest AL, and central AL, and in the fall of southwest GA and south GA. Cultivar GSS1170 had the highest yields in the spring for southwest AL, central AL, and southeast GA, and in the fall of southwest GA, south GA, and southeast GA. Cultivars Obsession and Passion had the highest yields in the spring of southwest AL, central AL, and southwest GA, and in the fall of southeast GA and south GA. Cultivar SCI336 had similar yield for all locations in both spring and fall seasons, except for the spring in south GA.

Table 3.4. Effect of the interaction among sweet corn cultivar, season, and location on sweet corn total yield.

Cultivar	Southwest GA		Southeast GA		South GA		Southwest AL		Central AL	
	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall
						Mg ha^{-1}				
Affection	22.8±1.7 B[y]a[z]	25.0±1.2 Aab	18.7±2.5 Bbc	28.2±2.2 Aa	17.7±2.2 Bab	32.1±4.6 Aa	20.4±5.9 Abcd	12.3±1.3 Ba	25.2±2.7 Aa	16.4±0.3 Bab
BSS1075	21.3±0.7 Aa	19.6±0.2 Ac	20.1±0.2 Abc	22.3±0.7 Abcd	16.4±0.8 Bab	19.1±0.6 Ae	23.9±1.5 Aab	8.5±2.6 Ba	23.1±2.0 Aab	16.7±0.4 Bab
BSS8021	22.1±0.8 Aa	21.3±1.8 Bbc	16.3±1.8 Ac	19.1±2.0Ad	14.2±1.1 Bab	19.6±0.7 Ae	23.1±2.7 Aab	9.5±0.8 Ba	19.2±3.0 Ab	8.7±0.6 Bc
Coastal	19.9± 1.6 Ba	22.1±0.5 Abc	23.7±3.7 Bab	27.8±1.9 Aab	19.1±2.0 Ba	25.7±1.1 Abcd	35.8±1.2 Aa	9.5±0.3 Ba	24.8±2.5 Aab	12.1±0.8 Bbc
EX08767143	23.2±1.7 Aa	22.2±0.4 Abc	26.7±2.5 Aa	25.4±0.6 Babc	17.2±1.0 Bab	26.1±1.2 Abc	19.7±2.4 Abcd	11.7±0.7 Ba	26.5±3.3 Aa	19.7±0.8 Ba
Flagler	22.0±1.1 Aa	20.6±0.5 Abc	19.9±0.9 Abc	23.5±1.0 Aabcd	17.2±1.3 Bab	23.8±0.8 Acde	26.7±0.9 Ab	12.1±0.2 Ba	23.7±3.1 Aab	15.1±0.7 Babc
GSS1170	22.5±1.1 Ba	27.6±2.3 Aa	19.9±2.4 Abc	24.9±2.1 Aabc	17.7±1.9 Bab	25.8±1.1 Abc	21.1±1.1 Aabcd	14.8±1.6 Ba	25.0±2.2 Aab	11.5±1.2 Bbc
Obsession	24.3±3.1 Aa	19.6±0.7 Bc	18.2±2.3 Bc	24.5±1.3 Aabc	14.6±2.1 Bab	20.7±1.6 Ade	16.4±2.8 Ad	11.8±0.8 Ba	23.2±1.0 Aab	14.9±0.7 Babc
Passion	24.3±0.6 Aa	20.7±1.2 Bbc	19.2±1.5 Abc	21.3±1.5 Acd	12.7±1.8 Bb	22.2±1.0 Acde	20.0±10.8 Abcd	11.9±0.8 Ba	23.4±2.0 Aab	16.4±0.5 Bab
SCI336	23.2±0.5 Aa	23.9±0.7 Aabc	23.5±3.2 Aab	24.8±3.2 Aabc	15.0±1.5 Bab	30.5±2.1 Aab	16.8±7.5 Acd	15.0±1.0 Ba	25.7±2.0 Aa	21.2±0.1 Aa

[y] Values followed by similar uppercase letters among season (column) within cultivar (row) indicate no significant difference according to the Tukey mean test. [z] Values followed by similar lowercase letters among cultivar (row) within season (column) indicate no significant difference according to the Tukey mean test.

Ear quality parameters

Among all ear quality parameters (i.e., ear diameter, ear length, KR, KIR, and KTG, there was a significant interaction between cultivar and location for KTG (Table 3.5); between location and season for ear diameter, KR, KIR, and KTG (Table 3.6); and between cultivar and season for ear diameter and ear length (Table 3.7).

For the main effect of cultivar on KTG (Table 3.5), location cultivars SCI336 (671) and BSS1075 (651) had the highest KTG in southwest GA, cultivars Obsession (596) and BSS1075 (594) had the highest KTG in southeast GA, cultivar GSS1170 (602) had the highest KTG in south GA, cultivar Coastal (528) had the highest KTG in southwest AL, and cultivars Passion (640), EX08767143 (627), and SCI336 (620) had the highest KTG in central AL.

For the main effect of location on KTG within cultivars, southwest GA had the highest KTG within cultivars Affection (581), BSS1075 (651), EX08767143 (617), and SCI336 (671). Southeast GA had the highest KTG within cultivars BSS8021 (533), GSS1170 (588.0), and Obsession (596). South GA had the highest KTG within BSS8021 (526), Costal (571), Flagler (572), GSS1170 (602), and Obsession (546). Southwest AL had the highest KTG only within cultivar BSS8021 (465). Central AL had the highest KTG within cultivars BS8021 (511), Costal (576), EX08767143 (627), Obsession (581), and Passion (640).

Table 3.5. Effect of the interaction between sweet corn cultivar and location for kernel total grains (KTG).

Cultivar	Southwest GA		Southeast GA		South GA		Southwest AL		Central AL	
Affection	581 ± 30.4	A[y]bc [z]	520 ± 17.3	ABbc	504 ± 27.7	BCc	444 ± 24.3	Cb	574 ± 34.7	ABabc
BSS1075	651 ± 25.4	Aa	594 ± 17.8	Aba	581 ± 18.4	Bab	476 ± 53.8	Cab	594 ± 24.5	ABabc
BSS8021	533 ± 21.6	Ac	514 ± 23.1	Ac	526 ± 20.7	Abc	465 ± 23.1	Aab	511 ± 37.2	Ac
Coastal	552 ± 19.2	Abc	470 ± 16.2	Bc	571 ± 38.3	Aab	528 ± 45.5	ABa	576 ± 37.4	Aabc

EX08767143	617 ± 43.3	Aab	521 ±24.2	Bbc	526 ± 18.4	Bbc	491 ± 45.0	Bab	627 ± 30.4	Aa
Flagler	533 ± 21.9	ABc	512 ± 27.0	ABc	572 ± 23.3	Aab	467 ± 37.8	Bab	534 ± 31.3	ABbc
GSS1170	551 ± 16.1	ABbc	588 ± 23.8	Aab	602 ± 36.0	Aa	487 ± 3.81	Bab	574 ± 36.3	ABabc
Obsession	576 ± 38.1	Abc	596 ± 31.4	Aa	564 ± 28.5	Aabc	478 ± 44.1	Bab	581 ± 39.2	Aabc
Passion	580 ± 30.0	ABbc	589 ± 25.9	ABab	529 ± 29.4	BCbc	471 ± 25.6	Cab	640 ± 52.3	Aa
SCI336	671 ± 50.1	Aa	583 ± 21.9	Bab	581 ± 26.2	Bab	487 ± 48.9	Cab	620 ± 25.0	Aba

[y]Values followed by similar uppercase letters among location (column) within cultivar (row) indicate no significant difference according to the Tukey mean test. [z]Values followed by similar lowercase letters among cultivars (row) within location (column) indicate no significant difference according to the Tukey mean test.

In the interaction between location and season for ear quality parameters (Table 3.6), the main effect of location within season indicated that ear diameter means were similar between spring and fall seasons in southwest GA (4.3 and 4.4 cm, respectively) and central AL (4.7 and 4.8 cm, respectively). In southeast GA and southwest AL, ear diameter was higher in the spring (4.4 and 4.6 cm, respectively) compared to the fall season (4.2 and 4.3 cm, respectively); contrarily, ear diameter was higher in the fall (4.5 cm) compared to spring (4.2 cm) in south GA. For the main effect of season within location, ear diameter was largest in Central AL for both the spring and fall seasons.

The KR were similar between spring and fall seasons for all locations, except in southwest GA where the KR were larger in spring (17.7) compared to fall (16.3). Contrarily, the KIR was higher in the spring compared to the fall for all locations, except in southeast GA where KIR was statistically similar in the spring (33.7) and fall (34.2). The average KTG in the spring was higher than in the fall for all locations, except in southeast GA where the KTG were statistically similar between spring and fall seasons (552 and 544, respectively). For the main effect of season, individually, the largest KR in the spring was in southwest GA (17.7), and the largest KR in the fall was in south GA and southwest GA (16.6 and 16.3, respectively). The largest KIR in the spring was in central AL (39.0), and the largest KIR in the fall was in southeast GA and central AL (34.2 and 34.1, respectively). The KTG in the spring was the highest in southwest GA and central AL

(632 and 621, respectively), and the largest KTG in the fall was in the southeast GA (544), central AL (539), southwest GA (536), and south GA (528).

Table 3.6. The interaction between season and location for ear diameter, kernel rows (KR), kernel grains in a row (KIR), and kernel total grains (KTG).

Location	Season							
	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall
	Ear diameter		Kernel rows		Kernel grains in a row		Kernel total grains	
	cm		#		#		#	
Southwest GA	4.3±0.02 A[y]cd[z]	4.4±0.02 Abc	17.7±0.3 Aa	16.3±0.3 Ba	35.8±0.3 Abc	32.9±0.4 Bab	632±13.4 Aa	536±12.5 Ba
Southeast GA	4.4±0.03 Abc	4.2±0.02 Bd	16.4±0.3 Ab	16.0±0.2 Aab	33.7±0.5 Ad	34.2±0.5 Aa	552±13.0 Abc	544±11.0 Aa
South GA	4.2±0.07 Bd	4.5±0.03 Ab	15.9±0.4 Abc	16.6±0.3 Aab	37.0±0.5 Ab	31.9±0.5 Bab	583±12.6 Ab	528±10.9 Ba
Southwest AL	4.6±0.12 Aab	4.3±0.02 Bcd	15.2±0.3 Abc	15.4±0.2 Ab	35.3±0.7 Ac	27.9±0.6 Bc	534±15.8 Ac	428±11.1 Bb
Central AL	4.7±0.03 Aa	4.8±0.06 Aa	16±0.4 Abc	15.8±0.3 Aab	39.1±0.5 Aa	34.1±0.5 Ba	621±15.7 Aa	539±12.9 Ba

[y] Values followed by similar uppercase letters among season (column) within location (row) indicate no significant difference according to the Tukey mean test. [z] Values followed by similar lowercase letters among location (row) within season (column) indicate no significant difference according to the Tukey mean test.

There was a significant interaction between cultivar and season for ear diameter and ear length (Table 3.7). For the main effect of cultivar within season, the ear diameter was similar between spring and fall seasons for all cultivars, except by Coastal which ear diameter was higher in spring (4.7 cm) compared to fall (4.5 cm), and cultivar SCI336 which ear diameter was higher in the fall (4.5 cm) compared to spring (4.3 cm). Ear length was higher in the spring compared to fall, regardless of cultivar. For the main effect of season within cultivar on ear diameter, the highest ear diameter in the spring was measure within cultivar Coastal (4.7 cm) but the lowest within cultivar BSS8021 (4.3 cm). The highest ear diameter in the fall was measured within cultivars SCI336 (4.5 cm) and Affection (4.5 cm) and the lowest within cultivar BSS8021 (4.1 cm). The longest ear length in the spring season was measured within cultivar EX08767143 (18.8 cm); while cultivar Costal (17.3 cm) had the longest ear length in the fall season. The cultivar Affection had the lowest ear length in both the spring and fall seasons (17.5 and 16.4 cm, respectively).

Table 3.7 The interaction between sweet corn cultivar and season for ear diameter and ear length.

Cultivar	Season							
	Spring		Fall		Spring		Fall	
	Ear diameter				Ear Length			
	cm				cm			
Affection	4.4 ± 0.10	A[y]bc [z]	4.5 ±0.06	Aa	17.5 ± 0.33	Ae	16.4 ± 0.33	Bd
BSS1075	4.5 ± 0.06	Aab	4.5 ± 0.08	Aab	18.2 ± 0.13	Aabcd	16.5 ± 0.30	Bcd
BSS8021	4.3 ± 0.06	Ac	4.1 ± 0.04	Ad	17.6 ± 0.17	Ade	17.0 ± 0.20	Babc
Coastal	4.7 ± 0.18	Aab	4.5 ± 0.05	Babc	18.6 ± 0.28	Aab	17.3 ± 0.27	Ba
EX08767143	4.4 ± 0.08	Abc	4.5 ± 0.06	Aab	18.8 ± 0.24	Aa	16.7 ± 0.25	Bbcd
Flagler	4.4 ± 0.06	Abc	4.5 ± 0.05	Aab	18.6 ± 0.21	Aab	17.0 ± 0.20	Bab
GSS1170	4.4 ± 0.05	Abc	4.4 ± 0.06	Abc	17.7 ± 0.17	Acde	16.9 ± 0.18	Babcd
Obsession	4.3 ± 0.07	Abc	4.4 ± 0.05	Ac	18.1 ± 0.31	Abcde	16.7 ± 0.26	Bbcd
Passion	4.4 ± 0.08	Abc	4.4 ± 0.05	Abc	18.4 ± 0.34	Aabc	16.8 ± 0.25	Babcd
SCI336	4.3 ± 0.07	Bbc	4.5 ± 0.08	Aa	17.9 ± 0.30	Acde	16.7 ± 0.20	Bbcd

[y] Values followed by similar uppercase letters among season (column) within cultivar (row) indicate no significant difference according to the Tukey mean test. [z] Values followed by similar lowercase letters among cultivar (row) within season (column) indicate no significant difference according to the Tukey mean test.

Multivariate and Correlation Analysis

For the PCA, cultivars within location and season were considered an individual (Figure 3.2). For example, cultivar Affection grown in the spring season of southwest GA was an individual. Individuals were clustered in two groups, with PC1 and PC2 explaining 58.1% of the total variance of the data. Most individuals were clustered together in the largest group (represented by the blue color in Figure 3.2a) that had the highest values for all variable responses, except for the number of ears per plant (EAR). The second cluster group (represented in red color in Figure 3.2a) had a lower number of individuals compared to the first cluster group. Particularly, the second cluster group had higher values of EAR compared to the first cluster group.

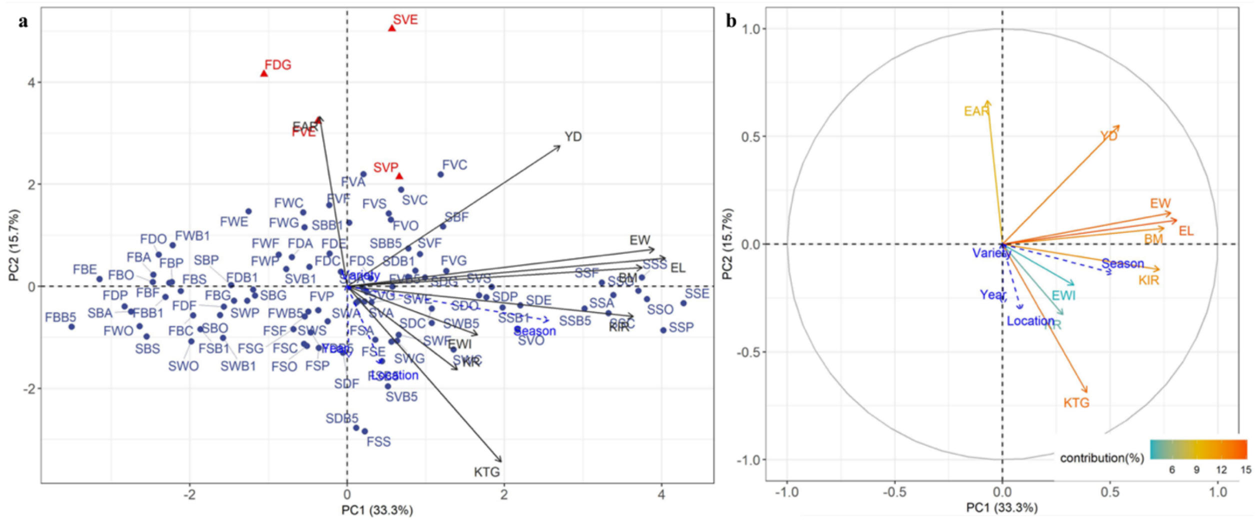

Figure 3.2 The principal component analysis (PCA) biplot is split into two graphics of all individuals and variables distribution and clustering (a) and variables correlation and contribution plot (b). Note: In figure a, first letter indicates season (S=Spring, F=Fall); second letter indicates location (D=Southwest GA, W=South GA, V=Southeast GA, S=Central AL, B=Southwest AL); third and fourth letter indicates cultivars (A=Affection, B5=BSS1075, B1=BSS8021, C=Coastal, E=EX08767143, F=Flagler, G=GSS1170, O=Obsession, P=Passion, S=SC1336). In figure b, EAR=number of ears, YD=yield, EW=ear weight, EL=ear length, BM=biomass, KIR=kernel grain in a row, EWI=ear width or diameter, KR=kernel row grain, KTG=kernel total grains.

In the variable correlation analysis (Figure 3.2b), variable responses were all clustered on the right side of the plot, except for EAR, indicating that yield, ear weight, biomass, ear length, and KIR are positively correlated. Variables KTG, KR, and ear width were negatively correlated with EAR. The quality of the response variables can be analyzed through the distance between them and the origin in the plot. Variables that are far away from the origin are well represented in the data, for instance, the EAR, yield, ear weight, ear length, biomass, KIR, and KTG are variables with the highest quality of response. The contribution of the response variables is represented in percentage (%) where the "warmer" color represents a high percentage of contribution. For instance, the KR and ear width had a lower percentage of contribution; contrarily, yield, ear weight, ear length, and KTG had a higher percentage of contribution.

The Person's correlation analysis (Figure 3.3) indicated that sweet corn yield is positively correlated to ear weight and biomass. Similarly, ear length had a positive correlation with biomass, ear weight, and KIR. The KTG was positively correlated with KIR and KR; contrarily, the KTG has a negative correlation with EAR.

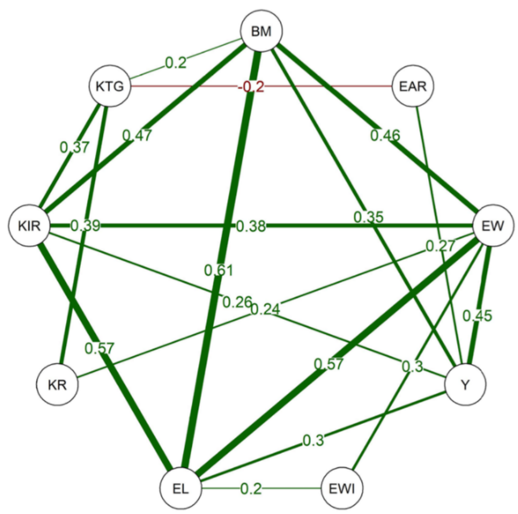

Figure 3.3 Correlation-based network analysis using Pearson's correlation method to compare all response variables, number of ears per plant (EAR), ear weight (EW), yield (Y), biomass (BM), ear diameter (EWI), ear length (EL), kernel rows (KR), kernel grains in a row (KIR), and kernel total grains (KIR).

Discussion

Climate change and weather variability have impacted growth and development of vegetable crops worldwide [17-23]. In the southeastern U.S., heavy rainfall events, unpredictable heat and drought stress, and frequent high-temperature fluctuation reduce sweet corn crop development, resulting in decreased yields and quality [19,24-27]. The impact of the weather variability is further enhanced by the common use of super sweet cultivars of sweet corn, which have the highest potential yield but are the most sensitive for drastic changes in daily air temperature and soil water availability [28]. Understand the plant response to environmental conditions and selecting the most adaptable cultivar for the subtropical environmental conditions is the first step of developing best management practices for sweet corn production in the southeastern U.S.

Rainfall accumulations were similar across locations and seasons, matching the crop water requirements of 268 mm for sweet corn grown in the southeastern U.S. [29]. However, scattered heavy rainfall events caused soil water saturation conditions, creating anaerobic conditions that reduce root growth while induce soil nutrient leaching [30]. Such heavy rainfall events occurred at 8 DAP (110 mm) in the spring and at 21 DAP (104 mm) in the fall of southwest GA, at 32 DAP (50 mm) in the spring and at 20 DAP (42 mm) in the fall of southeast GA, at 21 DAP (58 mm) and 70 DAP (68 mm) in the spring and 29 DAP (65 mm) in the fall of south GA; as well as, at 18 DAP (81 mm) and 32 DAP (59 mm) in the spring and at 24 DAP (65 mm) in the fall of southwest AL, and at 10 DAP (52 mm) and 21 DAP (65 mm) in the spring of central AL. Particularly, southwest AL was the location with the largest number of rainfall events and accumulated rain, which explain the lowest yield of sweet corn cultivars within that location for both growing seasons. Cultivar Coastal stood out from the other cultivars in southwest AL and showed a high potential to have a good ear development and yield even in waterlogging conditions.

Average daily air temperatures were also similar among locations and seasons and were within optimal range for sweet corn production, which varies between 20-30 ºC [24,26]. In general, daily air temperatures were lower than the optimal for sweet corn production early spring, when sweet corn plants were in the vegetative stage, but daily air temperature increased and reached optimum levels during late spring, when sweet corn plants were at ear development. Low daily air temperatures in the early spring reduced GDD accumulation in the vegetative stage. Consequently, there was an increase in sweet corn l that allowed higher NM values during spring compared to fall. Ultimately, the extended growing season in the spring compared to fall allowed for the highest sweet corn yields [31-33]. Particularly, daily air temperatures later in the spring increased and were within optimum levels during sweet corn reproductive stages for all location, except in southeast GA, which had 20 days with daily air temperatures above 30 ºC during reproductive stages. Daily air temperatures above the optimum for sweet corn crop development decreased yield potential [16]; still, cultivars EX08767143 (26.7 Mg ha^{-1}), Coastal (23.7 Mg ha^{-1}), and SCI336 (23.5 Mg ha^{-1}) had the largest yields for that location demonstrating tolerance to heat stress.

During the fall season, daily air temperatures were higher early season and reduced with crop development. In response, there was a quick GDD accumulation that increased sweet corn k and shortened the period between planting and harvest. This negatively impact ear diameter, KIR, KR, and KTG, which was caused because the poor biomass accumulated during the vegetative stage was not able to ensure grain filling during the reproductive stage [34]. Consequently, the shorter growing season of fall compared to spring resulted in the lowest sweet corn yields. Similar results were previously reported in cabbage production for southeastern U.S., where high temperatures early fall shortened the vegetative stage and reduce cabbage head size [35].

Overall, season followed by location were the main factors impacting sweet corn cultivars performance according to the PCA, which corroborate with previous studies [24-26]. Cultivars with best performance in the spring were Affection, GSS1170, Passion, and SCI336, and in the fall were Affection, GSS1170, and SC1136. Results also indicate that sweet corn yield is strongly correlated to ear width and ear length but poorly correlated with KTG, suggesting that breeding programs trying to increase the potential yield in sweet corn should be focused on ear dimensions instead KR, KIR, and KTG.

Conclusion

Weather variability in the humid subtropical environmental conditions of southeastern U.S. is impacting sweet corn production. Particularly, heavy rainfall events, unpredictable heat and drought stresses, and frequent high-temperature fluctuation create challenges during crop growing seasons. In this study, sweet corn cultivars were evaluated for five locations of southeastern U.S. in the spring and fall. Daily air temperatures had a direct impact in sweet corn development, yield, and ear quality, while heavy rainfall events caused situations of waterlogging conditions in all locations for both growing seasons. Results indicated that cultivar performance was rather impacted by season than location. Low daily air temperatures early spring delayed crop growth and allowed for larger biomass accumulation in the spring compared to the fall, when high daily air temperatures shortened the growing season. Sweet corn yields were, thereby, higher in the spring compared to fall. Overall, heavy rainfall events negatively impacted sweet corn development, and cultivars with great potential against environmental stresses and best performance for most locations were Affection, GSS1170, Passion, and SCI336 in the spring growing season, and Affection, GSS1170, and SC1136 in the fall growing season.

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Chapter 4 (Rethinking the sweet corn nitrogen fertilization in the Southeastern U.S.)

Abstract

Sweet corn (*Zea mays* convar. *saccharata var. rugosa*) is a key crop in the U.S., particularly in the southeastern region. Nitrogen (N) management is critical for optimizing yields, yet sandy soils and variable precipitation in this area affects N uptake. This study evaluated the effects of N fertilizer rate and timing on sweet corn growth and yield under Southeastern U.S. conditions. Field experiments were conducted at the University of Georgia and Auburn University over three years. Field experiments were in a complete randomized block design, with 5 N rates (from 224 to 336 kg ha^{-1}) and two application timing (N_{eme} and N_{sd}) in a combination of 6 treatments. Higher N rates generally increased leaf area index (LAI), biomass, and total N uptake. However, excessive N led to increased N leaching, particularly during heavy rainfall events. Optimal yields were achieved at moderate N rates. The interaction between N rates and climatic conditions significantly influenced sweet corn performance. Effective N management, considering both application timing and environmental factors, is crucial for maximizing yields and minimizing negative impacts. This study highlights the importance of N management strategies in sweet corn production in the Southeastern U.S. to optimize yields while mitigating environmental risks. Further research is needed to refine these strategies and improve model predictions under varying climatic conditions.

Keywords: N fertilizer management, splitting N application, weather variability

Introduction

Sweet corn (*Zea mays* convar. *saccharata* var. *rugosa*) is one of the most important vegetables in the U.S., with more than 3 mil tons produced a year, and the southeastern region represents 44% of the total sweet corn national production (USDA, 2022). However, significant precipitation and sandy soils common in the southeastern U.S. can affect nitrogen (N) fertilizer uptake and utilization, impacting yields (Leghari et al., 2016; Morton et al., 2017).

N is the most crucial nutrient for crop productivity (Revilla et al., 2021) playing an essential role in plant growth and development, leading to increases in yield and food quality (Leghari et al., 2016). This is not different in sweet corn as N is the most critical nutrient and plays an essential role in both vegetative and reproductive stages (Khan et al., 2018) and can be a limiting factor in its production affecting plants growth and quality of the kernels (Oktem et al., 2010)

An adequate supply of N in sweet corn triggers increases in growth, and kernel quality (Sugiyama & Sabakibara, 2002); its deficiency or excess can lead to decreased plant growth, presence of chlorosis, low ear quality, and low yields (Leghari et al., 2016; Evans & Clarke, 2019; Oketem & Okte, 2005). Excessive applications of N fertilizer can reduce yields and have negative impacts on the environment, such as groundwater pollution, and harm human and animal health (Calabi-Floody et al., 2018).

At or before the planting date, the use of N fertilizer is recommended to provide adequate N for initial growth (Stephens & Liu, 2022). At early vegetative stages, rapid nutrient uptake by plants happens, and the use of N fertilizer enhances root development, ensures plant establishment, and promotes leaf and stem growth (Camberato et al., 2017; Jones et al.,1990). At the side dress stage or mid-vegetative stages, the N fertilizer application is crucial for proper ears and kernel development and consequently to increase the final yield (Panison et al., 2019). Khan et al (2018) showed significant increases in sweet corn yield when N rates were raised from an untreated control (0 kg N ha^{-1}) up to 120 kg N ha^{-1}. Gao et al (2017) achieve the highest yield with 250 kg N ha-1 in sweet corn trials. Oktem et al (2010) defined the best N rate for sweet corn yield and quality as being 320 kg N ha^{-1}.

In an effort to increase yields, sweet corn growers may overfertilize with N which can increase input costs, but also negatively impact the environment. Thus, the objectives of this study were to evaluate the effect of N fertilizer rate and application timing on sweet corn development and yield under the environmental conditions of the Southeastern U.S. Hence, knowledge of nutrient management and application timing is extremely important to find a balance that benefits both growers and the environment, reducing risks and increasing yield and quality.

Materials and Methods

Sites description and experimental design

Field experiments were conducted at the University of Georgia, Vidalia Onion and Vegetable Research Center (32.01814ºN 82.22138ºW), located in Southeast GA, in 2020; and at Auburn University, E.V. Smith Research Center (32.50053ºN 85.89281ºW), located in Central AL, during 2021 and 2022. Field experiments in each growing season were characterized with a loamy sand soil (Table 4.1). According to the Kopen-Geiger climate classification, all locations are classified as a humid subtropical climate or warm temperate climate (Cfa), with heavy rainfall events during a hot summer and dry periods during the winter (Beck et al., 2018; Kalvová et al., 2003).

Table 4.1 Location, geographic coordinates, year, season, soil type, planting spacing (IRS), planting date (PD), harvesting date, and accumulated growing degree days (GDD) from planting to harvest for each field experiment.

Location	Geographic Coordinates	Year	Season	Soil type	[1]IRS	[2]PS	[3]PD	Harvest	[4]GDD
Georgia	32.01814ºN 82.22138ºW	2020	Fall	Irvington loamy sand	91.44	17.78	Aug 26	Nov 2	928
Alabama	32.50053ºN 85.89281ºW	2021	Fall	Kalmia loamy sand	91.44	17.78	Aug 16	Nov 1	921
Alabama	32.50053ºN 85.89281ºW	2022	Fall		91.44	17.78	Aug 17	Nov 7	980

*[1]IRS = in-row spacing measured in cm; [2]PS: plant-spacing in cm, [3]PD: Planting date; [4]GDD: growing degree days (ºC; the base temperature for sweet corn is 10ºC).

A two-factorial experimental design of N fertilizer application timing and N fertilizer rate was arranged in a complete randomized block design with three replicates (r = 3). Individual plots consisted of four rows planted 91.4 cm apart and plants spaced 17.7 cm apart (24684 plants/ha). Planting occurred on August 26th, August 16th, and August 17th during 2020, 2021 and 2022, respectively; and harvest at the beginning of November for all seasons (Table 4.1). Crop management practices associated with soil preparation, irrigation, and management of pests, weeds, and diseases were carried out following the standard practices for sweet corn in the southeastern United States.

N fertilizer application treatments occurred before planting (N_{pl}), at emergence (N_{eme}), and at side dress (N_{sd}). The fertilizer source at N_{pl} was 10-10-10, and at N_{eme} and N_{sd} the fertilizer source was 34-0-0. At N_{pl}, a 34 kg N ha^{-1} was applied in each trial for all treatments following the growers' standard practices for the region. Afterwards, two N fertilizer rates (56 N kg ha^{-1} or 112 N kg ha^{-1}) were applied separately at N_{eme}, followed by a third application of three N fertilizer rates (134 N kg ha^{-1}, 162 N kg ha^{-1} or 190 N kg ha^{-1}) applied separately at N_{sd}. The combination of N_{eme} x N_{sd} application rates totaled six treatments (T1, T2, T3, T4, T5 and T6). N rates and timing of each treatment were detailed in (Table 4.2). Regarding the nature of the N fertilization applied, ammoniacal N (10% of N) was the source of N fertilizer applied at N_{pl}, and ammonium nitrate

(24% of N) and urea N (10% of N) were used as the sources of N (34% total of N) fertilizer applied at N_{eme} and N_{sd}. The N_{pl} occurred at 0 days after planting (DAP) for all growing seasons, while Neme occurred at 19, 25, and 16 DAP during 2020, 2021, and 2022; and N_{sd} at 40, 44, and 41 DAP in 2020, 2021, and 2022, respectively. Phosphorus (P) and potassium (K) were supplied only at planting using same 10-10-10 fertilizer source according to the growers' standard practices.

Table 4.2 Nitrogen fertilizer rates applied at planting (N_{pl}), at emergence (N_{eme}), and at side dress (N_{sd}) growth stages, and total N applied for each of the experimental fields in 2020, 2021, and 2022 in the Southeastern U.S.

Treatments	N_{pl}	N_{eme}	N_{sd}	Total N
		N rates (kg ha^{-1})		
1	34	56	134	224
2	34	56	162	252
3	34	56	190	280
4	34	112	134	280
5	34	112	162	308
6	34	112	190	336

Weather conditions

Daily maximum and minimum air temperature, and rainfall events were monitored using the closest weather station from the Georgia Automated Weather Network in the state of Georgia during 2020, and the Auburn University Mesonet in Alabama during 2021 and 2022.

Accumulated growing degree days (GDD) were determined using the following formula (1):

$$GDD = \frac{(T\max - T\min)}{2} - Tbase \qquad (1)$$

where “Tmax” as the average daily maximum temperature, “Tmin” as the average daily minimum temperature, and “Tbase” as the sweet corn base temperature (10ºC).

Soil nitrogen availability and total nitrogen

Soil samples were collected and analyzed for nitrate (NO_3^-) and ammonium (NH_4^+) content in the soil in all growing seasons for all treatments. Soil samples were comprised of 5 subsamples per plot and collected at 0.30-0.60 m soil depth. In each growing season, samples were collected at least 4 times during crop development. Three samples were collected right before each N fertilizer application at 0, 19, and 40 DAP in 2020; at 0, 25, 44 DAP in 2021; and at 0, 28, and 40 DAP in 2022, while the last samples were collected at silk and maturity (harvest) periods, as described in Table 4.3. Samples were dried and sent to waters agricultural laboratories (Water Agricultural Laboratories Inc., Camilla, GA; USA), for nitrate and ammonium analyses.

Table 4.3 Sampling events, in days after planting (DAP), for soil nitrogen availability, nitrogen uptake accumulation, and biomass accumulation, in 2020, 2021, and 2022.

	NO3 + NH4			Biomass and total N		
	2020	2021	2022	2020	2021	2022
[1]PL	0	0	0	-	-	-
[2]EME	19	25	28	19	25	28
[3]SD	40	44	40	40	44	40
[4]SILK	54	66	62	54	66	62
Harvest	68	74	82	68	74	82

*[1]PL: planting day sampling; [2]EME: emergence stage sampling; [3]SD: side-dress stage sampling; [4]SILK: silk stage sampling.

Biomass accumulation and nitrogen uptake accumulation

Plant tissue samples (leaf and stem) were collected four times at emergence (EME), side-dress (SD), silk, and at maturity (harvest) growing stages during each growing season (Table 4.3). Green leaf area index (LAI) was measured with an optical-electronic area meter LI-3100 (LI-COR Inc.) on two representative plants from each plot, then both plants were oven-dried at 65.5°C until constant weight and biomass dry weight was recorded. Dried samples were sent to waters agricultural laboratories (Waters Agricultural Laboratories Inc., Camilla, GA: USA) for total N Kjeldahl content (TKN).

Plant tissue samples were used to measure biomass accumulation. To calculate the whole plant N uptake, the sum of the product of total dry biomass and total N (TKN) sampled throughout each growing season was used.

In each growing stage, the nitrogen use efficiency (NUE) was calculated by as the ratio of the whole plant N uptake (TKN) by the total N supplied (total N fertilizer applied in each treatment minus the residual N fertilizer in the soil sampled before the planting date in each growing season) as shown in equation (2):

$$NUE\ (\%)\ =\ \frac{N\ uptake}{(N\ fertilizer\ -\ residual\ N\ fertilizer\ in\ the\ soil)}$$

Yield and ear quality

Sweet corn ears were harvested at maturity in all locations (Table 4.1), which ranged from 68 to 82 DAP. Ears were hand harvested, and the total weight and number of ears were recorded for each row. Subsequently, five ears were randomly selected from each plot to determine the ear length and diameter, the number of kernels per row (KR), the number of kernels in an ear row (KIR), and the total number of kernels (KTG) per ear.

Statistical analysis

Statistical analyses were performed using linear mixed techniques as implemented in the SAS PROC GLIMMIX (SAS/STAT 9.4; SAS Institute Inc., Cary, NC; USA). When the P value was significant, least-square means comparisons were performed using Tukey, adjusted at a probability value of 0.05, and means were portioned using the slice command in SAS. A correlation-based network analysis was performed using Pearson's method in R Studio (R Foundation for Statistical Computing, Vienna, Austria).

Results

Weather data and growing degree days (GDD)

Rainfall events and minimum and maximum daily air temperature of all locations are shown in Figure 4.1, and the total accumulated GDD for Georgia 2020, Alabama 2021, and Alabama 2022 was 928, 921, and 980 ºC, respectively.

In Georgia 2020, the average minimum and maximum daily air temperatures were 18 and 28°C, and rainfall events accumulated 175 mm during the entire growing season. In Alabama 2021, the average minimum and maximum daily air temperatures were 17 and 29°C with 271 mm of precipitation during the entire growing season. Ultimately, minimum, and maximum daily air temperatures averaged 14 and 29°C and rainfall events accumulated 245 mm in Alabama 2022.

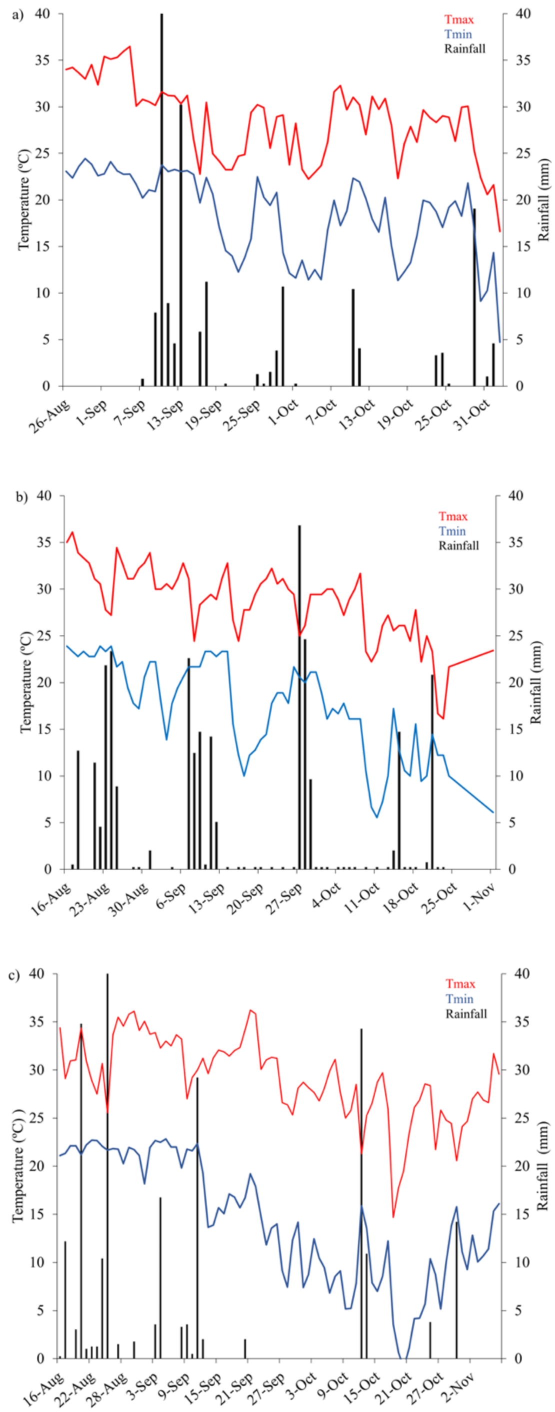

Figure 4.1 Rainfall and maximum and minimum daily air temperature during the sweet corn fall season of Georgia 2020 (a), Alabama 2021 (b), and Alabama 2022 (c).

Leaf area index, biomass accumulation, total N accumulated, and soil total N

The LAI, biomass accumulation, total N, and soil total N were compared among locations by stages (Table 4.4).

For LAI, there was a statistically significant difference among locations for EME, SD, and SILK stages. For biomass accumulation, there was significant differences among locations for SD, SILK, and Harvest stages. For total N, there were significant differences among locations for EME, SD, SILK, and Harvest stages. For soil total N, there were significance differences among locations for EME, SD, and SILK stages.

Table 4.4 Effect of LAI, biomass accumulation, total N, and soil total N among locations by stages (EME, SD, SILK, and harvest).

Location	LAI cm^2	Biomass $kg\ ha^{-1}$	Total N $kg\ ha^{-1}$	Soil total N $kg\ ha^{-1}$
		EME		
Georgia 2020	323 c^y	167 a	-	9.9 b
Alabama 2021	852 b	446 a	15.2 b	5.8 b
Alabama 2022	1357 a	830 a	36.5 a	31.8 a
P_{value}	***	ns	*	**
		SD		
Georgia 2020	1792 b	1409 c	48.7 b	53.9 a
Alabama 2021	1818 b	2014 b	53.5 b	3.4 b
Alabama 2022	2282 a	3012 a	94.1 a	60.2 a
P_{value}	**	***	***	**
		SILK		
Georgia 2020	1858 b	2288 c	58.9 b	49.7 b
Alabama 2021	1424 c	2748 b	68.5 b	194.5 a
Alabama 2022	2251 a	3066 a	162.2 a	69.2 b
P_{value}	***	***	***	**
		Harvest		

Georgia 2020	1416 a	2108 b	-	9.3 a
Alabama 2021	1364 a	1857 b	40.6 b	98.8 a
Alabama 2022	1181 a	2695 a	166.2 a	93.6 a
P_{value}	ns	***	***	ns

[y]Values followed by similar lowercase letters among locations (row) indicate no significant difference according to the Tukey mean test. Levels of significance (P_{value}): ns, non-significant; *, P<0.05; **, P<0.01.

At the EME stage, the highest LAI was in Alabama 2022 (1357 cm^2), followed by Alabama 2021 (852 cm^2) and Georgia 2020 (323 cm^2); the highest total N was in Alabama 2022 (36.5 kg ha^{-1}), followed by Alabama 2021 (15.2 kg ha^{-1}); and the highest soil total N was in Alabama 2022 (31.8 kg ha^{-1}), followed by Georgia 2020 (9.9 kg ha^{-1}) and Alabama 2021 (5.8 kg ha^{-1}).

At the SD stage, the highest LAI was in Alabama 2022 (2282 cm^2), followed by Alabama 2021 (1818 cm^2) and Georgia 2020 (1792 cm^2); the highest biomass accumulation was in Alabama 2022 (3012 kg ha^{-1}), followed by Alabama 2021 (2014 kg ha^{-1}) and Georgia 2020 (1409 kg ha^{-1}); the highest total N was in Alabama 2022 (94.1 kg ha^{-1}), followed by Alabama 2021 (53.5 kg ha^{-1}) and Georgia 2020 (48.7 kg ha^{-1}); and the highest soil total N was in Alabama 2022 (60.2 kg ha^{-1}) and Georgia 2020 (53.9 kg ha^{-1}).

At the silk stage, the highest LAI was in Alabama 2022 (2251 cm^2), followed by Georgia 2020 (1858 cm^2) and Alabama 2021 (1424 cm^2); the highest biomass accumulation was in Alabama 2022 (3066 kg ha^{-1}), followed by Alabama 2021 (2748 kg ha^{-1}) and Georgia 2020 (2288 kg ha^{-1}); the highest total N was in Alabama 2022 (162.2 kg ha^{-1}), followed by Alabama 2021 (68.5 kg ha^{-1}) and Georgia 2020 (58.9 kg ha^{-1}); and the highest soil total N was in Alabama 2021 (194.5 kg ha^{-1}), followed by Alabama 2022 (69.2 kg ha^{-1}) and Georgia 2020 (49.7 kg ha^{-1}).

At the maturity stage (harvest), the highest LAI and soil total N were not statistically significant among locations. The highest biomass accumulation was in Alabama 2022 (2695 kg ha^{-1}), followed by Georgia 2020 (2108 kg ha^{-1}) and Alabama 2021 (1857 kg ha^{-1}); and the highest total N was in Alabama 2022 (166.2 kg ha^{-1}), followed by Alabama 2021 (40.6 kg ha^{-1}).

Biomass accumulation, total N, and soil total N were statistically compared between N_{eme} treatment by stages (Table 4.5). For biomass accumulation, there was statistical significance between N_{eme} treatments for the SD and SILK stages. For total N, there was a statistical difference between N_{eme} treatments for the SD and Harvest stages. For soil total N, there was a statistical difference between N_{eme} treatments for the EME and SD stages.

Table 4.5 Effect of biomass accumulation, total N, and soil total N between N_{eme} treatment by stages.

N_{eme} (kg ha^{-1})	Biomass kg ha^{-1}		Total N kg ha^{-1}		Soil total N kg ha^{-1}	
	SD	SILK	SD	Harvest	EME	SD
56	2298 a^{y}	2604 a	69.5 a	98.0 a	12.4 a	27.3 b
112	1992 b	2797 a	61.4 b	108.8 a	19.3 a	50.9 a
P_{value}	**	ns	*	ns	ns	***

^{y} Values followed by similar lowercase letters among locations (row) indicate no significant difference according to the Tukey mean test.

At the EME stage, the highest soil total N was found in the N_{eme} 112 kg ha^{-1} treatment (19.3 kg ha^{-1}). At the SD stage, the highest biomass accumulation was found in the N_{eme} 56 kg ha^{-1} treatment (2298 kg ha^{-1}); the highest total N was found in the N_{eme} 56 kg ha^{-1} treatment (69.5 kg ha^{-1}); and the highest soil total N was found in the N_{eme} 56 kg ha^{-1} treatment (50.9 kg ha^{-1}). At the Silk stage, the highest biomass accumulation was found in the N_{eme} 112 kg ha^{-1} treatment (2797 kg ha^{-1}). At the maturity stage (harvest), the highest total N was found in the N_{eme} 112 kg ha^{-1} treatment (108.8 kg ha^{-1}).

LAI and soil total N were statistically compared among N_{sd} treatments by stages (Table 4.6). For LAI, there was a statistical difference among N_{sd} treatments for the SD stage. For soil total N, there was a statistical difference among N_{sd} treatments for the silk stage.

Table 4.6 Effect of LAI and soil total among N_{sd} treatments by stages.

N_{sd} (kg ha^{-1})	LAI cm^2	Soil total N kg ha^{-1}
	SD	SILK
190	1870 a^y	138.9 a
162	2069 a	93.1 b
134	1953 a	81.4 b
P_{value}	ns	*

^{y}Values followed by similar lowercase letters among N_{sd} treatment (row) indicate no significant difference according to the Tukey mean test.

At the SD stage, the highest LAI was found in the treatment N_{sd} 162 kg ha^{-1} (2069 cm^2), followed by treatment N_{sd} 134 kg ha^{-1} (1953 cm^2) and 190 kg ha^{-1} (1870 cm^2). At the silk stage, the highest soil total N was found in the treatment N_{sd} 190 kg ha^{-1} (138.9 kg ha^{-1}), followed by N_{sd} 162 kg ha^{-1} (93.1 kg ha^{-1}) and N_{sd} 134 kg ha^{-1} (81.4 kg ha^{-1}).

There was a significant interaction between locations and N_{eme} treatments for total N and soil total N, by stage (Table 4.7). For total N, there were significant differences between locations and N_{eme} treatments for the maturity (harvest) stage. For soil total N, there were significant differences between locations and N_{eme} treatments for the SD stage.

Table 4.7 Effect of the interaction between location and N_{eme} treatment for total N and soil total N.

	Location		
	Georgia 2020	Alabama 2021	Alabama 2022

N_{eme} (kg ha^{-1})	Harvest Total N (kg ha^{-1})		
56	-	41.40 aB	154.59 bA
112	-	39.78 aB	177.77 aA
P_{value}	-	*	*
	SD Soil total N (kg ha^{-1})		
56	24.36 b[y]B[z]	3.78 aB	53.93 aA
112	83.54 aA	2.99 aB	66.41 aA
P_{value}	**	**	**

[y]Values followed by similar lowercase letters between N_{eme} treatments within each location (column), individually, indicate no significant difference according to the Tukey mean test. [z] Values followed by similar uppercase letters between each N_{eme} treatment (row), individually, indicate no significant difference according to the Tukey mean.

For the main effect of location on total N (Table 4.7), at the maturity (harvest) stage, in Georgia 2020, total N was not statistically compared due to missing data; in Alabama 2021 total N was not different between N_{eme} treatments but the highest was in the N_{eme} 56 kg ha^{-1} treatment (41.40 kg ha^{-1}). In the Alabama 2022 study N treatments were significantly different and the highest total N was in the N_{eme} 112 kg ha^{-1} treatment (177.77 kg ha^{-1}) followed by N_{eme} 56 kg ha^{-1} treatment (154.59 kg ha^{-1}).

For the main effect of N_{eme} treatment on total N (Table 4.7), at the maturity (harvest) stage, the highest total N for the N_{eme} 56 kg ha^{-1} treatment was in Alabama 2022 (154.59 kg ha^{-1}), followed by Alabama 2021 (41.40 kg ha^{-1}); and the highest total N for the N_{eme} 112 kg ha^{-1} treatment was in Alabama 2022 (177.77 kg ha^{-1}), followed by Alabama 2021 (39.78 kg ha^{-1}).

For the main effect of location on soil total N (Table 4.7), at the SD stage, in Georgia 2020, the highest soil total N was in the N_{eme} 112 kg ha^{-1} treatment (83.54 kg ha^{-1}) followed by the N_{eme} 56 kg ha^{-1} treatment (24.36 kg ha^{-1}). In the Alabama 2021 study there were not differences between N_{eme} treatmentsbut the highest was in the N_{eme} 56 kg ha^{-1} treatment (3.78 kg ha^{-1}). In the Alabama

2022 study there were no differences between N_{eme} treatments, but the highest value was in the N_{eme} 112 kg ha^{-1} treatment (66.41 kg ha^{-1}).

For the main effect of N_{eme} treatment on soil total N (Table 4.7), at the SD stage, the highest soil total N for the N_{eme} 56 kg ha^{-1} treatment was in Alabama 2022 (53.93 kg ha^{-1}), followed by Georgia 2020 (24.36 kg ha^{-1}) and Alabama 2021 (3.78 kg ha^{-1}). The highest soil total N for the N_{eme} 112 kg ha^{-1} treatment was in Georgia 2020 (83.54 kg ha^{-1}), followed by Alabama 2022 (66.41 kg ha^{-1}) and Alabama 2021 (3.99 kg ha^{-1}).

There was a significant interaction between locations and N_{sd} treatments for LAI, biomass accumulation, and total N, by stage (Table 4.8). For LAI, there was a statistical difference between locations and N_{sd} treatments at the EME stage. For biomass accumulation, there was a statistical difference between locations and N_{sd} treatments for the EME stage. For total N, there was a statistical difference between locations and N_{sd} treatments for the EME and SD stages.

For the main effect of location on LAI (Table 4.8), at the EME stage, in Georgia 2020 the LAI was not statistically different among N_{sd} treatments but the highest LAI value was in the N_{sd} 190 kg ha^{-1} treatment (344 cm^2). In Alabama in 2021 the highest LAI was in the N_{sd} 190 kg ha^{-1} treatment (965 cm^2), followed by N_{sd} 162 kg ha^{-1} treatment (814 cm^2) and N_{sd} 134 kg ha^{-1} treatment (777 cm^2) In Alabama in 2022 the highest LAI was in the N_{sd} 134 kg ha^{-1} treatment (1467 cm^2), followed by N_{sd} 162 kg ha^{-1} treatment (1335 cm^2) and N_{sd} 190 kg ha^{-1} treatment (1268 cm^2).

For the main effect of N_{sd} treatment on LAI (Table 4.8), at the EME stage, the highest LAI for the N_{sd} 134 kg ha^{-1} treatment was in Alabama 2022 (1467 cm^2), followed by Alabama 2021 (777 cm^2) and Georgia 2020 (303 cm^2); while the highest LAI for the N_{sd} 162 kg ha^{-1} treatment was in Alabama 2022 (1335 cm^2), followed by Alabama 2021 (814 cm^2) and Georgia 2020 (322 cm^2).

The highest LAI for the N_{sd} 190 kg ha^{-1} treatment was in Alabama 2022 (1268 cm^2), followed by Alabama 2021 (965 cm^2) and Georgia 2020 (344 cm^2).

For the main effect of location on biomass accumulation (Table 4.8), at the SD stage, in Georgia 2020 and Alabama 2021, the biomass accumulation was not statistically different among N_{sd} treatments. In Alabama in 2022 there were statistical differences among N rates where the highest biomass accumulation was in the N_{sd} 134 kg ha^{-1} treatment (3217 kg ha^{-1}), followed by N_{sd} 190 kg ha^{-1} treatment (3095 kg ha^{-1}) and N_{sd} 162 kg ha^{-1} treatment (2724 kg ha^{-1}).

For the main effect of N_{sd} treatment on biomass accumulation (Table 4.8), at the SD stage, the highest biomass accumulation for the N_{sd} 134 kg ha^{-1} treatment was in Alabama 2022 (3217 kg ha^{-1}), followed by Alabama 2021 (2116 kg ha^{-1}) and Georgia 2020 (1179 kg ha^{-1}). The highest biomass accumulation for the N_{sd} 162 kg ha^{-1} treatment was in Alabama 2022 (2724 kg ha^{-1}), followed by Alabama 2021 (1890 kg ha^{-1}) and Georgia 2020 (1573 kg ha^{-1}); and the highest biomass accumulation for the N_{sd} 190 kg ha^{-1} treatment was in Alabama 2022 (3095 kg ha^{-1}), followed by Alabama 2021 (2035 kg ha^{-1}) and Georgia 2020 (1475 kg ha^{-1}).

Table 4.8 Effect of the interaction among locations and N_{sd} treatments for LAI, biomass, and total N, by stages.

	Location		
	Georgia 2020	Alabama 2021	Alabama 2022
Stage	EME		
N_{sd} (kg ha^{-1})	LAI (cm^2)		
134	303 a^{y}C^z	777 bB	1467 aA
162	322 aC	814 abB	1335 abA
190	344 aC	965 aB	1268 bA
P_{value}	*	*	*
	SD		

		Biomass (kg ha^{-1})	
134	1179 aC	2116 aB	3217 aA
162	1573 aB	1890 aB	2724 bA
190	1475 aC	2035 aB	3095 aA
P_{value}	*	*	*
		EME	
		Total N (kg ha^{-1})	
134	-	13.00 aB	67.58 aA
162	-	15.01 aA	21.36 bA
190	-	17.71 aA	20.67 bA
P_{value}	-	*	*
		SD	
		Total N (kg ha^{-1})	
134	41.91 aB	57.37 aB	96.44 aA
162	53.83 aB	50.52 aB	83.18 bA
190	50.54 aB	52.61 aB	102.61 aA
P_{value}	*	*	*

[y]Values followed by similar lowercase letters among N_{sd} treatments within each location (column), individually, indicate no significant difference according to the Tukey mean test. [z] Values followed by similar uppercase letters among each N_{sd} treatment (row), individually, indicate no significant difference according to the Tukey mean.

For the main effect of location on total N (Table 4.8), at the EME stage, in Georgia 2020, total N was not compared due to missing data. When evaluating total N in Alabama in 2021 there were differences among N_{sd}. However, in Alabama in 2022 there were differences between N rates for total N, where the highest total N was in the N_{sd} 134 kg ha^{-1} treatment (67.58 kg ha^{-1}), followed by N_{sd} 162 kg ha^{-1} treatment (21.36 kg ha^{-1}) and N_{sd} 190 kg ha^{-1} treatment (20.67 kg ha^{-1}).

For the main effect of N_{sd} treatment on total N (Table 4.8), at the EME stage, the highest total N for the N_{sd} 134 kg ha^{-1} treatment was in Alabama 2022 (67.58 kg ha^{-1}), followed by Alabama 2021 (13.00 kg ha^{-1}); the highest total N for the N_{sd} 162 kg ha^{-1} treatment was in Alabama 2022 (21.36 kg ha^{-1}), followed by Alabama 2021 (15.01 kg ha^{-1}); and the highest total N for the N_{sd} 190 kg ha^{-1} treatment was in Alabama 2022 (20.67 kg ha^{-1}), followed by Alabama 2021 (17.71 kg ha^{-1}).

For the main effect of location on total N (Table 4.8), at the SD stage, in Georgia 2020 and Alabama in 2021, the total N was not statistically different among N_{sd}. In Alabama in 2022 there were had statistical differences, with the the highest total N in the N_{sd} 190 kg ha^{-1} treatment (102.61 kg ha^{-1}) and N_{sd} 134 kg ha^{-1} treatment (96.44 kg ha^{-1}); followed by N_{sd} 162 kg ha^{-1} treatment (83.18 kg ha^{-1}).

For the main effect of N_{sd} treatment on total N (Table 4.8), at the SD stage, the highest total N for the N_{sd} 134 kg ha^{-1} treatment was in Alabama 2022 (96.44 kg ha^{-1}), followed by Alabama 2021 (57.37 kg ha^{-1}) and Georgia 2020 (41.91 kg ha^{-1}); the highest total N for the N_{sd} 162 kg ha^{-1} treatment was in Alabama 2022 (83.18 kg ha^{-1}), followed by Georgia 2020 (53.83 kg ha^{-1}) and Alabama 2021 (50.52 kg ha^{-1}); and the highest total N for the N_{sd} 190 kg ha^{-1} treatment was in Alabama 2022 (102.61 kg ha^{-1}), followed by Alabama 2021 (52.61 kg ha^{-1}) and Georgia 2020 (50.54 kg ha^{-1}).

Sweet corn yield and ear quality parameters

There was statistical significance among locations for yield, ear/plant, EWI, EL, KIR, and KTG (Table 4.9).

Sweet corn yield was not significantly affected by treatment but was significantly affected by location (Table 4.9) where Alabama in 2022 had the highest yield (17,380 kg ha^{-1}), followed by Georgia in 2020 (15,951 kg ha^{-1}) and Alabama in 2021 (14,470 kg ha^{-1}).

Moreover, ear quality parameters were also not significantly affected by treatment, but instead were significantly affected by location (Table 4.9). Alabama 2022 had the highest average number of ears per plant (1.13), followed by Alabama 2021 (1) and Georgia 2020 (1). For the EWI, Alabama had the highest value (4.77 cm), followed by Alabama 20202 (4.49 cm) and Georgia 2020 (4.17 cm). For the EL, Alabama in 2022 was the highest (19 cm), followed by Alabama in 2021 (18 cm) and Georgia in 2020 (17 cm). For the number of KIR, Alabama 2021 had the highest value (36), followed by Georgia 2020 (33) and Alabama 2022 (30). For the number of KTG, Alabama 2021 had the highest value (503), followed by Georgia 2020 (472) and Alabama 2022 (437).

Table 4.9 Effect of yield, ear/plant, EWI, EL, KIR, and KTG among locations.

Location	Yield	Ear/plant	EWI	EL	KIR	KTG
	kg ha^{-1}	#	cm	cm	no.	no.
Georgia 2020	15,951 ab[y]	1 b	4.17 c	17 c	33 a	472 ab
Alabama 2021	14,470 b	1 b	4.77 a	18 b	36 a	503 ab
Alabama 2022	17,380 a	1.13 a	4.49 b	19 a	30 b	437 b
P_{value}	***	***	***	***	***	**

[y]Values followed by similar lowercase letters among locations (column) indicate no significant difference according to the Tukey mean test for each variable responsible in the table.

There was a statistical difference between N_{eme} treatment for the ear quality parameter EL (Table 4.10). For the EL, the treatment N_{eme} 122 kg ha^{-1} was the highest value (18 cm), followed by N_{eme} 56 kg ha^{-1} (17.6 cm)

Table 4.10 Effect of EL between N_{eme} treatment.

N_{eme}	EL
Kg ha^{-1}	cm
56	17.6 b[y]
112	18.0 a
P_{value}	**

[y]Values followed by similar lowercase letters between N_{eme} treatment indicate no significant difference according to the Tukey mean test.

Nitrogen use efficiency (NUE)

There was a statistical difference among locations for NUE_{eme}, NUE_{sd}, NUE_{silk}, and NUE_{harv} (Table 4.11). For the main effect of location, the highest NUE_{eme} was in Alabama 2022 (28.9%), followed by Alabama 2021 (23.0%); the highest NUE_{sd} was in Alabama 2022 (60.6%), followed by Georgia 2020 (43.0%) and Alabama 2021 (37.5%); the highest NUE_{silk} was in Alabama 2022 (51.0%), followed by Alabama 2021 (22.1%) and Georgia 2020 (15.5%); and the highest NUE_{harv} was also in Alabama 2022 (51.6%), followed by Georgia 2020 (21.0%) and Alabama 2021 (13.2%).

Table 4.11 Effect of NUE at EME (NUE_{eme}), SD (NUE_{sd}), SILK (NUE_{silk}), and harvest (NUE_{harv}) among locations, between treatment N_{eme} and among treatment N_{sd}.

Effect	NUE_{eme}	NUE_{sd}	NUE_{silk}	NUE_{harv}
		%		
Location				
Georgia 2020	-	43.0 b	15.5 b	21.0 b
Alabama 2021	23.0 b	37.5 b	22.1 b	13.2 c
Alabama 2022	28.9 a	60.6 a	51.0 a	51.6 a
P_{value}	*	***	***	***
N_{eme} (kg ha_{-1})				
56	26.5 a	58.8 a	31.7 a	29.3 a
112	25.4 a	35.2 b	27.3 b	27.8 a
P_{value}	ns	***	*	ns
N_{sd} (kg ha^{-1})				
135	25.9 a	46.3 a	33.7 a	29.8 ab
163	25.2 a	45.2 a	27.6 b	30.5 a
191	26.8 a	49.5 a	27.2 b	25.4 b
P_{value}	ns	ns	*	**
Location*N_{eme}	ns	ns	ns	ns
Location*N_{sd}	ns	ns	ns	ns
N_{eme}*N_{sd}	ns	ns	ns	ns

Location* N_{eme}*N_{sd}	ns	ns	ns	ns

* < 0.05; ** < 0.01, *** < 0.001

There was a statistical difference between N_{eme} treatments for NUE_{sd} and NUE_{silk}, (Table 4.11). For the main effect of N_{eme}, the highest NUE_{sd} was at N_{eme} 56 kg ha^{-1} (58.8%), followed by N_{eme} 112 kg ha^{-1} (35.2%); and the highest NUE_{silk} was at N_{eme} 56 kg ha^{-1} (31.7%), followed by N_{eme} 112 kg ha^{-1} (27.3%).

There was a statistical difference among N_{sd} treatments for NUE_{silk} and NUE_{harv}, (Table 4.11). For the main effect of N_{sd}, the highest NUE_{silk} was at N_{sd} 135 kg ha^{-1} (33.7%), followed by N_{sd} 163 kg ha^{-1} (27.6%) and N_{sd} 191 kg ha^{-1} (27.2%); and the highest NUE_{harv} was at N_{sd} 163 kg ha^{-1} (30.5%), followed by N_{sd} 135 kg ha^{-1} (29.8%) and N_{sd} 191 kg ha^{-1} (25.4%).

Correlation analysis

Pearson's correlation analysis (Figure 4.2) indicated that sweet corn yield is positively correlated with the number of ears per plant, ear weight, biomass, EW, BD biomass, total N, NUE, and ear length. It was negatively correlated with the number of KIR and KTG.

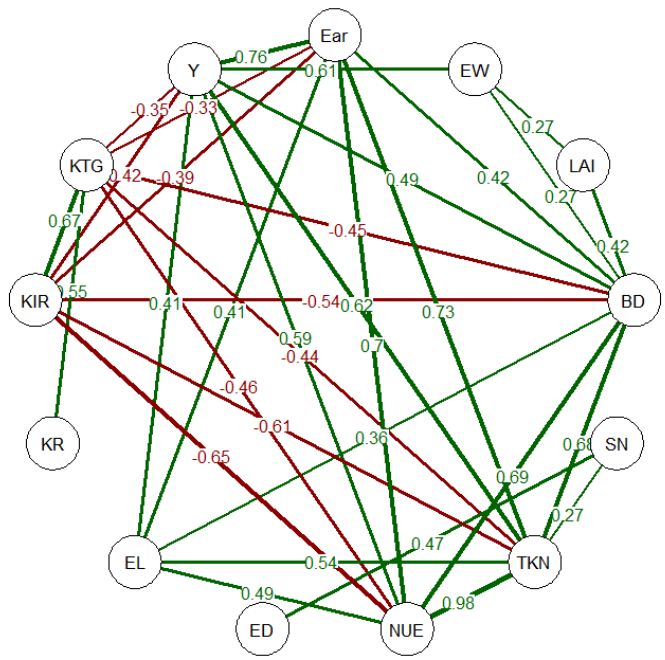

Figure 4.2 Correlation-based network analysis using Pearson's correlation method to compare all response variables, number of ears per plant (EAR), ear weight (EW), leaf area index (LAI), biomass (BD), yield (Y), soil total N (SN), total N (TKN), nitrogen use efficiency (NUE), ear diameter (ED), ear length (EL), kernel rows (KR), kernel grains in a row (KIR), and kernel total grains (KIR).

NUE was positively correlated with the number of ears per plant, biomass, total N (TKN), and ear length, while it was negatively correlated with the number of KIR and KTG. LAI was positively correlated with ear weight and biomass (BD). Biomass was positively correlated with the number of ears per plant, ear weight, ear length, and TKN; and it was negatively correlated with the number of KIR and KTG. TKN was positively correlated with the number of ears per plant, ear length, and soil total N (SN), and it was negatively correlated with the number of KIR and KTG. The SN was positively correlated with ear diameter. The number of KIR was positively correlated only with the number of KTG, and KTG was also positively correlated with the number of KR. Moreover, the EL did not correlate with KR, KIR, and KTG; and SN did not correlate with BD.

Discussion

N fertilization is essential in sweet corn production to achieve high yields and profits, but sweet corn has shown different responses to N in different environments (Evans & Clarke, 2019; Khan et al., 2017). Different N fertilizer rates have a significant impact on sweet corn yield (Revilla et al., 2021) and choosing the adequate N fertilization rate and timing for sweet corn production will increase yield and total N uptake (Kar et al., 2006). Moreover, appropriate N applications have been reported to lead to better ear quality results, such as increased ear diameter, ear length, number of ears per plant, and ear weight (Khan et al., 2017; Revilla et al., 2021). Alternatively, excessive N applications can have negative effects, such as reduced plant growth as well as poor ear quality (Leghari et al., 2016). Many commercial growers in the southeastern U.S. were do not follow current N fertilizer recommendations for sweet corn, instead, they are overfertilizing (over a 340 kg ha^{-1} of N) in an attempt to reach high yields (Malik et al., 2019).

In addition to N fertilizer application rates and timing, weather events in the southeastern U.S. can also impact vegetable crop growth and development, nutrient absorption, and subsequently yield (Abewoy, 2018). Temperature, rainfall, and drought may influence N uptake and utilization by plants. Temperature has a significant impact on the rate of nutrient absorption and plant metabolism. In warmer conditions, metabolic processes in plants tend to be more active, which can lead to increased N uptake (Maranon et al., 2018). However, excessively high temperatures cause stress in plants and affect their ability to absorb nutrients efficiently (Jones et al., 2013). Adequate moisture is essential for N uptake as well; however, excessive rainfall can leach N from the soil, making it less available to the plants. Conversely, drought conditions can limit the availability of water, affecting N uptake and consequently yield (Cazetta et al., 1999; Leghari et al., 2016). Understanding the importance of N for the plant's growth, development, and yield, the ideal application timing, and how the weather may impact it is the first step in developing a better N fertilizer recommendation for sweet corn production in the Southeastern U.S. Sweet corn fields in the southeastern U.S. are typically characterized by soils with a sandy to loam sandy texture with low water holding capacity (Kemble et al., 2023), which combined with frequent heavy rainfall events may induce N leaching, which can bring negative affects to plants and to the environment (Guo et al., 2008; Subedi & Ma, 2009).

Rainfall accumulations were similar in Alabama 2021 and Alabama 2022, matching the crop water requirements of 268 mm for sweet corn growth in the southeastern U.S. (Ertek & Kara, 2013), while in Georgia 2020, the rainfall accumulation was about 100 mm less compared to the other two locations. In Georgia 2020, at 19 DAP, exactly in the day of N_{eme} fertilization, there was 31 mm of rainfall, which likely resulted in N leaching. After the N_{sd} fertilization there was a period of occurred reduced soil moisture, where there was only 14.5 mm of rain in the next 18 days post fertilization. In Alabama 2021, there were 70 mm of rainfall after N_{eme} fertilization and 71 mm of rainfall after the N_{sd} fertilization, increasing soil moisture levels and possibly resulting in some N loss. In Alabama 2022, the rainfall events were better distributed during the growing season and the isolated periods of heavy rainfall did not impact the N_{eme} or N_{sd} fertilizations, and consequently did not impacted yield. The yield potential is defined in the vegetative stage of the sweet corn crop, thus, limiting N fertilizations or increased N leaching in this phase cause reductions in the yield (Ciam-pitti &Tony, 2011), and excessive soil moisture levels may have negative impacts on grain filling and the grain weight of sweet corn (Nemeskeri & Helyes, 2019). Conversely drought periods lead to osmotic stress which also reduce the nutrient absorption (Revilla et al., 2021), reasons that may explain a reduced yield in Alabama 2021 (14,470 kg ha^{-1}) and in Georgia 2020 (15,951 kg ha^{-1}).

Average daily air temperatures were similar among locations, where the average daily air minimum temperatures were below the ideal range to grow sweet corn, which ranges between 20 and 30 °C (Ben-Asher et al., 2008; Dhaliwal & Williams, 2022; Liliane & Charles, 2020). In general, daily air temperatures were lower in Georgia 2020 and in Alabama 2021, with lower GDD accumulated when compared to Alabama 2022, which had the lower average minimum temperature but had the higher GDD accumulated. It also can explain the higher yield in this last location because the warmer temperatures increased the N uptake (Maranon et al., 2018).

The LAI, biomass, total N, and the soil total N at EME were higher in Alabama 2022. In this case, the treatment N_{pp} was the same for all plants and there is no influence in the result. Therefore, it is likely that weather factors impacted those variables instead of N fertilization rate, as has been reported previously (Cazetta et al., 1999; Leghari et al., 2016; Revilla, 2021). The LAI, biomass, total N, and the soil total N at SD, silk, and harvest stages were also higher in Alabama 2022.

The interaction between N_{eme} treatment and location indicated that total N at harvest stage was higher for all N_{eme} rates in Alabama 2022 compared to other locations. In this location plants were likely able to uptake more N more efficiently. Similarly, the interaction between N_{sd} treatment and location showed the LAI and total N at EME stage, and the biomass and total N at SD stage, were higher for all N_{sd} rates in Alabama 2022 compared to other locations and were higher at the lower N_{sd} rate of 134 kg ha^{-1}. In both cases, the results showed that higher amount of N did not lead to increased values of LAI and biomass and did not increase the N uptake by the plants, which is supported by Capon et al. (2017), where lower N rates lead to higher NUE by the plants. This contradicts some results in the literature which report that N uptake, LAI, biomass, yield, and ear quality are increased when supplied with higher rates of N (Abkar et al., 2002; Chen et al., 2017; Khan et al., 2018).

Kernel development, higher LAI, biomass, and yield depend on N availability (Cazetta et al., 1999; Leghari et al., 2016). Besides N availability, drought stress also leads to reduced LAI, biomass, ear diameter, weight per ear, and yield (Revilla et al., 2021). The higher number of ears per plant and EL were found in Alabama 2022, were positively correlated with yield. The treatment N_{eme} 122 kg ha^{-1} was responsible for an increased EL compared to the treatment N_{eme} 56 kg ha^{-1}, showing the importance of N fertilization on ear quality and yield since they are positively correlated. These results corroborated with Oketem & Oktem (2005) who showed that higher N rates promoted an increase in EL and in the number of ears per plant.

NUE represents the percentage of N uptake by the plants of the total N fertilizer applied, therefore this is a way to describe how effectively plants are using applied N (Kumar et al., 2002; Subedi & Ma, 2009). N uptake was more efficient in Alabama 2022 for all stages NUE_{eme}, NUE_{sd}, NUE_{silk}, and NUE_{harv}, and this location had higher yields. Several factors can impact NUE, such as environmental stresses, soil type, temperature, and moisture, years, locations, and application timing, for example (Subedi & Ma, 2009; Nielsen, 2006), thus, we can see the location Alabama 2022 had the lowest impact on NUE.

The N_{eme} fertilization impacted the NUE at SD and silk, where the higher NUE came from the lower N_{eme} fertilization. Similarly, the N_{sd} fertilization impacted the NUE at silk and harvest where the higher NUE also came from the lower N_{sd} fertilizations. Strategies to fertilize N sweet corn are very important and help minimizing costs and harms to the environment as well as optimize crop results and NUE. Identification of the most effective N rate, timing, and split application (ie., N_{eme} and N_{sd}) of N fertilizer over a single application can lead to an increased N uptake by the plants and reduced leaching (Panison et al., 2019; Subedi & Ma, 2009).

Conclusions

The differences among locations and year are expected once the weather and soil vary among them impacting nutrient absorption and crop results. Higher total soil N was found in treatments with high N rate; however, it was not translated to yield. Moreover, yield did not show a significant difference among treatments, which is explained by the same amount of N uptake by the plant in all treatments. However, yield was different among location; Alabama 2022 had the higher yield (17,380 kg ha^{-1}), which can be explained by the high NUE for all stages (EME, SD, SILK, and Harvest). NUE translates how efficient plants are using the available N. Therefore, there is no need to increase N fertilization to achieve higher yields, instead it will increase N leaching and waste. Moreover, it is clear the understanding of N fertilizer is important to achieve good yield while minimizing costs and harms to the environment, humans, and animal's health. Split applications at the right timing are extremely beneficial to sweet corn growth and development. Finally, according to all results presented in this study, treatment 3 (280 kg ha^{-1}) had increased NUE and yield.

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Chapter 5 (Impact of N management on sweet corn performance under varying climate in the state of Alabama, USA)

Abstract

Efficient N fertilizer use is critical to maximize sweet corn yields, but over fertilizer application can lead to environmental issues. Alabama's coarse textured soils exacerbate N loss, which is further impacted by weather variability. The use of crop models can optimize N fertilizer management for sweet corn production. Field experiments in the E.V. Smith Research and Extension Center from Auburn University were conducted in 2021 and 2022 using different N rates (224 to 336 kg ha^{-1}), and timings of fertilizer application at pre-planting (N_{pp}), emergence (N_{eme}), and at side dress (N_{sd}).The CSM-CERES-Sweetcorn model, calibrated and validated with these data, was used to simulate growth, N uptake, and N leaching across 25 years of historical weather data. The model effectively simulated leaf area index and total soil N but was less accurate in predicting N uptake, biomass, and yield. Higher N rates resulted in increased N leaching, particularly in years with high rainfall. The model's performance highlighted the complexity of N management under variable weather conditions, suggesting that while it is a useful tool, it requires further refinement to improve sensitivity of the model to different N fertilizer rates. The CSM-CERES-Sweetcorn model provided valuable insights into sweet corn N management in Alabama's subtropical climate; however, further research is needed to enhance its predictive accuracy for optimizing N management in sweet corn production and minimizing environmental impacts.

Keywords: CSM-CERES-Sweetcorn, N management, sustainability

Introduction

The availability of nitrogen in the soil can be a limiting factor for sweet corn production (Rosenblueth et al., 2018). In modern agriculture, the efficient use of nitrogen fertilizers is extremely important to ensure higher yields. However, overapplication by growers has been described in the literature, leading to excessive N losses and negative impacts to crops and the environment (Kumar et al., 2024).

The combination of sandy soils in the state of Alabama (Herawati et al., 2021) and the mobility of N increase the chances that N fertilizer is lost (Panison et al., 2019). Additionally, the literature describes that the relationship between soil N and crop response to N may vary according to the weather. The weather variability may impact N uptake and N leaching, due to variations in precipitation (Congreves et al., 2016; Fowler et al., 2013; Galloway et al., 2008; Iqbal et al., 2017; Kay et al., 2006). Consequently, weather variability increases the complexity to determine the best N management practices.

One way to optimize N management for sweet corn production is using crop models. Crop models can be used to provide insights and support strategies to optimize N fertilizer management and minimize the impact of weather variability. Importantly, crop models can contribute to a more sustainable agriculture (Kumar et al., 2024). The DSSAT (Decision Support System for Agrotechnology Transfer) is an example of group of crop models modeling that can be used (Hoogenboom et al., 2019; Kumar et al., 2024; Jones et al., 2003; Zhao et al., 2019). It requires a minimum data set to be able to describe crop's growth and development as a function of genotype, crop management, soil characteristics, and weather conditions. After a model calibration and evaluation, the model simulates results to support data analysis and decision making towards some agronomic practices, such as N fertilizer management (Boote, 2019; Jones et al., 2003; Jin et al., 2018).

In the DSSAT, there is model CERES series (Crop Estimation through Resource and Environment Synthesis), which is a powerful tool to simulate growth, biomass accumulation, yield, among other, in different environments and with different crop management (Geng et al., 2017; Zhao et al., 2019), including the CSM-CERES-Sweetcorn. The CSM-CERES-Sweetcorn is the only well-established model for sweet corn, but it still requires further research to increase the sensitivity of the model and allow better simulations (Lizaso et al., 2007). Nevertheless, using the CSM-CERES-Sweetcorn to simulate coarse-textured soils in a subtropical environment can provide valuable information on crop growth, yield, N uptake, and N leaching under different management scenarios N fertilizer application rate.

In this context, the objectives of this study were: i) to evaluate the performance of the CSM-CERES-Sweetcorn to simulate plant growth and N dynamics, using data from field trials with different N rate treatments; and ii) to assess the impact of weather variability, using historical data, on N fertilizer rate treatments to provide insights for N leaching reduction and optimization of sweet corn yield.

Materials and Methods

Site description and experimental design

Field experiments were conducted at Auburn University, E.V. Smith Research and Extension Center (32.50053ºN 85.89281ºW), located in Central AL, in 2021 and 2022. Field experiments in each growing season were characterized by a loamy sand soil (Table 5.1). According to the Kopen-Geiger climate classification, all locations are classified as a humid subtropical climate or warm temperate climate (Cfa), with heavy rainfall events during a hot summer and dry periods during the winter (Beck et al., 2018; Kalvová et al., 2003).

Table 5.1 Location, geographic coordinates, year, season, soil type, planting spacing (IRS), planting date (PD), harvesting date, and accumulated growing degree days (GDD) for each field experiment.

Location	Geographic Coordinates	Year	Season	Soil type	[1]IRS	[2]PS	[3]PD	Harvest	[4]GDD
Alabama 2021	32.50053ºN 85.89281ºW	2021	Fall	Kalmia loamy sand	91.44	17.78	Aug 16	Nov 1	921
Alabama 2022	32.50053ºN 85.89281ºW	2022	Fall		91.44	17.78	Aug 17	Nov 7	980

*[1]IRS = in-row spacing measured in cm; [2]PS: plant-spacing in cm, [3]PD: Planting date; [4]GDD: growing degree days (ºC).

A two-factorial experimental design of N fertilizer application timing and N fertilizer rate was arranged in a complete randomized block design with three replicates (r = 3). Individual plots consisted of four rows planted 91.4 cm apart and plants spaced 17.7 cm apart. Planting occurred on August 16th and August 17th of 2021 and 2022, respectively. Sweet corn ears were harvested at the beginning of November for both growing seasons (Table 5.1). Pursuit (Syngenta, Attribute II) was the sweet corn cultivar used in both years. Crop management practices associated with soil preparation, irrigation, and management of pests, weeds, and diseases were carried out following the Alabama Cooperative Extension System recommendations.

The N fertilizer application treatments occurred before planting (N_{pl}), at emergence (N_{eme}), and at side dress (N_{sd}). At N_{pl}, a 34 kg N ha^{-1} was applied for all treatments following the growers' standard practices, afterwards, two N fertilizer rates (56 N kg ha^{-1} or 112 N kg ha^{-1}) were applied separately at N_{eme}, followed by a third application of three N fertilizer rates (134 N kg ha^{-1}, 162 N kg ha^{-1} or 190 N kg ha^{-1}) at N_{sd}. The combination of N_{eme} x N_{sd} application rates totaled six treatments (T1, T2, T3, T4, T5 and T6). N fertilizer rates and application timing of each treatment were detailed in Table 5.2. The ammoniacal nitrogen (10% of N) was the source of nitrogen fertilizer applied at N_{pl}, and ammonium nitrate (24% of N) and urea nitrogen (10% of N) were used as the sources of nitrogen (34% total of N) fertilizer applied at N_{eme} and N_{sd}. The N_{pl} occurred at 0 days after planting (DAP) for both growing seasons, while N_{eme} occurred at 25 and 16 DAP during 2021 and 2022; and N_{sd} at 44 and 41 DAP in 2021 and 2022, respectively.

Table 5.2 Nitrogen fertilizer rates applied at planting (N_{pl}), at emergence (N_{eme}), and at side dress (N_{sd}) growth stages, and total N applied for each of the experimental fields in 2021 and 2022 in the Southeastern U.S.

Treatments	N_{pl}	N_{eme}	N_{sd}	Total N
		N rates (kg ha^{-1})		
1	34	56	134	224
2	34	56	162	252
3	34	56	190	280
4	34	112	134	280
5	34	112	162	308
6	34	112	190	336

Data collection

Daily air temperatures, solar radiation, and precipitation were recorded for both years using an on-site weather station (WatchDog Wireless Station, WD Wireless ET Weather Station, LTE-M 50500102).

Soil samples were collected and analyzed for nitrate (NO_3^-) and ammonium (NH_4^+) content in the soil in all growing seasons for all treatments. Soil samples were comprised of 5 subsamples per plot and collected at 0.30-0.60 m soil depth. In each growing season, samples were collected at least 4 times during crop development. Three samples were collected right before each N fertilizer application at 0, 25, and 44 DAP in 2021; and at 0, 28, and 40 DAP in 2022, while the last samples were collected at silk and harvest (maturity), 66 and 74 DAP in 2021, and at 62 and 82 DAP in 2022, as described in Table 5.3. Samples were dried and sent to Waters Agricultural laboratories (Water Agricultural Laboratories Inc., Camilla, GA; USA), for nitrate and ammonium analyses.

Table 5.3 Sampling events, in days after planting (DAP), for soil nitrogen availability, nitrogen uptake accumulation, and biomass accumulation, for 2021 and 2022.

	Soil NO_3 NH_4		+Biomass and total N	
	2021	2022	2021	2022
[1]PL	0	0	-	-
[2]EME	25	28	25	28
[3]SD	44	40	44	40
[4]SILK	66	62	66	62
Harvest	74	82	74	82

*[1]PL: planting day sampling; [2]EME: emergence stage sampling; [3]SD: side-dress stage sampling; [4]SILK: silk stage sampling.

Plant tissue samples (leaf and steam) were collected four times at emergence (EME), side-dress (SD), silk, and at maturity (harvest) growth stages (Table 5.3). Green leaf area index (LAI) was measured with an optical-electronic area meter LI-3100 (LI-COR Inc.) on two representative plants from each plot, then the plant tissue was oven-dried at 65.5°C until constant weight and biomass dry weight recorded. Dried samples were sent to Waters Agricultural laboratories (Waters Agricultural Laboratories Inc., Camilla, GA: USA) for the analysis of total nitrogen Kjeldahl content (TKN).

Plant tissue samples were used to measure biomass accumulation. Subsequently, to calculate the whole plant N uptake, we used the nitrogen content (TKN) multiplied by the total dry biomass and TKN sampled throughout each growing season was used. Sweet corn ears were harvested at maturity in both years (Table 5.1), which was 77 and 82 DAP in 2021 and 2022, respectively. Ears were hand-harvested, and the total weight was recorded.

CERES-Sweet Corn Model evaluation

CSM-CERES-Sweetcorn is a processed-based simulation model adapted from the CSM-CERES-Maize module (version 4.0) (Lizaso et al., 2007) to improve simulations of sweet corn growth and development, ear quality, and yield.

Cultivar coefficients, experimental, soil, and weather data were used as inputs for the evaluation of the CSM-CERES-Sweetcorn model. Field experiment data from 2021 were used for the model calibration, and the field data from 2022 were used for the model validation. The model's ability to predict growth and N accumulation for the cultivar "Pursuit" required further calibration from the predetermined cultivar coefficients provided for the refereed sweet corn cultivar (BSS0977) as shown in Table 5.4. The genetic coefficients of the standard cultivar (BSS0977) were used for proper parameterization. Table 5.4 shows the adjustable genetic coefficients used in the model calibration comparing the standard cultivar and the new cultivar.

Table 5.4 Cultivar genetic coefficients used in the calibration of the CSM-CERES-Sweetcorn model.

Genetic Parameters	Description	BSS0977 (sh2[1])	Pursuit (se[2])
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8°C) during which the plant is not responsive to changes in photoperiod.	175.0	158.4
P2	Extent to which development (expressed as days) is delayed for each hour increases in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is 12.5 hours).	0.3	0.3
P5	Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8°C).	700.0	695.8
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	50.0	50.0
G2	Maximum possible number of kernels per plant.	500.0	593.0
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).	5.0	16.0

[1]sh2: Shrunken genotypes ('super sweet' cultivars). [2]se: sugar enhanced.

Crop model performance was evaluated by comparing simulated and observed data. Experimental crop and soil measurements included LAI, total biomass accumulation (kg ha^{-1}), total yield (kg ha^{-1}), total soil N (kg ha^{-1}), N uptake (kg ha^{-1}), and N leached (kg ha^{-1}). Model performance was evaluated by the mean error or bias (ME), the mean absolute error (MAE), the root means square error (RMSE), the relative RMSE (RRMSE), and Willmott's agreement index (*d*) (Willmott et al., 1985) as follow:

$$ME = \frac{1}{n} \times \sum_{i=1}^{n} (Simi - Obsi)$$

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} (|Simi - Obsi|)$$

$$RSME = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (Simi - Obsi)^2}$$

$$RRMSE = \left(\frac{RMSE}{Obsm}\right) \times 100$$

$$d = 1 - \frac{\sum_{i=1}^{n} (Simi - Obsi)^2}{\sum_{i=1}^{n} (|Simi - Obsm| + |Obsi - Obsm|)^2}$$

Where: Sim_i and Obs_i are the simulated and observed values, respectively; Obs_m is the average of observed values.

Values close to 1 for *d* (ranges from 0 to 1) and lower values of error metrics imply better model performance. Graphs and data processing were built using the support of the *DSSAT* package (Alderman, 2020).

Seasonal analysis

The analysis of different environmental scenarios was performed after the CSM-CERES-Sweetcorn model evaluation using a historical weather data set from 1998 to 2023. Weather data consisted of maximum and minimum air temperatures, solar radiation, wind speed, relative humidity, and precipitation, all collected from the Prediction of Worldwide Energy Resources (POWER; https://power.larc.nasa.gov/). This analysis provides an evaluation of the variability of the data according to the weather variability over the years.

The seasonal analysis was conducted using the six N fertilizer treatments combined with 25 years of weather data; thereby, there was a total of 150 simulations. For this analysis, leaf area index (LAI), total biomass accumulation (kg ha^{-1}), total yield (kg ha^{-1}), total soil N (kg ha^{-1}), N uptake (kg ha^{-1}), and N leached (kg ha^{-1}) were compared among treatments.

Results

Model evaluation

The CSM-CERES-Sweetcorn model was evaluated for simulation of LAI, biomass, N uptake, total soil N, and total yield, according to soil parameters, weather conditions (Table 5.1), and N fertilizer treatments (Table 5.2) from field trials conducted in 2021 and 2022. Overall results for the performance of the CSM-CERES-Sweetcorn model (Table 5.5) shows there was a good accuracy by the model in predicting N leaching; moderate accuracy in the model for LAI and N uptake predictions but still room for improvement; and a weak accuracy in the model in predicting biomass, total soil N, and yield, indicating the model can be improved.

Table 5.5 Performance of CSM-CERES-Sweetcorn to simulate crop over seasons 2021 and 2022 for all nitrogen treatments in Tallassee, Alabama, USA. *n* is the number of observations, ME is the mean error (variable unit), MAE is the mean absolute error (variable unit), RMSE is the root mean square error (variable unit), RRMSE is the relative root mean square error (%), and *d* is the Willmott's agreement index (unitless).

Variable	*n*	ME	MAE	RMSE	RRMSE	*d*
Leaf area index	15	0.03	0.5	0.58	68	0.66
Biomass (kg ha^{-1})	18	95	1307	2679	175	0.61
Total soil N (kg ha^{-1})	15	4.7	57	105	211	0.46
N uptake (kg ha^{-1})	15	-5.3	64	18.3	10.9	0.1
N leached (kg ha^{-1})	15	1.3	16.2	13.6	14.7	0.57
Yield (kg ha^{-1})	15	93	1116	1511	46	0.3

The RSME for LAI was 0.58 and MAE was 0.5, indicating moderate accuracy by the model for LAI prediction. Willmott's agreement index and ME, 0.66 and 0.03, respectively, indicated moderate agreement and very small bias. Moreover, the prediction values made by the CSM-CERES-Sweetcorn model tended to overestimate LAI (Figure 5.1) mainly after 40 DAP.

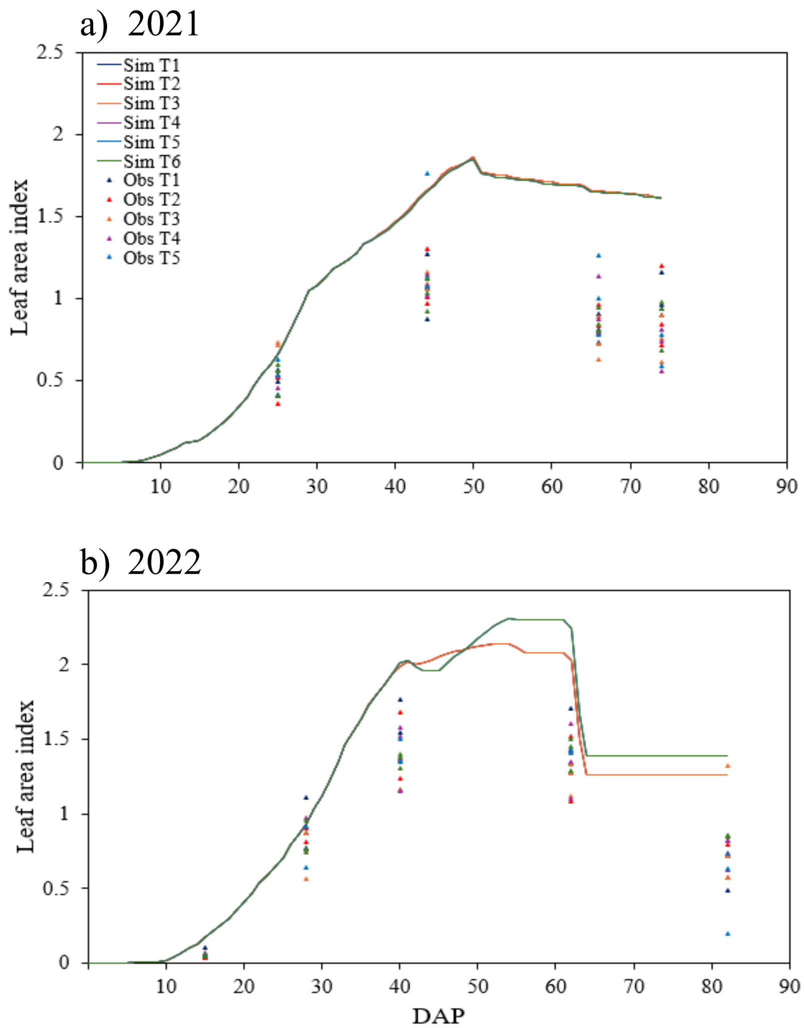


Figure 5.1 Simulated (lines) and observed (symbols) data of leaf area index for each N treatment over days after planting (DAP) in both years, 2021 and 2022.

The RSME for biomass was 2679.3 kg ha^{-1} and MAE of 1307 kg ha^{-1} indicating the accuracy by the model for biomass predictions can be improved. Willmott's agreement index was 0.61, and ME was 95.2 kg ha^{-1} indicating moderate agreement and small bias. There was an exponential increase in biomass accumulation for both simulated and observed values (Figure 5.2) after planting, however, the CSM-CERES-Sweetcorn model overestimated biomass accumulation close to harvest, where values typically decrease. A slight difference is observed between simulated treatment 3 (280 kg of N applied) and treatment 6 (336 kg of N applied).

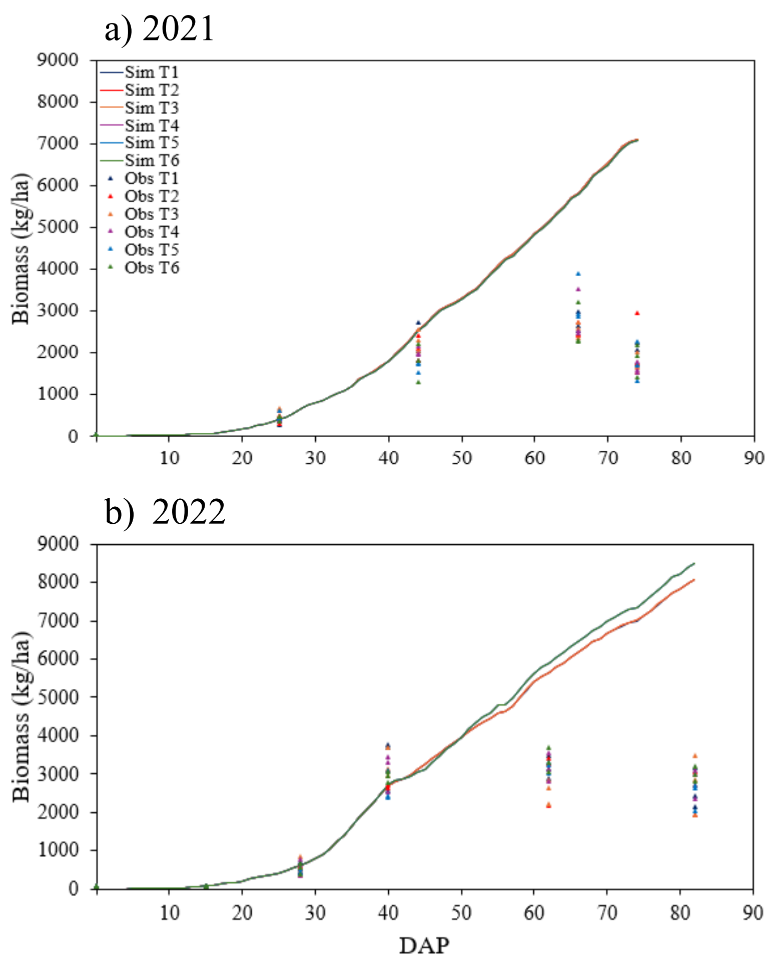


Figure 5.2 Simulated (lines) and observed (symbols) data of biomass (kg ha^{-1}) for each N treatment over days after planting (DAP) in both years, 2021 and 2022.

The RSME for N uptake was 18.3 kg ha^{-1} and MAE was 64 kg ha^{-1}, indicating a moderate accuracy by the model for N uptake prediction. Willmott's agreement index of 0.1 and ME slight negative of -5.3 kg ha^{-1} indicating very low agreement but small bias. The negative value of ME indicates an underestimation of the simulated values by the CSM-CERES-Sweetcorn model (Figure 5.3). It is observed a slight difference between treatments where higher N fertilizer rates had a slight increase in simulated N uptake over lower N fertilizer rates after the second N fertilizer application, followed by a plateau.

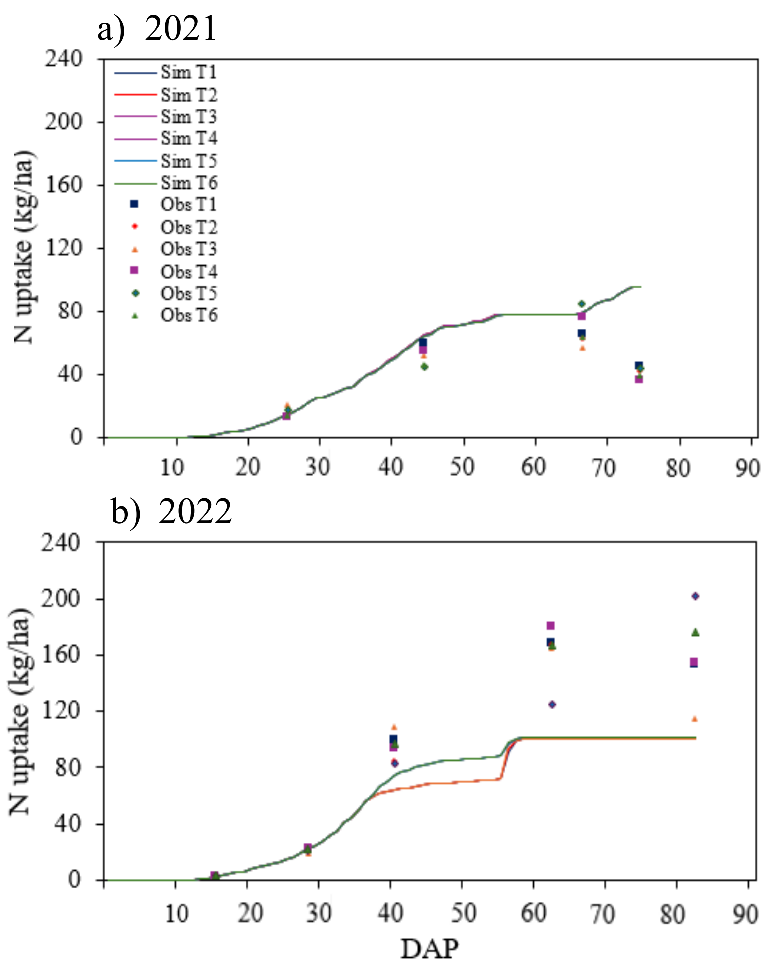


Figure 5.3 Simulated (lines) and observed (symbols) data of N uptake (kg ha^{-1}) for each N treatment over days after planting (DAP) in both years, 2021 and 2022.

The RSME for total soil N was 105.7 kg ha^{-1} and MAE was 57 kg ha^{-1}, indicating moderate accuracy by the model for total soil N predictions. Willmott's agreement index of 0.46 and ME of 4.7 kg ha^{-1} indicating low agreement but small bias. Total soil N accumulation over time was well represented by the CSM-CERES-Sweetcorn model for different N fertilizer rates (224 kg of N -T1 to 336 kg of N -T6). Figure 5.4 shows an overestimation by the model of soil total N predictions. Total soil N simulated by the model is higher for the highest N fertilizer rate (T6) and lower for the lowest N fertilizer rate (T1). It is also observed a peak of total soil N content after each N fertilizer application, followed by a plateau established after 40 DAP, however, soil samples were collected shortly before N fertilizer applications.

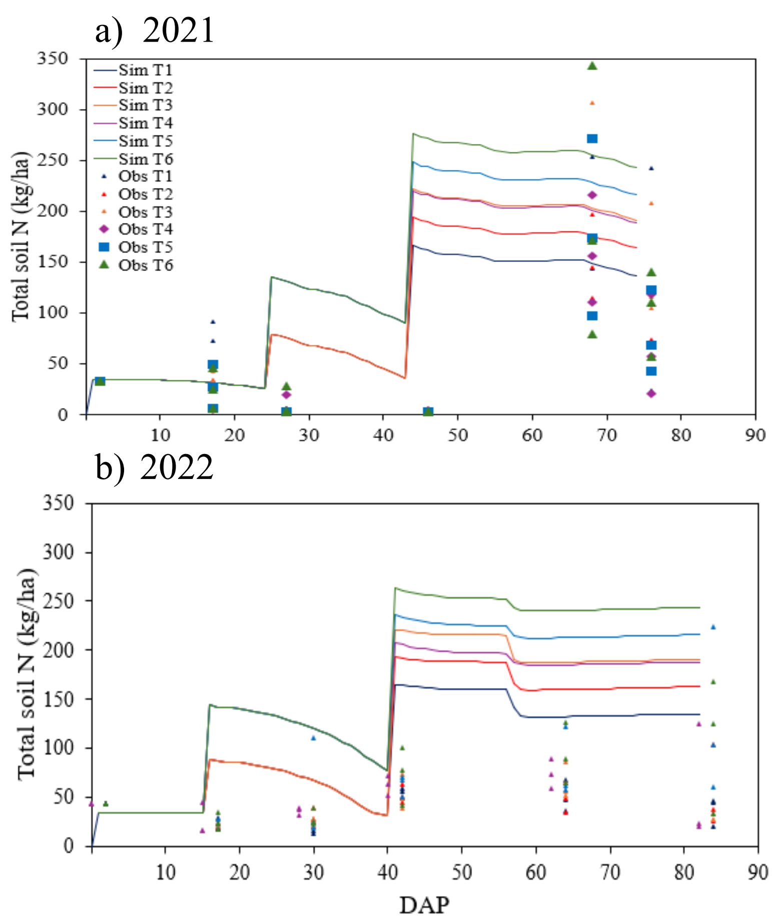


Figure 5.4 Simulated (lines) and observed (symbols) data of total soil N (kg ha^{-1}) for each N treatment over days after planting (DAP) in both years, 2021 and 2022.

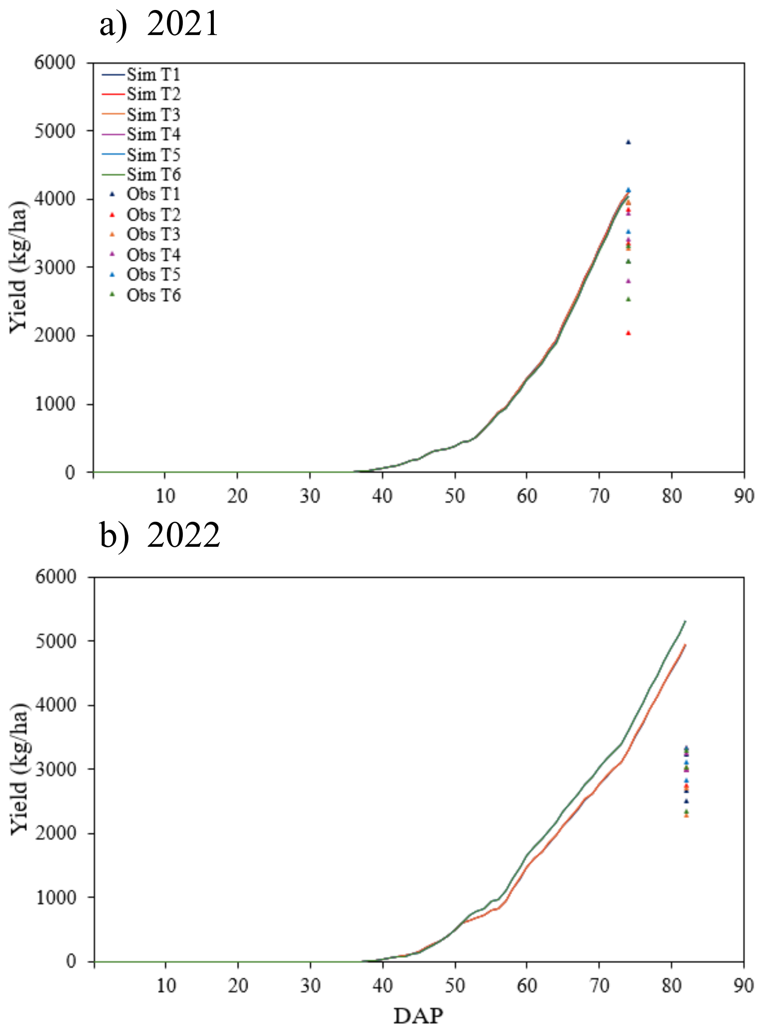


Figure 5.5 Simulated (lines) and observed (symbols) data of total yield (kg ha^{-1}) for each N treatment over days after planting (DAP) in both years, 2021 and 2022.

The RSME for yield was 1511.8 kg ha^{-1} and MAE was 116 kg ha^{-1}, indicating moderate accuracy by the model for yield predictions. Willmott's agreement index of 0.3 and ME of 93 kg ha^{-1} indicating low agreement but small bias. Simulations for yield by the CSM-CERES-Sweetcorn model show no difference between simulated N fertilizer treatments (Figure 5.5), which reflects the previous results of biomass and N uptake. Besides, the model overestimated the yield for N fertilizer treatments. It is observed a slight difference between treatments where higher N fertilizer rates had a slight increase in simulated yield over lower N fertilizer rates.

Seasonal analysis

Following the model evaluation, CSM-CERES-Sweetcorn was employed to assess crop responses between N fertilizer treatments over different climate scenarios, for biomass, N uptake, and N leached. The analysis of different environmental scenarios was performed using a historical weather data set from 1998 to 2022.

Average rainfall accumulation during the fall sweet corn season (August to November) for the 25 years studied was 228 mm. The highest volume of rainfall was in 2009 with 435 mm while the lowest volume of rainfall was in 2016 with 103 mm (Figure 5.6). Increases in rainfall accumulation impacted the N leached. In the Figure 5.6, it was observed the N leached had a peak when rainfall accumulation was higher in 2009, leading to a reduction in the N uptake and consequently in biomass accumulation. Contrarily, when rainfall accumulation is low, the N leached reduces considerably leading to higher N uptake and biomass accumulation.

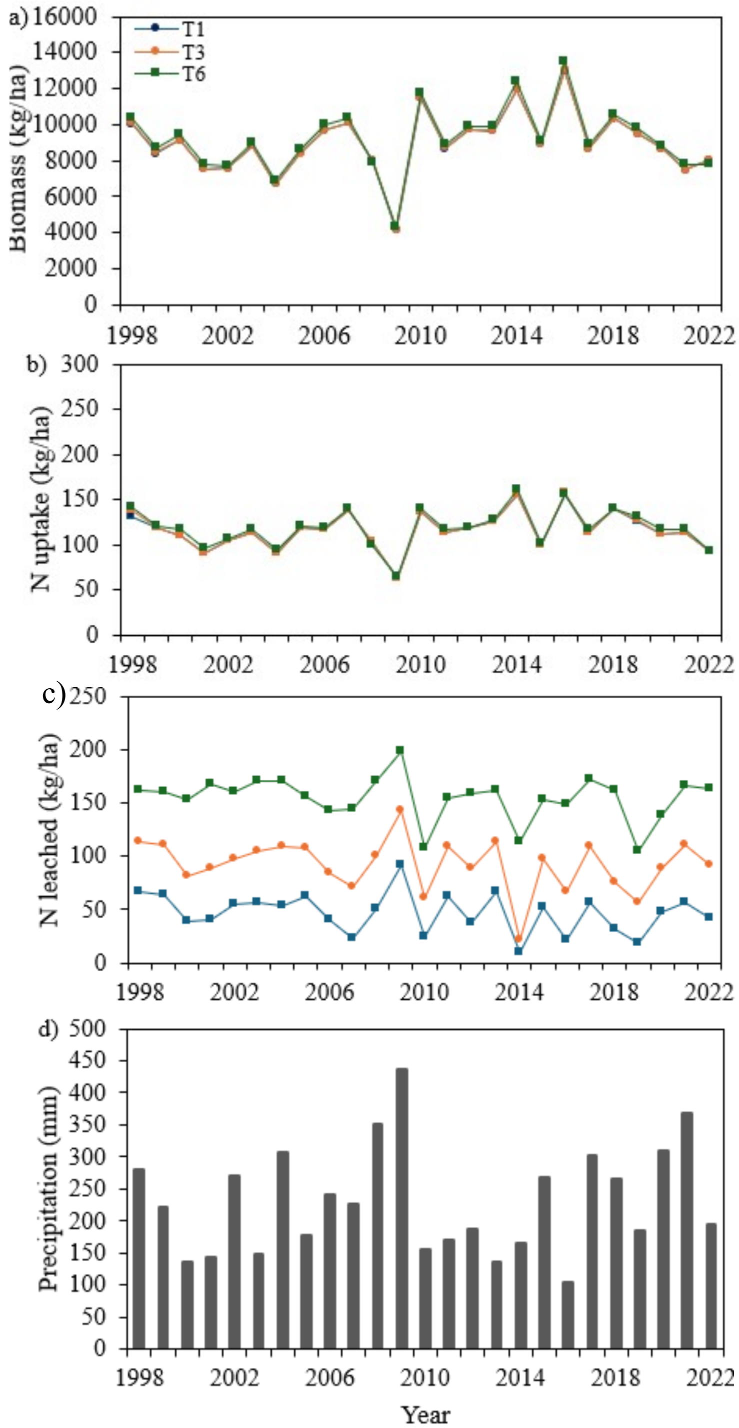
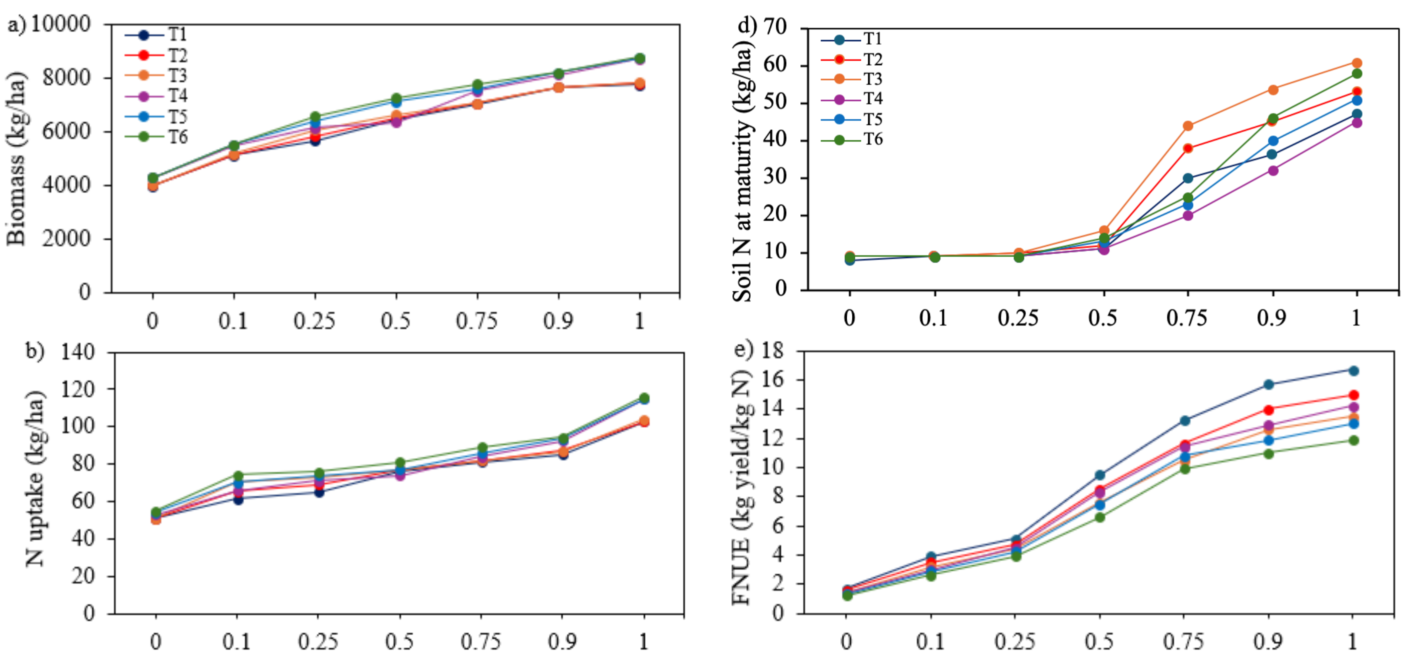


Figure 5.6 Simulated biomass (a, kg ha^{-1}), N uptake (b, kg ha^{-1}), N leached (c, kg ha^{-1}) and observed precipitation accumulated from the start of the simulation to harvest (d, mm) from 1998 to 2022, for N rate T1 (224 kg ha^{-1} of N), T3 (280 kg ha^{-1} of N) and T6 (336 kg ha^{-1} of N).

Simulated N fertilizer rate treatments were applied to this scenario analysis. The N fertilizer treatments chosen were 224 kg of N ha^{-1} (T1), 280 kg of N ha^{-1} (T3), and 336 kg of N ha^{-1} (T6) seeking to identify the best total N fertilizer application that along 25 years could reduce the N leached with no effect on biomass, N uptake; consequently, total yield. The difference in biomass accumulation, N uptake, and N leached for the 25 years simulated considering T1, T3, and T6 is shown in the Figure 5.6. The CSM-CERES-Sweet corn model did not detect significative difference between simulated biomass averages, which averaged 8980, 8993, and 9185 kg ha^{-1} for T1, T3, and T6, respectively. The same was observed for N uptake, which averaged 116, 117, and 119 kg ha^{-1} for T1, T3, and T6, respectively. Overall, biomass was responsive to total soil N availability, where T1 had lower N leached than T3 and T6. Simulated N leached averaged 47, 92, and 154 kg ha^{-1} for T1, T3, and T6, respectively.

Cumulative probability function plots, where the distribution is ordered from the smallest to the largest value and plotted against equal increments of cumulative probability, are presented in Figure 5.7.



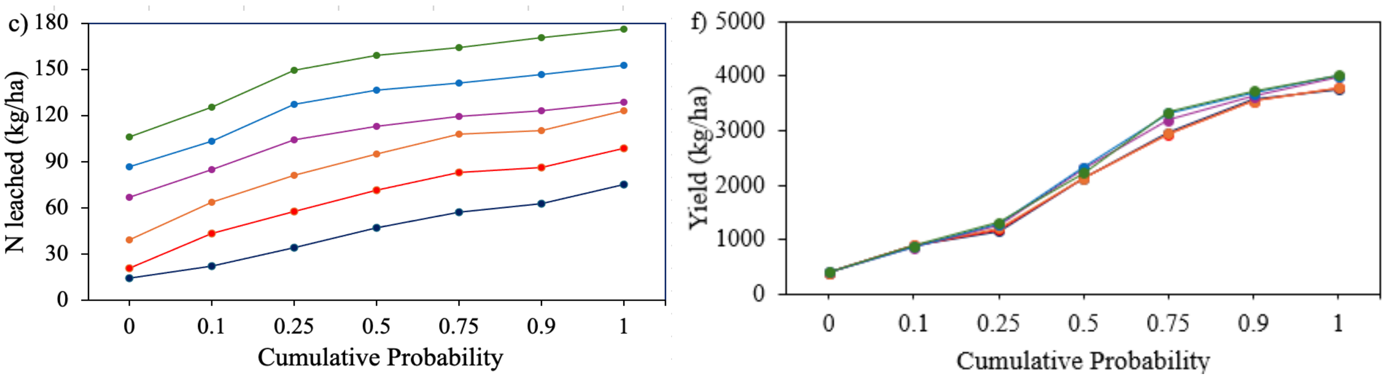


Figure 5.7 Cumulative probability distribution of simulated biomass (a, kg ha^{-1}), N uptake (b, kg ha^{-1}), N leached (c, kg ha^{-1}), soil N at maturity (d, kg ha^{-1}), fertilizer N use efficiency (FNUE) (e, kg[yield]/kg[N fertilizer]), and total yield (f, kg ha^{-1}) from 1998 to 2022, for N treatments 1 (T1, blue), 2 (T2, red), and 3 (T3, green).

Cumulative probability (Figure 5.7) showed the worst-case scenario of 4000 kg ha^{-1} for biomass accumulation for all treatments. Treatments had similar probability performance; however, T6, T5, and T4 had a high probability (75% or more) of reach biomass accumulation higher than 7000 kg ha^{-1}. Cumulative probability of N uptake performed similarly to biomass accumulation for all treatments. The cumulative probability of N leached showed a high probability of high N leaching according to the increase in N fertilizer rate applied. Cumulative probability of the total soil N showed higher cumulative probabilities (75% to 100%) of T2 and T3 show higher soil N levels at maturity compared to other treatments; T1, T4, T5, and T6 had more consistent and lower soil N levels; T2 and T3 may be preferred for maximizing soil N. The FNUE had a medium to high probability (>50%) of reaching high FNUE with the lower N fertilizer rates (T1 and T2).

Discussion

CSM-CERES-Sweetcorn was the first simulation model, adapted from CSM-CERES-Maize, mainly to improve simulations of ear growth and yield components (Lizaso et al., 2007). A preliminary new sweet corn model was developed by Reid (2017), which can be considered the second model for sweet corn, can be considered useful in predicting factors that may affect ear and yield but still requires adjustments. It can explain the lack of studies using the CSM-CERES-Sweetcorn model, mainly for N fertilizer management. Despite that, the literature cites the use of CSM-CERES-Maize model for sweet corn crops (Beltrao et al., 1992; He et al., 2009; He et al., 2011; He et al., 2012; He et al., 2012-1; Rawat, 2020; y Garcia et al., 2005).

In the present study, the response of the sweet corn crop to N fertilizer treatments was reasonably simulated by the CSM-CERES-Sweetcorn model with only one change in the genotype coefficient G3. The G3 is the potential kernel growth rate during the linear grain filling stage, the original value of 5 given by the model was changed to 16 for the cultivar Pursuit used in this study (Table 4). The new value for the G3 coefficient is very similar to the sweet corn cultivar 'Saturn' (G3=15), as described by Lizaso et al. (2007).

A study using CSM-CERES-Maize for maize growth and N dynamics predictions showed a RSME for biomass yield of 1439 kg ha^{-1}, which was considered a strong performance. However, this value was lower than the value found for RSME in sweet corn biomass (2679.3 kg ha^{-1}). The RSME for leaf area index of maize was 0.57, very similar value was found in the present study for sweet corn (RSME = 0.58). The RSME value for simulated N uptake in maize was 16.21 kg ha $^{-1}$, similar value was found in the present study (RSME = 18.3 kg ha $^{-1}$). The RSME for simulated yield of maize was 1755 kg ha^{-1}, similar value was found in the present study (RSME = 1116 kg ha $^{-1}$) (Kumar et al., 2024). Thus, we can consider both models performed similarly for their respective crops, sweet corn using CSM-CERES-Sweetcorn and maize using CSM-CERES-Maize.

As part of Lizaso et al. (2007) study, two total N fertilizer rates of 252 and 419 kg ha^{-1} were used to validate the CSM-CERES-Sweetcorn model. Simulated and observed values showed no difference between N fertilizer rates for shoot dry mass (RSME = 690 kg ha^{-1}), ear dry mass (RSME = 509.2 kg ha^{-1}), and ear fresh mass (RSME = 2649.3 kg ha^{-1}). This was similar to what was shown in the present study, with no difference between the N fertilizer treatments that ranged from 224 to 336 kg of N ha^{-1} for simulated values for leaf area index, biomass, N uptake, and yield, except by the total soil N.

Simulations of N management in sandy soils for sweet corn crop, using CERES-Maize, showed an increase in N leaching with the increase of N fertilizer rate applied (He et al., 2012). Similar results were observed in the present study, where higher N fertilizer rates showed higher N leaching rates. A rate of 168 kg ha^{-1} was defined as enough to reach marketable yield with reductions in N leaching. N rates above 168 kg ha^{-1} were not statistically different, while N leaching continued to increase (He et al., 2012), which is harmful to the environment and increases growers' costs of N fertilizers.

A study, using the CSM-CERES-Maize, showed grain yield was increased in higher N fertilizer rates, however, the highest yield observed was at N fertilizer rate of 252 kg ha^{-1} (Irmak et al., 2024). Similar results were reported in the literature, where the N fertilizer rate of 140 kg ha^{-1} resulted in increased yield and reduced N leaching (Xu et al., 2020). Moreover, da Silva et al. (2024) described results using the CSM-SUBSTOR-Potato model where lower N fertilizer treatment result was more accurate for potato production.

The CSM-CERES-Sweetcorn model overestimated simulated values mainly for biomass, total soil N, and yield. According to da Silva et al. (2024), the CSM-SUBSTOR-Potato model also overestimated simulated values for tuber dry biomass and soil N accumulation for potato and it may be attributed to the lack of maturation prediction by the model or even by other crop yield-limiting factors. Total soil N content was satisfactorily simulated by the CSM-CERES-Sweetcorn model, however, discrepancies between observed and simulated data were observed in the present study and reported in the literature for other crops (da Silva et al., 2024; Lizaso et a., 2007). It can be attributed to the reduced number of soil samples collected during the season.

Rainfall events during a sweet corn crop season increased the N leached, which had a negative impact on N uptake and dry, especially in sandy soils, that easily moves the N across soil layers, increasing the chances of soil N leaching (He et al., 2011; Jhonson et al., 2021).

Overall, the CSM-CERES-Sweet corn evaluation was able to mimic sweet corn growth and development under subtropical environmental conditions, the model was not sensitive enough to detect differences in the N fertilizer application, mainly when the N fertilizer rates are high (>150 kg of N ha^{-1}). The model detected how much was applied in the soil, however, it was not able to detect difference of how much was uptake by the different N fertilizer treatments. Similar results were found by Lizaso et al. (2007), who described the lack of sensitivity in the model and the need of further research to improve simulations of yield in response to soil N supply.

Conclusion

The CSM-CERES-Sweetcorn model was able to simulate sweet corn growth and development under different N fertilizer rates across two years with different weather patterns. Weather conditions have directly impacted N management. The combination of high rainfall events with high N rate led to an increase in N leaching and consequently, reduction in N uptake, biomass, and yield. However, the model is not sensitive enough to detect differences in the N fertilizer rates applied, which require further research to improve the model and allow better predictions among the different N fertilizer rates.

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Chapter 6 (Overall Conclusion)

Weather variability in the humid subtropical environmental conditions of southeastern U.S. is impacting sweet corn production. Particularly, heavy rainfall events, unpredictable heat and drought stresses, and frequent high-temperature fluctuation create challenges during crop growing seasons and bring negative impacts. Daily air temperatures had a direct impact in sweet corn development, yield, and ear quality, while heavy rainfall events and drought impacted N leaching and uptake.

The importance of N fertilization is known for crops growth and development. Our experiment evaluated different N rates and and timing and we concluded that higher total soil N comes from treatments with high N rate; however, it did not translate to higher yield. Moreover, yield did not show a significant difference between treatments, which may be explained by the same amount of N uptake by the plant in all treatments. Yield was directly related to NUE, which shows how efficient plants are using the available N. Therefore, there is no need to increase N fertilization to achieve higher yields, but there is a need to understand the best N fertilizer management strategy to achieve adequate yield and minimize input costs and environment. Splitting applications associated with the right timing are extremely benefic to sweet corn growth and development.

The CSM-CERES-Sweetcorn model was able to simulate sweet corn growth and development under different N fertilizer rates across two years with different weather patterns. However, the model is not sensitive enough to detect differences in the N fertilizer rates applied, which require further research to improve the model and allow better predictions among the different N fertilizer rates.