Evaluation of Irrigation Scheduling and Sustainability Indicators as Tools to Increase the Adoption of Conservation Practices Among Central Alabama Farmers

by

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ABSTRACT

In recent years, there has been a significant surge in the adoption of conservation practices in agriculture, driven by a collective understanding of the urgent need to minimize risks, enhance profitability, and protect the environment. Practices such as cover crops, crop rotation, reduced tillage, and precision agriculture mitigate the risks associated with unpredictable weather patterns and climate change. By enhancing soil health and structure, conservation techniques mitigate the impact of extreme weather events, such as droughts and floods, making farms more resilient. Furthermore, these practices boost profitability by optimizing the use of resources. Through efficient water management and reduced need for chemical inputs, farmers can cut costs while maintaining or even increasing yields. Additionally, conservation methods protect the environment by reducing soil erosion, preserving biodiversity, and mitigating greenhouse gas emissions.

Due to unpredictable weather patterns, such as the increased frequency of flash droughts and extreme weather events, climate-related crop production challenges faced by Alabama necessitate a deep understanding of peanut growth and water requirements. Evaluating irrigation management strategies is crucial to comprehend the impact of irrigation on peanut yield and enhance irrigation water use efficiency. Simultaneously, sustainable agriculture practices are essential for environmental preservation and food security. This study merges these critical aspects, focusing on peanut crops and increasing adoption of sustainable agriculture in Alabama, USA.

The first chapter focuses on irrigation scheduling in peanut cultivation. The study aimed to evaluate the impact of various soil water deficit levels on peanut growth and yield using seasonal analyses with 30 years of weather data. The peanut growth model CROPGRO-peanut in the Decision Support System for Agrotechnology Transfer (DSSAT) software was

calibrated and validated to achieve this objective. The calibration used parameters such as leaf area index, leaf and stem weight, total biomass, pod weight, pod number, and volumetric water content. The study used 30 years of weather data and on-farm experimental data collected in 2021 and 2022 from Lee County, AL. Model validation affirmed its reliability in predicting crop output. Abundant and well-distributed rainfall parameters were employed to categorize dry and wet years, and despite complexities, it simulated various variables, demonstrating its capability. The study highlighted the relationship between weather conditions and irrigation management. The results showed that yield losses increase as the soil water deficit increases due to the lack of irrigation frequency.

In parallel, the second chapter explored the use of sustainability indicators inside the Fieldprint Calculator developed by the Field to Market consortium to evaluate the impact of various crop management strategies towards sustainability. The study's objectives involved understanding the current applications and benefits of the indicators and identifying opportunities and barriers to their adoption, thereby contributing valuable insights to sustainable agriculture knowledge. The study engaged five Central Alabama farmers in comparative analyses to assess the impact of crop management in diverse metrics such as soil carbon, soil conservation, water quality, energy use, and greenhouse gas emissions. These analyses revealed variations in water quality and energy consumption and underscored the importance of adopting strategies to strengthen nutrient management and irrigation efficiency. Conservation practices, reduced tillage, and cover cropping were crucial for soil carbon preservation as indicated by the soil carbon indicator. These results, indicators outputs and comparison of indicator values resulted from farmers management practices, were presented at field days with farmers, consultants, industry personnel, and governmental agencies employees. The challenges the team had engaging farmers with these topics, the questions participants had regarding the indicators, the potential for using the indicators as conservation practices benchmarking tools suggested the need for more of this type of educational programs and active farmer participation. Overcoming resistance to change and addressing social barriers were recognized as essential steps toward fostering a sustainable farming culture.

This research underscored the importance of the right time of irrigation application and the use of irrigation scheduling in peanut crops, emphasizing the need for tailored strategies to balance water conservation and yield enhancement. Additionally, the study highlights the challenges and opportunities in promoting sustainable agricultural practices, such as integrating sustainability indicators into extension, and using tools like Fieldprint Calculator to track and measure field performance against state and national benchmarks. Collaboration, education, and community involvement emerged as pivotal components for fostering a culture of sustainable farming, ensuring the long-term viability of agriculture in Alabama.

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I. LITERATURE REVIEW

1. Peanut Crop Physiology and Irrigation Requirements

Peanut (*Arachis hypogaea* L.) is an annual and essential economic oilseed crop in the tropics and subtropical regions. Peanuts carry around 43-55% edible oil, 25-28% protein, and 2.5% minerals (Abou Kheira, 2009). Peanut production in the United States has led to four market classes, which generally align with specific subgroups and varieties: Runner, Virginia, Spanish, and Valencia (Nthupisang, 2018). Runner varieties contributes to approximately 80% of the country's total peanut production and is predominantly cultivated in states like Georgia, Alabama, Florida, and Mississippi. In 2021, Alabama peanut growers produced 622,2 million pounds of peanut, being the second-largest producer in the country, with Georgia taking the first place (USDA-NASS, 2022). Generally, peanuts in the USA are grown under rain-fed conditions, with only a tiny acreage being irrigated. Although the Southeastern USA receives substantial annual rainfall, averaging between 1000 mm to 1270 mm, irregular distribution and unpredictable patterns can negatively affect peanut yield. Studies have reported that insufficient soil moisture can significantly decrease yield (Wright et al., 1991; Abou Kheira, 2009) and the water use efficiency of peanut plants (Jyostna Devi et al., 2009). To reach optimal growth, peanuts require approximately 559 millimeters of water from planting to harvest (Garcia et al., 2007). Drought stress is a significant abiotic factor leading to decreased agricultural productivity and food security on a global scale (Kambiranda et al., 2011). The lack of water interferes with plant development, specifically photosynthesis, nutrient uptake, and grain and yield (Tardieu and Tuberosa, 2010). Moreover, drought conditions are recognized to make peanuts more susceptible to aflatoxin contamination, as evidenced by studies conducted by Blankenship et al. (1989), making them unsuitable for animal or human consumption. Therefore, irrigation strategies might be adopted to decrease the impact of water stress on peanut crops.

2. Peanut Crop Simulation Modeling and Deficit Irrigation Strategies

Understanding peanut physiology and irrigation requirements is crucial for successful peanut farming. Computer simulation models, like the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2019), are valuable tools for the evaluation of crop yield response to irrigation scheduling and other crop management strategies. These models combine information about the soil, plants, and the atmosphere to simulate crop growth and development under various conditions. DSSAT is useful in understanding the crop productivity impact of drought conditions (Tojo Soler et al., 2013), to simulate the potential impacts of climate change (Mubeen et al., 2020), fertilizer management (Jiang et al., 2019), pest and disease management, crop rotations and others.

In the DSSAT models, calculations of soil water balance are done adding up irrigation and rainfall and subtracting surface runoff, drainage, plant transpiration, and soil evaporation. The rainfall and irrigation are provided as inputs. For soil drainage, a method called the tipping bucket approach (Ritchie, 1998) is used. This method imagines the soil's water movement like a series of connected buckets, considering parameters such as the drained upper limit, lower limit, and saturated water content for each soil horizon. This method allows water to move downward in the soil layers. The amount of water moving down depends on the soil's properties. The actual use of water by plants (called evapotranspiration) depends on the demand for water (ETo) and the plant's ability to take it up. The DSSAT models use different methods to calculate this, considering factors like weather conditions and plant characteristics. If there is not enough water in the soil, plants cannot use it as much, affecting their growth. This information helps scientists and farmers understand how much water plants need and how different factors impact their growth. The CSM-CROPGRO-Peanut model can simulate the growth and development of peanuts under various soil moisture conditions (Singh et al., 1994). Dangthaisong et al. (2006) reported that the CSM-

CROPGRO-Peanut model could determine appropriate management strategies for peanut crops under drought stress, including irrigation requirements.

When rainfall is low and not well distributed, providing additional irrigation becomes crucial for achieving optimal yields. In DSSAT, soil-water flow and root water uptake simulation occur for each soil layer. The soil profile is treated as a series of horizontal layers, where each layer may be different in terms of water-holding capacity, moisture content, and root length density (Hoogenboom et al., 2019). According to the study by Tojo Soler et al. (2013), who tested the impact of various irrigation deficit scenarios, the treatment with 90% of the irrigation requirement (90% irrigation threshold - IT), which means that irrigation trigged after 10% of soil water depleted, resulted in higher yields. In contrast, the 30% and 40% IT treatments led to yield reductions of 92% and 45%, respectively, compared to the 90% IT, frequent irrigation treatment. As drought stress represented by the various deficit irrigation treatments intensified, there was a corresponding decrease in crop yield. The incorporation of computer simulation models, like those provided by DSSAT, shows great potential in evaluating irrigation scheduling decisions (Hoogenboom et al., 2019), particularly during drought stress, consequently contributing to achieving optimal yields in peanut crops. However, before employing the software to aid in making irrigation scheduling decisions, it is essential to verify its ability to predict crop response to various levels of drought stress accurately.

3. Irrigation and Methods of Irrigation

Improving irrigation management requires real time estimation of crop water use and soil water status. Real time assessment of plant available water is useful to determine the amount of irrigation required to reach economic yield potential. This parameter is calculated by finding the difference between two fundamental points in the soil's moisture spectrum,~~:~~

field capacity (FC) and permanent wilting point (PWP) (Souza et al., 2018). FC represents the soil's ideal moisture level after irrigation or rainfall, where excess water has drained away, and the soil is holding as much water as it can (Evett et al., 2019). FC can be determined by measuring the water content of a soil core after a pressure of -33 kPa is applied after saturating the soil. PWP is the minimum amount of moisture in the soil at which plants can no longer extract water effectively. This parameter is often determined by measuring the water content of a soil core under a pressure of -1.5 MPa after saturating the soil. Soils at this point are extremely dry, and plants begin to wilt, adversely affecting their growth and health. The plant-available water capacity (AWC) is the range between FC and PWP (de Jong van Lier, 2017). This information and the daily crop water use helps determining irrigation scheduling which ultimately maximizes plant growth and water usage efficiency.

Regarding irrigation systems, three common types are center pivots, drip irrigation, and surface irrigation. Each system provides benefits and is employed based on specific agricultural requirements and available resources. Proper irrigation is crucial in mitigating the risk of yield losses caused by water stress. However, it is essential to avoid over- and under-irrigation, as these could adversely affect crops and the environment. Various management practices can be implemented to enhance water use efficiency, such as incorporating cover crops and conservation tillage, as Hatfield et al. (2001) suggested, along with adopting improved irrigation management practices.

3.1 Irrigation scheduling

A practical approach for enhancing irrigation practices is irrigation scheduling, which involves determining the optimal timing and rate of irrigation (Liang et al., 2016). This method offers numerous benefits, including reducing crop water stress, energy expenses, and labor inputs. Furthermore, it aids in the mitigation of fertilizer expenses and the environmental consequences arising from leaching and runoff (Evans and Sadler, 2008). Various irrigation scheduling methods are available, each utilizing distinct criteria to determine the appropriate irrigation strategy to trigger irrigation.

3.1.1 Evapotranspiration

The major component of water balance is evapotranspiration (ET), and the ET irrigation scheduling approach has proven to be highly effective in optimizing crop growth. ET is the sum of water evaporated from the soil surface and water lost through plant transpiration (Allen et al., 1998). This method estimates soil water levels by carefully tracking irrigation, precipitation, crop evapotranspiration, runoff, and deep percolation water in the root zone. Due to its demand for various type of data, many farmers tend to avoid using this method. The estimation of crop evapotranspiration (ETo) is commonly done using the Penman-Monteith equation. This equation considers the solar radiation, air temperature, humidity, and wind speed factors. These parameters are then multiplied by a crop coefficient (Kc), which represent the water requirements of a crop (the ratio of actual crop evapotranspiration to reference evapotranspiration). Allen et al. (1998) provided insights into peanut Kc based on climate, cropping season, and crop height. However, they did not consider cultivar specifications. Nonetheless, Bandyopadhyay et al. (2005) discovered that the highest average peanut Kc recorded in a humid tropical region was 1.19. This peak value was observed approximately nine weeks after planting, compared to the reference grass evapotranspiration (ETo). The effective utilization of evapotranspiration for irrigation scheduling depends on several factors. Among these, weather conditions play a crucial role, requiring the installation of weather stations as close to the field as possible. Furthermore, the crop coefficient varies across diverse regions and crop varieties. These disparities have the potential to influence the recommended irrigation recommendation significantly.

3.1.2 Soil sensor-based irrigation

Soil sensors represent an additional technological tool with the potential to enhance irrigation choices. These sensors offer the unique benefit of promptly measuring soil moisture information and providing real-time readings. Furthermore, some sensor companies enable remote access to the collected data. Soil moisture sensors can be divided into direct and indirect monitoring (Yoder et al., 1998). Direct methods involve collection of soil samples to measure gravimetric water content and therefore are very time-consuming. In contrast, indirect methods measure soil water content using sensors that most times use a principle based on soil physics. The most common sensors are tensiometers, which measure the soil matric potential (soil water tension), and the time domain reflectometry (TDR) soil moisture sensors, such as the Acclima sensor (ww.acclima.com). Sensors, like TDR, send an electromagnetic wave through the soil using three rods from a transmission line. The increased frequency results in a reaction that relies less on soil characteristics such as texture, salinity, or temperature when compared to alternative methods (Evett and Heng, 2008).

3.1.3 Checkbook

The irrigation checkbook method, called water balance accounting, operates by computing the soil water balance deficit. This process involves tracking the water entering the soil through rainfall and irrigation and exiting the soil through evapotranspiration and percolation (Lundstrom and Stegman, 1988). To implement this method effectively, it is crucial to evaluate the current weather conditions, soil type, and crop status. Essentially, the net irrigation requirement indicates the quantity of water necessary to restore the soil water content in the root zone to its field capacity. This value, representing the difference between the current soil water level and the field capacity, indicates the extent of the soil water deficit. However, the checkbook method's primary drawback is its inadequate performance when confronted with substantial within-field variability, leading to over-irrigation (Vellidis et al., 2016). Nonetheless, checkbook methods provide irrigators with an economical approach to meeting crop water requirements, thus averting detrimental impacts on crop growth and yield. This is accomplished without requiring expensive or specialized machinery (Shortridge et al., 2018).

3.1.4 Deficit Irrigation Strategy

Deficit irrigation (DI) is a water-saving irrigation strategy used in many parts of the world (Fernández et al., 2013) in which irrigation water is applied at lower amounts than the full crop water requirement (i.e., ET), thereby increasing water use efficiency (WUE). Deficit irrigation has been extensively examined in various arid and semi-arid regions to enhance and maximize yield (English, 1990; Xiying et al., 1999). The suggested irrigation level for DI ranges from 60% to 100% of ET (Sidhu et al., 2021). This method enhances water productivity (WP) by increasing crop ET proportionally with small irrigation amounts until maximum yield is achieved. During non-critical growth stages, irrigation is minimized or left out, relying on rainfall to meet the minimum water requirements. For instance, in the case of peanuts, the critical growth phases are flowering and pod-filling. Therefore, implementing this technique requires understanding how different crop stages respond to water deficits. In regions with limited water availability, achieving higher water efficiency can be more economically profitable for the farmer than maximizing yield (Mitchell-McCallister et al., 2021).

Essentially, deficit irrigation aims to stabilize crop yield and achieve optimal water efficiency (Zhang and Oweis, 1999). DI can also reduce water by irrigating only the plant root zone and increasing the time between irrigations. Some experiments conducted in India revealed that providing two supplemental irrigations led to WP values of 0.55, 0.22, 0.23, 0.41, and 2.27 kg m^{-3} for corn, peanut, sunflower, wheat, and potato, respectively. Increasing the irrigation frequency to three times enhanced WP by 40%, 14%, 22%, 38%, and 7% for these crops, respectively (Kar et al., 2004). This technique is widely used in various crops, such as wheat (Ali et al., 2007; Ahmadian et al., 2021), corn (Igbadun et al., 2008; Zou et al., 2021), cotton (Cheng et al., 2021), and peanut (Rathore et al., 2021; Zhang et al., 2021) aiming to strike a balance between water conservation and satisfactory yields.

4. Sustainability in Agriculture

Sustainable agriculture refers to a comprehensive approach involving specific practices. Its long-term goals include meeting human food and fiber needs, improving environmental conditions, using non-renewable and on-farm resources efficiently, incorporating natural biological cycles, maintaining economic viability for farms, and enhancing the overall well-being of farmers and society (Congress, 1990). Some of the practices that encompasses sustainable agriculture are crop rotation, use of cover crops, integrated pest management, conservation tillage and efficient irrigation. Crop rotation, where farmers rotate different crops in the same field over several seasons can prevent soil erosion, maintains soil fertility, and reduces the risk of pests and diseases, reducing the need for chemical inputs. Cover crops grown during off-seasons prevent soil erosion, improve soil quality, and improve nutrient cycling. Integrated pest management involves combining biological, cultural, mechanical, and chemical control methods to manage pests effectively while minimizing environmental impact. Conservation tillage involves minimal disturbance of the soil, preserving soil structure and reducing erosion. Efficient irrigation methods reduce water wastage, conserves groundwater resources, and prevent soil salinity.

Sustainability in agriculture has gained importance as it holds the potential to address both food security and climate change concerns effectively. To promote sustainable agricultural practices, farmers need approaches that are not only economically viable but also environmentally and socially responsible (Robertson, 2015). However, a significant barrier for farmers in adopting sustainable practices revolves around reducing inputs without compromising agricultural production and economic profitability (Foley et al., 2011). The yield and profitability of an agriculture operation are influenced by multiple factors, including crop type, climate, soil conditions, management practices, and more, which affect the yield and profitability of an agricultural operation. Pursuing sustainable agriculture is pivotal for addressing pressing global issues. However, its successful implementation hinges on balancing economic viability, environmental responsibility, and social sustainability in diverse agricultural conditions.

5. Increasing Farmer's Awareness of the Importance of Sustainable Agriculture Using Indicators

For numerous years and across various global regions, research has investigated the circumstances in which farmers choose to implement sustainable farming practices. Usually, farmers' decision-making processes linked to agriculture practices are primarily profitability driven. Therefore, these decisions differ from their everyday choices and are generally driven by economic factors (Rodriguez et al., 2008). Sustainable farming practices have long-lasting effects and can involve substantial investments. Boosting earnings, securing higher price premiums, and reducing expenses are frequently cited motivations, as acquiring licenses or gaining advantages in marketing and branding are common objectives (Trujillo-Barrera et al., 2016). Characteristics of the farm itself also influence the adoption of sustainable practices in farming. Farms with more significant income and acreage, indicating larger size, may have an advantage in adopting sustainable practices because they possess more operating capital and have improved access to credit (Shiferaw et al., 2009; Kemp et al., 2014). Besides demographic influence in adopting conservation practices, age, education, experience, gender, and household income influence adoption (Hoek et al., 2021).

Farmers may perceive the adoption of new practices as risky. Consequently, the dissemination of information plays a crucial role in boosting adoption rates and reducing associated risks. Additional research has indicated that knowledge sharing, mainly involving collaborative efforts with research and outreach specialists, enhances participation and improves the effectiveness of implemented measures (Fujisaka, 1994; Gielen et al., 2003; Kemp et al., 2014). Observability and trialability are crucial factors that decrease the perceived risk of adopting new agricultural practices. When the benefits are easily observable, and farmers can experiment with new practices on a small scale, they are more likely to adopt them, as it becomes a less daunting and lower-risk proposition (Serebrennikov et al., 2020).

In recent years, multi-stakeholder initiatives (MSIs) have gained prominence as a prominent method of private governance aimed at promoting sustainability within the food system. Traditionally, many MSIs have created specific standards against which farmers can achieve certification. However, some sustainability-focused MSIs have recently shifted their approach toward using metrics, as Freidberg (2017) and Hatanaka et al. (2022) highlighted. The critical distinction between metrics and standards lies in their function. Metrics do not prescribe specific requirements or benchmarks that farmers must meet. Instead, they serve as tools that farmers can use to measure and evaluate their performance. The data from these metrics enables farmers to assess their practices more effectively and make informed decisions to improve their sustainability efforts (de Olde et al., 2016).

The study by Hoffelmeyer et al. (2022) investigates farmers' motivations, perceived benefits, and power dynamics within Field to Market's metrics program using a combination of surveys and interviews. The study's findings indicate that the influence of sustainability metrics on farmers' practices and profitability exhibits significant variation. While sustainability metrics programs provide valuable learning opportunities and benchmarks for farmers, it becomes evident that more than economic benefits are needed to serve as a compelling factor to sustain their participation. Consequently, future program design and implementation must consider farmers' nuanced motivations and concerns to ensure their success and the equitable distribution of benefits.

According to (Strube et al., 2021) farmers care about conserving the land and passing on to future generations. However, he indicated in his study that companies and sustainability groups are asking farmers for detailed reports, making farming more complicated. Despite this, some suppliers are proactively adopting sustainability metrics, even before being asked. They are doing this to stay ahead, expecting future demand for this data. Suppliers are also trying to find effective ways to tell others, like consumers, about their sustainability efforts. However, farmers feel that their sustainability efforts are often misunderstood by people not involved in farming.

Therefore, the need for improved communication of sustainability information to consumers has emerged as a critical concern (Robertson, 2015). However, a significant barrier for farmers in adopting sustainable practices revolves around reducing inputs without compromising agricultural production and economic profitability (Foley et al., 2011). The outcome of this attempt varies substantially, as multiple factors, including crop type, climate, soil conditions, management practices, and more, influence the yield and profitability of an agricultural operation. Consequently, when comparing sustainable practices with conventional techniques, one can observe wide variations in yield outcomes (Marcillo and Miguez, 2017; Laborde et al., 2020; Allam et al., 2021). In essence, pursuing sustainable agriculture is pivotal for addressing pressing global issues. Still, its successful implementation hinges on balancing economic viability, environmental responsibility, and social sustainability in diverse agricultural conditions.

Although government programs and policies play a crucial role in enhancing the sustainability of the agriculture sector, a significant portion of the initiatives to increase agriculture sustainability are happening independently of governmental involvement (Ponte, 2014). Consequently, diverse private and multi-stakeholder initiatives have emerged, covering every aspect of agriculture globally. These initiatives can serve either as assessment tools or as standards. Assessment initiatives involve the creation of empowering farmers to measure and evaluate their performance in terms of sustainability (Marchand et al., 2014). Standards initiatives also establish specific requirements that farmers must meet, often involving third-party certification processes (Hatanaka et al., 2005). Both approaches use indicators, which measure variables to evaluate the sustainability performance (FAO, 2012).

6. Use of Sustainability Indicators and Tools

6.1 Fieldprint Calculator

Measuring sustainability in agriculture employs various methods, including utilizing sustainability indicators, models, and input requirements (Denef et al., 2012). Each approach uses distinct tools, such as calculators, to evaluate sustainability. For instance, consider the Field to Market group, which focuses on commodity crop agriculture within the United States - established in 2006 through the collaboration of various stakeholders in the agriculture and environmental sectors. Today, this consortium includes prominent names such as ADM, Bayer, Cargill, Coca-Cola, Corteva, John Deere, universities, extension services, and others.

The primary mission of Field to Market revolves around creating and implementing a standardized framework for quantifying sustainability in agriculture. This framework is intended for farmers and supply chain use to enhance comprehension of sustainable practices and enable continuous improvement assessments. The core idea behind this is that measuring and evaluating sustainability encourages farmers to continually improve their sustainable practices by identifying areas that require improvement.

One of Field to Market's notable contributions is the development of the Fieldprint Calculator, which was utilized in the study. This tool is designed to measure and benchmark the sustainability performance of commodity crops based on eight key indicators. These indicators include biodiversity, energy use, greenhouse gas emissions (GHG), irrigated water use, land use, soil carbon, soil conservation, and water quality (Field to Market, 2023).

For instance, biodiversity plays a role in supporting species and ecosystem diversity through habitat conservation and enhancement. Energy use and greenhouse gases are evaluated both directly (i.e.,based on fuel usage for irrigation and tillage) and indirectly (i.e., based on energy consumed in crop production, manufacturing, transportation, and emission reductions). Water use efficiency and conservation are based on irrigation water use, while land use efficiency and soil conservation aim to increase land productivity by examining soil carbon sequestration and reduced soil erosion. Additionally, water quality improvements target the reduction of sediment, nutrient, and pesticide loss.

The Fieldprint Calculator is a free online resource that enables growers to document their management systems and understand their impact on local, state, and national sustainability benchmarks based on indicator metrics. The calculator automatically prompts users to input field coordinates to link soil and topography data to their location. Furthermore, it requires data related to crop rotation, tillage systems, irrigation methods, chemical inputs, product transportation, harvest practices, and conservation efforts.

6.2 Cool Farm Tool

Similarly, Cool Farm Tool (CFT) is a suite of online tools developed by the Cool Farm Alliance. It allows farmers to measure and reduce their agricultural practices' carbon footprint and environmental impact. Created in the United Kingdom, initially by Hillier et al. (2011) and updated in 2016, the CFT has gained significant recognition and adoption within the agricultural community.

The CFT utilizes a tiered approach to estimate greenhouse gas emissions in agriculture. The CFT offers a user-friendly interface that allows farmers and supply chain actors to input relevant data quickly. This data may include climate, soil parameters, pH, applications of inputs, fuel type, yield, and drainage (Haverkort and Hillier, 2011). Using the CFT, users can assess the environmental sustainability of their farming practices. It provides insights into how different decisions, such as crop rotation or fertilizer use changes, can impact greenhouse gas emissions (Cool Farm Alliance, 2021).

In summary, the Cool Farm Tool (CFT) is a valuable resource for farmers and supply chain actors to estimate and assess greenhouse gas emissions associated with agricultural activities. It offers a tiered approach, making it adaptable to different data availability and complexity levels. Through the CFT, users can gain valuable insights into the sustainability of their farming practices and make informed decisions to reduce their environmental impact.

6.3 Indigo Ag.

Indigo Ag is a company that created an integrated business platform that allows farmers and others in the agricultural industry to embrace and benefit from sustainable opportunities. The company actively contributes to sustainability efforts through its innovative sustainability calculator, which applies scientific models and data analysis to assess the environmental impact of farming practices (Indigo Ag., 2022). This calculator employs data science, agronomy expertise, and life cycle assessment techniques to evaluate how agricultural practices influence critical sustainability metrics such as carbon footprint, water use efficiency, and soil health (Indigo Ag., 2022).

Some agrifood companies, like Indigo, have introduced microbial seed treatments designed to function as plant growth promoters. These treatments claim to reduce the need for chemical products in agriculture, potentially leading to decreased greenhouse gas (GHG) emissions, particularly in producing carbon dioxide and nitrous oxide associated with fertilizer manufacturing. Moreover, these companies actively advocate specific sustainable farming practices to their clientele, including cover crops and no-till farming, potentially enhancing soil carbon sequestration.

To further promote microbial products and sustainable agricultural techniques, Indigo has initiated mitigation programs that aim to amplify GHG reduction efforts with active farmer involvement (Indigo Ag., 2022). These programs offer farmers interested in suppressing GHG emissions an opportunity to participate. However, in exchange for their involvement, participating farmers must commit to adhering to specific crop management practices, using designated products, and providing comprehensive data regarding their agricultural activities, inputs, and land use history. As an incentive, Indigo Ag promises to share 75% of the profits resulting from GHG reduction efforts with participating farmers (Indigo Ag., 2022).

Notably, these corporate mitigation programs aim to promote GHG emission reductions in agriculture and create new revenue streams tied to the sale of carbon credits and low-carbon products. Mitigation programs follow established carbon accounting standards to ensure their GHG reduction achievements can be certified. For instance, Indigo's 'Carbon' program assists farmers in certifying their GHG emission reductions through the VERRA

VM00042 methodology, effectively transforming these reductions into tradable carbon credits (Indigo Ag., 2022).

It is worth noting that compliance with carbon accounting standards involves technical complexity and incurs substantial certification costs. Consequently, it can be challenging for small-scale and less financially equipped farmers to independently measure, certify, and monetize their GHG reduction accomplishments.

7. Benchmark as an engagement tool

Benchmarking is a widely adopted strategy employed by various industries, including agriculture, to drive performance improvements by identifying superior practices. This practice has gained significant momentum in agriculture since the late 20th century, aiming to enhance productivity and sustainability. The Fieldprint Calculator, a pivotal tool in this endeavor, has been instrumental in benchmarking sustainability performance in agriculture, enabling agribusinesses and marketing firms to validate claims and make necessary improvements (Field to Market, 2023). Despite its widespread acceptance, concerns have been raised regarding the practical interpretation of benchmarking reports, data accuracy, and the program's overall benefits (Hoffelmeyer et al., 2022).

Parrish's (2016) study focused on establishing benchmarks for the environmental impact of cotton production, demonstrating that, on average, Georgia cotton producers exhibit higher sustainability than the national Fieldprint Calculator average. While the study identified minor obstacles, such as workload and data entry challenges, it underscored the critical need for improved communication of sustainability information to consumers.

The practice of benchmarking in agriculture has gained significant traction, mainly through organizations like the Food and Agriculture Organization of the United Nations (FAO, 2022). The FAO has actively published reports and guidelines on sustainable agriculture practices and performance measurement, often utilizing benchmarking approaches. In a study by Hoffelmeyer et al. (2022), participants acknowledged the value of the benchmarking feature offered by the Fieldprint Calculator. However, concerns persisted among participants regarding the accuracy of the generated data and their ability to effectively interpret benchmarking reports.

In summary, benchmarking is a basis in agriculture, fostering sustainable practices and performance improvements. The Fieldprint Calculator and organizations like the FAO have significantly contributed to advancing benchmarking methodologies. Addressing data accuracy and interpretation concerns while improving communication strategies will further strengthen the impact of benchmarking efforts in promoting sustainability within the agricultural sector.

II. PEANUT CROP SIMULATION MODELLING TO IDENTIFY DEFICIT IRRIGATION STRATEGIES USING SEASONAL ANALYSIS

ABSTRACT

Alabama, a prominent peanut producer in the United States, faces production challenges due to unpredictable weather patterns and increased frequency of flash droughts. Given the importance of peanut crops and the risk of yield losses associated with drought stress, evaluating irrigation management strategies is crucial in increasing profitability and irrigation water use efficiency. This study aims to assess the impact of soil water deficit levels on peanut yield using seasonal analyses with 30 years of weather data. To achieve this, the Peanut growth model in the Decision Support System for Agrotechnology Transfer (DSSAT) platform was calibrated and validated On-farm experimental data was collected in 2021 and 2022 from fields in Lee County, AL. Data used for model calibration were leaf area index, leaf and stem biomass, peanut yield, and volumetric water content measured at 20, 40, and 60 centimeters soil depths. The irrigation treatments involved three soil water deficit levels—30%, 50%, and 70% water depletion from plant available water over the top 30 cm of soil depth, a zone with the highest peanut root density. Dry and wet years were categorized based on an abundant and well-distributed rainfall index. The calibration involved modifying cultivar coefficients (EM-FL, FL-SH FL-SD, SD-PM, LFMAX, SLAVR, SIZLF, XFRT, WTPSD, SFDUR, SDPDV, PODUR, and THRSH), soil water content, leaf area index (LAI), and above-ground biomass. The model demonstrated capability in simulating pod weight, although discrepancies were present due to intricate interactions between genetics and environmental conditions. The model validation showed a good agreement between simulated and observed values of pod weight. At location 20 of the 2021 field ,the pod weight Root Mean Square Error (RMSE) was equal to 471 kg ha^{-1}, and the d-stat reached 0.951, while at location 49, the RMSE was 555 kg ha^{-1}, and the d-stat stood at 0.943. The main findings of the study reveal that the application of three distinct irrigation deficit treatments significantly influenced peanut crops' performance over 30 years of weather data in Society

Hill, AL. The analysis focused on key factors such as leaf area index (LAI), yield, frequency of irrigation, and volume of irrigation water. In particular, the study categorized years into dry and wet based on the Available Water Depletion Rate (AWDR), providing insights into the impact of water availability on crucial growth processes. The results indicate that, during dry years characterized by low AWDR, rainfall alone did not meet the water requirements of peanuts. Lower water depletion achieved through more frequent irrigation positively correlated with increased yields, emphasizing the critical role of irrigation in mitigating water stress. The study suggests that using a 50% soil water depletion over 30 cm soil depth as irrigation triggering threshold offers an optimal balance between water conservation and ensuring an adequate water supply for plant growth, resulting in high yields. The analysis further delved into the influence of irrigation on the maximum leaf area index (LAI), highlighting the responsiveness of LAI to variations in plant-available water. This responsiveness, particularly pronounced during water-scarce periods, underscores the significance of effective irrigation management for optimal crop productivity and water resource conservation. The findings also revealed trends in irrigation water productivity (IWP), with higher depletion levels corresponding to a consistent decline in IWP. In both dry and wet years, the study emphasizes the adverse impact of reduced plant-available water on irrigation water productivity and, consequently, on crop growth and yield. In conclusion, these findings emphasize the critical importance of tailored irrigation practices, considering specific weather conditions, to optimize peanut yield while conserving water resources for sustainable and resilient agricultural practices in Alabama.

INTRODUCTION

Peanut (Arachis hypogaea L.) is a crop of high economic importance in Alabama agriculture, contributing significantly to the state's economy. In 2021, Alabama peanut growers produced 281,827,697 kilograms of peanuts, securing the state's position as the nation's second peanut producer (USDA-NASS, 2022). However, the region's variable climate increases the risks for yield losses and ultimately profitability. Despite the southeastern USA receiving an average annual rainfall ranging from 1000 mm to 1270 mm, the variable rainfall patterns can significantly impact peanut yields. Several studies have highlighted the adverse effects of soil water deficiency on yield reduction (Wright et al., 1991; Abou Kheira, 2009) and peanut water use efficiency (Jyostna Devi et al., 2009). Moreover, drought conditions increase the susceptibility of peanuts to aflatoxin contamination, rendering them unsuitable for human consumption (Blankenship et al., 1989). However, in the region of the southeastern United States where peanuts are cultivated, the scenario is further complicated by rapid urbanization and recurrent droughts that threaten irrigation water availability.

Suitable weather and soil conditions, appropriate varieties, sufficient water supply through rainfall or irrigation, and effective crop management practices are crucial to achieving a profitable peanut crop. Water availability plays a pivotal role in maximizing plant productivity. Peanut plants are susceptible to water stress during reproductive growth stages. Early-season water stress, which is between mid-May to mid-July, has been observed to lead to a 17 to 25% reduction in pod yield compared to well-irrigated conditions (Wright et al., 1991). The developmental period between 50-80 days after planting (DAP) is critical for pod formation, and a water shortage during this time can cause a significant reduction in flowering, pod formation, and ultimately the overall yield of the crop compared to any other growth stage (Butts et al., 2020). However, excessive water can negatively impact peanut yield and increase the incidence of fungal pathogens and limb and pod rot (Butts et al., 2020). Balancing water supply is vital for both yield and quality. Irrigation has positively impacted peanut quality factors such as edible seed yield, oil stock, and seed size (Lamb et al., 2010). However, the challenges of diminishing water availability due to urbanization and increasingly frequent droughts necessitate adopting more efficient irrigation practices to ensure peanut productivity.

The adoption of irrigation practices has indeed increased in Alabama to counter the effects of water stress and enhance yield potential. The period from 2012 to 2017 saw a rise of 3.7% in irrigated harvest cropland in Alabama, USA (USDA-NASS, 2017). In 2017, peanuts crop reported 2,787 acres of entire crop irrigated harvested, 31,126 acres of part of crop irrigated harvested, and 144,778 acres of none irrigated peanuts harvested (USDA-NASS, 2017). This trend underscores the importance of adopting appropriate irrigation strategies to ensure water-efficient crop production. With the pressure for sustainable water management, producers must balance maintaining yields and optimizing irrigation. Currently, irrigation methods range from being based on subjective judgments. The last NASS report (USDA-NASS, 2019) indicated that 1069 farms in Alabama, USA, use any irrigation method, 50.7% irrigate based on the feel of the soil, 9.3% based on day calendar-based scheduling, according to previous season and crop water demand, 7.7% on soil moisture sensing, and 1% start the irrigation when the neighbors irrigate. However, the varying levels of adoption suggest the potential for enhancing water use efficiency and precision irrigation through technical methods and improved management practices.

In this context, one option to identify the optimal irrigation rates and timing under various growing conditions is to use crop growth simulation models. The CSM-CROPGRO-Peanut, integrated within the Decision Support System for Agrotechnology Transfer

(DSSAT), serves as a powerful tool for predicting crop growth, development, and yield across diverse environmental conditions and management practices (Hoogenboom et al., 2019). The DSSAT model is assisted by database management for weather, soil, and crop management and measured data. Utilizing CSM-CROPGRO-Peanut justifies the application to choose the most suitable scheduling irrigation. For instance, a study by Tojo Soler et al. (2013) found that crop development was reduced for treating 30 and 40 % of thresholds, which reduced yield compared to the 60 and 90 % of thresholds, which means that waiting too long for the soil water to deplete may affect the yield. Another study by Garcia et al. (2007) in the southeastern USA employed the CROPGRO-Peanut model to investigate peanut water requirements across different maturity varieties, revealing the potential for irrigation management. Garcia et al. (2007) found that peanuts need approximately 559 millimeters of water from planting to harvest on fields located at the Sumter, Tift, and Burke Counties in Georgia. Such models are pivotal in optimizing irrigation strategies, enabling producers to navigate the complex terrain of water availability and demand to achieve sustainable yields.

Therefore, this study hypothesizes that increasing soil water depletion as a consequence of poor irrigation scheduling could negatively impact peanut yield. By using the CROPGRO-Peanut model within DSSAT, simulation of peanut growth and development across three irrigation scenarios – specifically, at 30%, 50%, and 70% depletion of soil available water over 30 cm soil depth supports the identification of irrigation rates and irrigation frequency minimize the risk of yield losses and increase water use efficiency. Through the calibration and evaluation of the CROPGRO-Peanut model and using seasonal analyses with 30 years of weather data, the study seeks to determine the impact of irrigation scheduling on the peanut variety ACI 3321 growing in Society Hill, Alabama. These findings will contribute to improving irrigation management practices, increase profitability of peanut producers and promote resource conservation.

MATERIAL AND METHODS

1. Study Area

Model calibration and validation was performed using crop and soil data collected from two peanut fields in Society Hill, Lee County, Alabama. The 2021 field had Malboro loamy sand soil, classified as fine, kaolinitic, thermic typic Paleudults. In 2022, the field had Marvyn sandy loam soil, classified as fine-loamy, kaolinitic, thermic typic kanhapludults. Before the current project, additional data on terrain elevation and soil electric conductivity (ECa) were collected in December 2020. This data was to understand the within-field variability, delineate potential management zones and within-field watersheds and identify locations for soil sampling and monitoring soil and nutrient changes during the 2021 growing season (Figure 1.1). Students and post-doctoral researchers collected Planet Satellite Images in 2019 and 2020 to assess crop growth and potential yield variability. Vegetation indices, including the Normalized Difference Vegetation Index (NDVI), Non-Linear Index (NLI), and Simple Ratio Index (SR), were calculated to study potential within-field crop biomass variability. The selection of soil sampling locations and installation of soil sensors was based on management zones determined using a combination of data layers of soil apparent electrical conductivity (soil EC_a), terrain elevation (e.g., topographic positioning index and topographic wetness index), and vegetation indices estimated from satellite images.

The data for the calibration of CROPGRO-Peanut model was collected during 2021 (Figure 1.2) and 2022 (Figure 1.3) crop-growing seasons (Table 1.1). The field used for calibration in 2021 (Figure 1.2a) was 25 hectares (ha) in size with 18 ha irrigated, and in 2022, this field was 26 ha in size (Figure 1.2b). Data for model validation was collected from various locations within two peanut fields, one of 8.5 ha (Figure 1.3a) and 26 ha in size (Figure 1.3b). The peanut cultivar ACI 3321, a high-yielding and high oleic runner-type variety developed in Georgia, USA, was planted on May 21-22, 2021 (Field 1.2a), May 26, 2021 (Field 1.3a) and May 19-20, 2022 (Fields 1.2b and 1.3b). The seeding rate was 168.13 kg ha^{-1} in 2021 and 145.71 kg ha^{-1} in 2022, with a row spacing of 0.91 meters. The study area is classified as subtropical humid (Cfa) climate (Koppen Climate Classification, 2023) with an average annual accumulated rainfall of 1380 mm for Northwest Alabama and 1360 mm for Southeast Alabama (Mishra and Srivastava, 2015).

2. Plant Measurements

During the 2021 peanut growing season at the field 1.2a, several locations for peanut biomass harvest were selected to account for various growing conditions (e.g., potential high and low peanut yielding areas). The first collection of peanut samples was done in June 17th with e total biomass collected at locations 1, 3, 4, 5, 6, 7, 8, 9, 14, 15, and 16. The day after this collection, plant partitioning (steam, leaves, pods, seeds) of locations 1, 5, 8, 9, and 15 was done. The second and third sampling occurred on July 21st and August 24th at locations 3, 4, 5, 6, 7, 8, 9, and 15 for total biomass and peanut biomass partitioning of steam, leaves, and pods biomass was done at locations 3 and 9. During harvest, October 11th 202, peanut samples were collected at all 11 locations, total biomass was estimated from all of them, and biomass partitioning was done at locations 3 and 9. However, since the model needs ideal conditions for calibration, data from three high-yielding peanut sampling locations within field 1.2a (locations 3, 6, and 7) were to input into the software. Because peanut yield was affected by frequent rain in 2021, additional data for model calibration was collected from one location (location 1.1) within field 1.2b in 2022. Peanut biomass was collected four times during the growing season at each location from an area comprised of four rows of 1-meter length. The collection dates were on June 17th (V5-V6), July 21st (R4), August 24th (R6), and October 11th (harvest) in 2021. In 2022, flowering occurred on June 1st. In 2021, Leaf Area Index (LAI) was measured five times for each sampling location using an LAI-2200C plant canopy analyzer (Li-Cor Biosciences, Lincoln, NE, 2023) and the sampling dates were in June 17th (V5-,V6) July 16th (R3), July 21st (R4), August 11th (R6), and September 24th. Plant biomass was oven-dried at 70 ºC to constant weight (dry matter). The dry weight values of leaves, steam, pods, and total above biomass were used to estimate biomass components per area basis with the values converted from g m^{-2} to kg m^{-2}. The dry weight was divided by the area harvested, either four or six rows, each one of one-meter length, and multiplying by the row spacing of 0.91 m. During the final harvest, six rows of one-meter length were collected, and pods and seeds were counted to estimate the pod and seed weight per unit area (kg ha^{-1}) and the number of pods per unit area (m^2).

3. Weather and Soil Data

The CROPGRO-Peanut model requires daily weather data, such as maximum and minimum temperature (ºC), solar radiation (MJ m^{-2} day^{-1}), and rainfall (mm) over the entire crop growing season. For this study, the data was collected by a Davis Vantage Pro 2 weather station (Davis® Instruments, Hayward, CA, 2023) installed next to the peanut fields. The predominant soil at Field 1.2a was Malboro loamy sand, and at Field 1.2b was Marvyn sandy loam, both soils well drained (SSURGO, 2023). After delineating crop management zones, locations with contrasting field growing conditions were selected. At fields 1.2a, locations 3, 4, 5, 6, 7, 8, 9, 13, 14, and 15 were chosen to assess the soil's physical and hydraulic properties, such as gravimetric water content, bulk density, water pH, NO_3, NH_4, total nitrogen, total carbon, and organic matter (Tables 1.4 and 1.5). At each location, two soil cores, each with a depth of 122 cm were collected and divided into the following soil depths: 0-5, 5-15, 15-23, 23-30, 30-46, 46-61, 61-76, 76-91, 91-106, and 106-122 cm. Soil physical and chemical properties were determined from each soil sampling depth. In 2021, irrigation was applied by the farmer on July 30th (11.43 mm), July 31st (11.43 mm), August 14th (19.05 mm), and September 08th (12.7mm) totalizing 54.61 mm.

4. Soil Water Balance

Soil water content (SWC) data at each sampling location was collected using Acclima soil sensors (Figure 1.4). These sensors use the Time Domain Reflectometry principle to measure changes in soil moisture (Acclima, 2023). The sensors were installed at 20, 40, and 60 cm of soil depth. The SWC data input into DSSAT corresponded to daily measurements collected by the sensors at 3 p.m. when plants have reached the peak of crop water use. The soil layers in DSSAT are divided into 15 cm depth, and then the layers considered for the soil water content observations were the 15 - 30 cm, 30 - 45 cm, 45 - 60 cm depth.

The total available water is the amount of water that exists between the permanent wilting point (PWP), referred as the lower limit (LL) in DSSAT, and the field capacity (FC), known as the drained upper limit (DUL) (Tables 1.10 and 1.11). The determination of PWP and FC at some locations within the field 1.2a l involved estimation of soil water retention curves (SWRC) using the Hyprop-2 (Meter Group, Pullman, 2023) and the WP4C (Meter Group, Pullman, 2023) sensors for the estimation of the FC and PWP, respectively.. This process included collection of undisturbed soil cores at depths of 20 cm, 40 cm, and 60 cm to generate the wet and dry ranges of the soil water retention curve. At each sampling locations, there was an SWRC that represented each one of those three soil depths.

Saturated water content (SAT, cm^3 cm^{-3}), bulk density (g cm^{-3}), and root growth factor were first generated by the SBuild Program of DSSAT Version 4.8 (Hoogenboom et al., 2019). The FC is the moisture content in the soil after complete saturation and drainage for about 24 hours, as explained by (Evett et al., 2019), or it can be determined by measuring the water content of a soil core under a pressure of -33 kPa after saturating the soil. In the same way, the PWP is often determined by measuring the water content of a soil core under a pressure of -1.5 MPa after saturating the soil, which refers to the soil moisture content in which plants cannot extract enough water from the soil.

5. Model calibration and evaluation

5.1 Calibration

Since the peanut variety ACI 3321 used in this study was unavailable in the CROPGRO-Peanut cultivar database, cultivar coefficients for this variety were generated using biomass and growth data collected in the 2021 and 2022 growing seasons. As a first step in the cultivar coefficient determination, the peanut variety Georgia Green cultivar coefficients were used as the basis for the generation of the ACI 3321 new cultivar coefficients. The estimation process involved using The Generalized Likelihood Uncertainty Estimation (GLUE) tool. Data related to biomass, crop growth, and phenology from four locations within Fields 1.2a and b were used to create the files X (experimental practices), T (observations data), and A (season average performance). This dataset was then selected using the GLUE tool. Through a total of 50,000 iterations, the tool generated new cultivar coefficients for phenology and growth parameters. After using the GLUE Tool, the sensitivity analysis was used to optimize the coefficient values and to minimize errors between simulated and measured values of phenology dates, biomass, crop yield, and yield components based on statistical analyses. The sensitivity analysis tool was used again to identify soil parameters to adjust the soil water balance. Model simulations of volumetric water content for the depths of 20, 40, and 60 cm were improved by adjusting the values of DUL and LL to match simulated and observed data.

5.2 Statistical Analysis

Using Eq. 1, the Root Mean Square Error (RMSE) was determined based on predicted values (Pi) and observed values (Oi) of various variables such as days from planting to anthesis, days from planting to physiological maturity, maximum LAI, biomass, yield, and yield components. These statistics were used to evaluate how well the model simulated the observed values model calibration could be improved.

$$RMSE = \left[N^{-1} \sum_{i=1}^{n} (P_i - O_i)^2 \right]^{0.5}$$

(1)

The index of agreement (d-stats) uses a predicted observation (Pi), a measured observation (Oi), and the mean of the observed variable (M). Where P'i = Pi - M, and O'i = O'I - M. The index ranges from zero to one, and the closer to one, the better the agreement between the two variables being compared. In other words, if the d-value is close to one, then the predicted and measured observations are in good agreement.

$$d - stat = \left[\frac{\sum_{i=1}^{n} \left(P_{i-O_i}\right)^2}{\sum_{i=1}^{n} \left(\left|P_i'\right| - \left|P_i'\right|\right)^2} \right], 0 \leq d \leq 1$$

(2)

5.3 Validation

For model validation of the CSM-CROPGRO-Peanut model, simulated and observed values of the first flower (R1), harvest maturity, and final pod weight were evaluated using statistical parameters. Data from fields 1.2a and 1.2b (location 1.1) was used for model calibration. The validation was conducted using data collected from several locations within fields 1.3c (locations 20, 49, 71) in 2021 and 1.3b (locations 1, 2, 4, 7, 19) in 2022.

6. Seasonal analysis to evaluate the impact of irrigation scheduling strategies

The seasonal analysis tool in DSSAT allows crop yield simulations under the same crop management strategy and over multiple years of weather data (Hoogenboom et al., 2019). Because this project aims to evaluate different irrigation scheduling treatments and crop water use and irrigation is affected by daily weather, a season analysis was selected to assess three irrigation scheduling strategies under 30 years of weather data (1990 to 2020) in the study region. The weather data was collected online at NASA's Prediction of Worldwide Energy Resources (https://power.larc.nasa.gov/) for this analysis. The soil was Marvyn sandy loam characterized by a sandy clay soil texture throughout most of the soil profile. The seasonal analysis simulation was conducted under the same management strategy used in 2022 data (crop management practices, row spacing, and plant population), and the irrigation efficiency of the center pivot for calibration and seasonal analysis was considered 95%.

This analysis evaluates potential interactions between irrigation and weather conditions on crop growth and yield. Therefore, the objective is to assess the impact of water deficit during various growth stages. For example, for peanuts planted in the Southeast USA, August corresponds to the peak of water use for peanuts as it corresponds to reproductive growth stages. This means supplying the crop with the right amount of water at the right time is essential, so the final yield is not compromised. Figure 1.6 displays the cumulative precipitation of August for the years 1990 to 2020. With a high precipitation variation between years, adjusting the irrigation rate and schedule is vital to avoid the reduction of peanut yields. Comparing years with lower rainfall, such as 1990, to years with more considerable rainfall, such as 2008, reveals that sufficient irrigation rates can change significantly between years; therefore, using seasonal analyses to determine the optimal irrigation rates from year to year might be helpful to understand water demand better and guide irrigation decisions.

7. Evaluation of the Impact of Irrigation Scheduling Strategies

The seasonal analysis tool in DSSAT was employed to evaluate three different scenarios of soil water depletion over the top 30 cm of soil depth. These scenarios included: 1) a 70% depletion, 2) a 50% depletion, and 3) a 30% depletion. The determination of soil water content is based on the concept of soil water depletion. This approach involves setting a maximum acceptable level of soil water depletion, ensuring the prevention of crop water stress and the potential reduction in crop yield (Allen et al., 1998). The simulated soil water content within the effective root zone guides the irrigation decisions. In the automatic irrigation mode, irrigation is initiated within the crop growth model when this simulated soil water content drops below a specific threshold determined by the available water capacity (AWC). In this context, the model defines the AWC as the difference between FC and wilting point WP.

Another point to help evaluating the impact of irrigation scheduling is the irrigation water productivity (IWP), especially in regions with scarce groundwater. Irrigation Water Productivity (IWP) is a measure used in agriculture to assess the efficiency of irrigation practices. It represents the amount of crop yield achieved per unit of water applied during irrigation. IWP is calculated by comparing the increase in yields attributed to irrigation (Y_I) with yields in non-irrigated, dryland conditions ($Y_{0.0}$). This ratio is then divided by the total of irrigation water applied (TIRR) (P Bordovsky et al., 2015). The formula for IWP is often expressed as:

$$IWP = \frac{Y_I - Y_{0.0}}{TIRR} = \frac{\Delta Y_I}{TIRR}$$

8. Abundant and Well-distributed Rainfall

Abundant and well-distributed rainfall (AWDR), a parameter proposed by Tremblay et al. (2012) to study the corn response to nitrogen as influenced by soil texture and weather. This parameter refers to the amount and distribution of rain within a specific area over time, which is crucial for sustainable agriculture. A high AWDR value indicates that an area receives frequent and abundant rainfall, while a low AWDR value would suggest that a location or area gets sparse and low rain (Tremblay et al., 2012). The specific values for what would be considered high or low AWDR can vary depending on the location and the period of data being analyzed.

This parameter was essential for this study to identify and categorize years where adequate irrigation for peanut crops would be necessary to ensure optimal growth through proper water distribution and quantity. The calculations were based on Tremblay et al. (2012) methodology using equation 3. This involved the multiplication of the rainfall amount in mm (PPT) by the frequency (SDI) for a specified period (n). Here, SDI represents the Shannon Diversity Index (Equation 4), with pi denoting PPT and n indicating the number of days within the designated timeframe (Bronikowski and Webb, 1996).

$$AWDR = PPT \times SDI$$

(3)

$$SDI = \left[-\sum pi \ln(pi)\right] \div \ln(n)$$

(4)

The AWDR was estimated for 32 years of peanut reproductive period, which is Mid-July to beginning of September, which is more critical for peanut yield (Attia et al., 2021). (Table 1.6). To differentiate between years with abundant and well-distributed rainfall (wet) and those with sparse and low rainfall (dry) we employed a statistical approach. First the mean was determined and then the standard deviation (STD) of annual rainfall averages of these values. Dry years were identified as those with AWDR values below the mean minus one STD, representing limited rainfall and distribution. Contrarily, wet years were identified as those with AWDR values exceeding the mean plus one STD, indicating high amount of rainfall and better distribution.

RESULTS AND DISCUSSION

1. Weather conditions

During the crop growing season 2021 in Society Hill (AL), the monthly total precipitation values exceeded the 30-year historical average in June, July, August, and October. This contrasted with May and September, which experienced below-average precipitation (Figure 1.2). The maximum and minimum temperatures during the peanut growing period varied between the two years of study in this project. Specifically, in 2021, the average minimum temperature was 18.9°C, and the maximum temperature was 30.2°C. On the other hand, in 2022, the temperatures were slightly higher, with averages of 19.6°C and 31.6°C for the minimum and maximum temperatures, respectively.

To further assess the impact of precipitation, a selection was made, comprising six dry years (2010, 2007, 1999, 1998, 1997, 1990) and seven wet years (2022, 2017, 2008, 2005, 2004, 1996, 1992) based on the AWDR values below 76 (representing the driest years) and exceeding 170 (describing the wettest years) (Table 1.6). Limited water supply and infrequent rainfall in dry years hinder crucial growth processes, including leaf expansion, the production of photosynthetic pigments, and pod yield (Tojo Soler et al., 2013). Particularly in dry years, inadequate water during critical growth stages slows nutrient uptake and affects overall plant health, ultimately impacting yield potential.

The exceptionally high precipitation during 2021, especially in June, July, and August (Figure 1.5), led to elevated precipitation levels during the peanut reproductive growth stage. While adequate moisture is favorable for plant growth, excessive rainfall can lead to waterlogging and increased humidity, creating a conducive environment for fungal diseases.

These conditions align with the observation of Ahmed et al. (2019), who noted a negative correlation between heavy rainfall and peanut yield due to disease risk. On the positive side, optimal water availability can promote leaf expansion, enhance photosynthetic pigment levels, and support pod development, contributing to improved yield potential.

2. Model Calibration

2.1 Cultivar Coefficients

The 18 peanut cultivar coefficients on the CSM-CROPGRO-Peanut model were modified to represent the phenology, growth, and yield of the ACI 3321 peanut variety utilized in this study (Table 1.7). The cultivar coefficients were estimated based on measured data of phenology, crop growth, above-ground biomass, yield components, and yield. The differences between the initial cultivar coefficient values (Georgia Green peanut variety) and the final values (ACI3321 variety used for this study) could be explained by the differences in the growing cycle and their own genetic characteristics. Using the coefficients of the Georgia Green, a variety planted in the Southeast USA in past years, as initial values to start calibrating and generating the new cultivar coefficients improved the process and decreased the time to do manual calibrations using the sensitivity analyses. The outcomes of the model simulations, incorporating the newly generated cultivar coefficients for the ACI 3321 variety, revealed that in 2021 (Table 1.8), the simulated day of anthesis (41 DAP) occurred two days after the observed day (39 DAP). Similarly, in 2022, the simulated anthesis day (40 DAP) was three days ahead of the measured value (43 DAP), as indicated in Table 1.9.

While the observed day of physiological maturity matched the simulated value in 2022, there was a difference in 2021. In 2021, the observed day of physiological maturity was delayed by ten days compared to the simulated day. This variation underscores the dynamic nature of the growth and maturation processes, which weather conditions and genetic responses can influence. These discrepancies reflect the complexity of plant growth dynamics and the interaction between genetics and environmental conditions.

2.2 Soil Water Content

The DUL and LL and the daily dynamics of the simulated soil water content at the 15-30 cm, 30-45 cm, and 45-60 cm soil depth were adjusted based on the DUL and LL values estimated for each layer under laboratory conditions. In 2021, at location 3 within Field 1.2a, the LL values for the 15-30 cm, 30-45 cm, and 45-60 cm ranged from 0.113 cm^3 cm^{-3} to 0.195 cm^3 cm^{-3} before the calibration process (Table 1.10). After calibration, these values shifted to 0.088 cm^3 cm^{-3} to 0.192cm^3 cm^{-3}. Similarly, the pre-calibration DUL values fluctuated between 0.207 cm^3 cm^{-3} to^3 0.28 cm^3 cm^{-3} before calibration and 0.176 cm^3 cm^{-3} to 0.284 cm^3 cm^{-3} after the calibration. The calibration results showed a good agreement between the observed and simulated values with a d-Stat value of 0.725 and RMSE of 0.04 cm3 cm-3 for layers 15-30 cm (Figure 1.7).

For 2022, Field 1.2b – location 1.1, the initial values for LL ranged from 0.095 cm^3 cm^{-3} to 0.186 cm^3 cm^{-3} before the calibration. After the calibration the LL value in the 45 cm layer was adjusted from 0.183 cm^3 cm^{-3} to 0.13 cm^3 cm^{-3}. For DUL, initial values ranged from 0.183 cm^3 cm^{-3} to 0.267 cm^3 cm^{-3} before the calibration, with the 45 cm and 68 cm layers having values of 0.268 cm^3 cm^{-3} and 0.267 cm^3 cm^{-3}, respectively. After calibration, these values were adjusted to 0.19 cm^3 cm^{-3} and 0.21 cm^3 cm^{-3} for the 45 cm and 68 cm layers, respectively (Table 1.11). The calibration of the soil water characteristics at Field 1.2b resulted in a good agreement between simulated and observed SWC values at the 15-30 cm soil depth with a d-Stat of 0.73 and RMSE of 0.034. At the depths of 30-45 cm and 45-60 cm, the RMSE decreased but the d-Stat increased (Figure 1.8). The model is a simplified representation of the soil-water dynamic, which involves complex interactions, such as soil characteristics, climate and weather patterns, crop requirement and root depth, hydraulic conductivity and porosity, and model precision and validation.

2.3 Leaf Area Index and Above-Ground Biomass

The Leaf Area Index (LAI) consistently increased during the vegetative phase. This phenomenon aligns with the observed data (Figure 1.9), where LAI values for the ACI 3321 variety showed a consistent increasing trend over time. After the model calibration, there was a good agreement between observed and simulated LAI values. LAI increased until it reached saturation towards the end of the vegetative period. The LAI was calculated from the average five subsamples and input into the model. The maximum LAI value for the simulated was 5.82 m^2 m^{-2}, while the observed value was 5.87 m^2 m^{-2} (Table 1.8). For the 2022 season, the simulated LAI was 6.12 m^2 m^{-2}, and the observed LAI was 6.31 m^2 m^{-2} (Table 1.8). Figure 1.9b shows that the d-stat between the observed and simulated value for LAI during 2022 season was 0.942, higher than 0.792. The high d-stat values for both years reflect the consistency between the simulated and observed LAI values. The variation in d-stat values between the two years (2021 and 2022) can be attributed to the impact of weather conditions. In a study conducted in Argentina, Haro et al. (2008) found that the maximum LAI for peanuts cultivated under water stress conditions was 3.93, while fully irrigated plots exhibited an LAI of 6.2. The relationship between LAI and biomass is intrinsic; a higher LAI usually corresponds to more significant biomass accumulation due to increased photosynthetic activity.

The leaf weight during the 2021 season (Figure 1.11a) does not show good agreement, as seems with a d-Stats of 0.609. However, the first and second collected point shows a good agreement between simulated and observed value, suggesting that that the lower d-stat might be the result of the low biomass value which could be due to a human error. In 2022 season (Figure 1.11b), the calibration had better results with a d-Stat of 0.816, indicative of the model's capability for simulating leaf weight. For steam weight (Figure 1.12), 2021 had a d-Stat of 0.914, indicating a good agreement between simulated and observed, and in 2022, the d-Stat was 0.809, which means the model can simulate this variable well.

The simulated above-ground biomass values at maturity, determined by adding the above ground biomass and the biomass of the pods, were higher than the observed values (Table 1.8). In 2021, the data input into the model was an average of four meters in specific locations. However, in 2022, the model incorporated individual values (each row) from each subsample collected at each respective location. In 2021, the final observed value was 7459 kg ha^{-1}, and the simulated was 11333 kg ha^{-1}, 34.2% lower than the observed value. An RMSE value of 1937 kg ha^{-1} and a high d-Stat value of 0.938 were found, indicating an agreement between the simulated and observed values for above-ground biomass (Figure 1.10a). Contrarily, for the 2022 season, the situation was reversed; the simulated value was lower than the observed value, measuring 11467 kg ha^{-1} and 15488 kg ha^{-1}, respectively. The RMSE and d-stat were 2588 kg ha^{-1} and 0.930.

2.4 Yield and Yield Components

After calibrating the cultivar coefficients and soil water balance, the final simulated yield for the 2021 season was 6014 kg ha^{-1}, higher than the observed average value of 4200 kg ha^{-1} (Table 1.8). In the 2022 season, the simulated was 5773 kg ha^{-1}, and the observed value was 6658 kg ha^{-1} (Table 1.9). The 2021 wet season might explain the main yield differences between the observed and simulated values. DSSAT requires ideal conditions for calibration; the study was conducted on-farm, and conditions could not be fully controlled. During 2022 in contrast, less rainfall and well-drained soil contributed to better peanut growth and yield. The model simulated the 2022 peanut crop well, Figure 1.3b, resulted in a d-Stat of 0.974, compared to 0.813 in 2021. These results align with the findings of Tojo Soler et al., (2013) who demonstrated the CMS-CROPGRO-Peanut model's accuracy in simulating yield reductions attributable to drought in Geogia.

3. Model Validation

Data from Field 1.3c in 2021 and Field 1.3b in 2022 were collected for model validation. In the 2021 growing season, pod weight was collected several times during the growing season. In the 2022 growing season, pod weight was collected at harvest (Figure 1.14). Pod weight in 2021 was well predicted, showing a good agreement between simulated and observed pod weights for locations 20 and 49, with d-Stats of 0.951 and 0.943, respectively (Figure1.15).

4. Seasonal Analysis – Evaluation of the impact of deficit irrigation on peanut growth and yield

Following the model calibration and evaluation, the application of the seasonal analysis tool aimed to evaluate three irrigation deficit treatments by examining their impact on leaf area index, yield, the frequency of irrigation during the growth season, and the volume of irrigation water (mm). Past studies have used seasonal analysis tools from DSSAT to explore different management scenarios over multiple years (Sarkar and Kar, 2006; Arshad Awan et al., 2021; Tekle, 2021; Singh et al., 2023), yet this tool has not been widely used to analyze irrigation strategies on peanut crops. However, there are similar uses of the tool, for example, in maize studies to predict irrigation and nitrogen application (Tekle, 2021).

Analyzing the peanut yield response to three distinct irrigation strategies over 30 years of weather data, growing on a light soil texture, shows significant variability (Figure 1.16). The impact of irrigation during dry years, categorized by low AWDR during the reproductive peanut growth period, indicates that rainfall alone did not meet the peanut's water requirements. Results show that lower water depletion, achieved through more frequent irrigation, leads to increased yield. For example, in 2019, the yield disparity between the rainfed scenario (374 kg ha^{-1}) and depletion levels of 70%, 50%, and 30% were 2,704 kg ha^{-1}, 3,808 kg ha^{-1}, and 4,691kg ha^{-1}, respectively (Fig. 1.16). The lowest yield observed in the 70% depletion strategy can be attributed to less frequent irrigation, resulting in prolonged periods of crop water stress. In contrast, the higher yield observed in the 30% depletion strategy can be attributed to timely and more frequent irrigation. In this approach, the crop received irrigation at regular intervals, ensuring that it did not experience prolonged periods of water stress.

To better analyze the impact of irrigation on peanut yield, differences among irrigation treatments during two distinct groups of peanut reproductive period years were considered: dry years with AWDR values below 89 (one standard deviation from the historic AWDR mean) and wet years with AWDR values exceeding 173 (Figure 1.6). Peanut yield differences among the irrigation treatments under the dry and wet years was analyzed using the Tukey-Kramer least square mean different test (Table 1.12). A broader comparison between wet and dry years reveals a substantial impact on yield, with a significant P-value of 0.0005. During wet years, the Tukey test indicated that treatments with 30% and 50% depletion did not result in significant yield differences, suggesting that a moderate reduction in plant-available water does not significantly affected peanut crop yield. However, treatment with 70% soil water depletion in wet years exhibited significantly lower yield compared to other treatments, suggesting that excessive water depletion negatively affects crop yield. Contrasting with wet years, significant yield differences among the three deficit irrigation treatments were observed in dry years. Higher and significantly different peanut yield was observed with 30% depletion than the other two depletion treatments. Peanut yield significantly decreased as the depletion level increased (Table 1.12). . The results demonstrate a yield loss trend as soil water depletion increases (Figure 1.17). Wet years consistently show higher yields across all soil water depletion levels compared to dry years. Within each AWDR year category, there is a decline in yield as the level of soil water depletion increases, emphasizing that a decrease in available soil water negatively impacts peanut yield. Maximum productivity is achieved under the 30% soil water depletion due to reduced water stress in this treatment, aligning with the findings of Rao et al. (1985) and highlighting the critical role of irrigation in mitigating water stress and optimizing peanut yield under varying weather conditions.

The number of irrigation events and irrigation amounts follow the same trend as yield (Figures 1.18 and 1.19). The 70% depletion treatment has fewer irrigation events and lower water application compared to other treatments, as expected. On the contrary, the 30% depletion treatment has the most significant amount of water applied and the highest number of irrigation events, aligning with the soil's behavior and the plant's water uptake dynamics. The seasonal analysis emphasizes the influence of weather conditions on irrigation application strategies for each specific year. It is noteworthy that in the 30% depletion treatment, there were years with up to 27 irrigation events, which may not be practical. Maintaining a soil water depletion rate of 50% provides an optimal balance between water conservation and ensuring an adequate water supply for plant growth. This threshold achieved high yields while limiting the maximum reported number of irrigation events to 17 in some years (Figure 1.18).

In wet years, the maximum leaf area index (LAI) (Table 1.13) exhibits no significant difference between the 30% and 50% depletion treatments (group A). However, in dry years, the 50% depletion treatment forms a distinct group (B), indicating a noticeable impact on maximum LAI compared to the 30% depletion. Regardless of rainfall conditions, the 70%

depletion consistently forms a separate group (C) with significantly lower maximum LAI, emphasizing a pronounced reduction in leaf area with more substantial water depletion. This difference is particularly pronounced in the driest years, underscoring maximum LAI's sensitivity to severe water limitations. Overall, the results underscore maximum LAI's responsiveness to variations in plant-available water, with depletion extent playing a crucial role, especially during water-scarce periods. Throughout the study, it has been emphasized that LAI is significantly influenced by water stress, impacting crop yield. Figure 1.20 illustrates the response of maximum LAI to three irrigation treatments, demonstrating how this response varies in years with insufficient rainfall distribution compared to those with abundant rainfall. In years with poor rainfall distribution (Figure 1.20a), maximum LAI shows higher variability, with the 50% depletion treatment exhibiting less variability. Conversely, during wet years (Figure 1.20b), the 50% depletion treatment displays less variation than other treatments. As expected, the 30% depletion treatment exhibits the highest LAI. Haro et al. (2008) noted that soil water stress influences peanut LAI, linking water availability to leaf growth. Effective irrigation management is highlighted as crucial for optimal crop productivity and water resource conservation.

The results for irrigation water productivity (IWP), as shown in Table 1.14, indicate that in dry years, IWP was highest at 30% depletion (22.3333, group A). However, as the depletion increased to 50%, the IWP decreased to 13.6667 (group B) and further to 8.3333 at 70% depletion (group C). In wet years, a similar trend is observed, with the highest IWP at 30% depletion (14.6667, group B), followed by 50% depletion (7.8333, group C), and the lowest IWP at 70% depletion (4.0000, group C). The box plots (Figure 1.21) further illustrate the trend, indicating that as the depletion of plant-available water increases, there is a consistent decline in IWP. This decline is likely due to reduced water availability for crops, affecting their growth and productivity. In dry years, the impact of higher depletion levels is evident, with lower IWP values. In wet years, while the impact is less pronounced, the trend still aligns with the general understanding that as plant-available water decreases, irrigation water productivity is adversely affected. Figure 1.21 illustrates the irrigated water productivity (IWP) differences among the soil water depletion treatments evaluated and how the response changes over the years. In the AWDR dry years, when the depletion level

SUMMARY AND CONCLUSIONS

In conclusion, the analysis of weather conditions, model calibration, and the impact of deficit irrigation on peanut growth and yield provides valuable insights about peanut crops in Society Hill, AL. The weather conditions during the study periods varied, with 2021 experiencing exceptional precipitation levels during certain months, creating challenges such as waterlogging and disease risk. The selection of dry and wet years based on the Available Water Depletion Rate (AWDR) offered a nuanced understanding of the impact of water availability on crucial growth processes.

The calibration of the CSM-CROPGRO-Peanut model involved modifying cultivar coefficients, soil water content, LAI, and above-ground biomass. The model demonstrated its capability to simulate variables, although discrepancies between simulated and observed values were present, attributed to the complexity of genetics and environmental factors.

The seasonal analysis, evaluating three irrigation deficit treatments over 30 years, revealed significant variability in peanut yield, emphasizing the critical role of irrigation in mitigating water stress. The impact of irrigation strategies on yield was particularly pronounced during dry years, where lower water depletion, achieved through more frequent irrigation, led to increased yields. The analysis of peanut yield response to irrigation during wet and dry years highlighted the importance of adapting irrigation strategies based on weather conditions. The influence of weather and irrigation management strategies on peanut yield evaluated for the conditions of peanut fields planted in Society Hill Alabama was evident, with a 50% soil water depletion rate identified as optimal strategy during wet years and 30% depletion in dry years. The identification of those strategies is important for balancing water conservation and ensuring an adequate water supply for plant growth.

In summary, this research contributes valuable insights into the intricate relationship between weather conditions, model dynamics, and irrigation strategies in peanut crops. The findings underscore the importance of considering both genetic and environmental factors when calibrating models and designing irrigation strategies for optimal crop productivity. This holistic approach is crucial for addressing the challenges posed by variable weather conditions and achieving sustainable peanut crops practices.

Table 0.1 Location and crop management practices of peanut fields included in this study.

	Field 2(a)	Field 2(b)	Field 3(c)	Field 3(b)
	Calibration 2021	Calibration 2022	Validation 2021	Validation 2022
Location	32°25'18" N 85°24'56" W	32°25'08" N 85°26'10" W	32°29'59" N 85°26'24" W	32°25'08" N 85°26'10" W
Field sampling locations per year	4	1	3	5
Planting date	May 21st and 22nd	May 19th and 20th	May 26th	May 19th and 20th
Seeding rate, kg ha^{-1}	168.13	145.71	168.13	145.71
Row width, m	0.91	0.91	0.91	0.91
Area planted, ha	25	26	8.5	26
Irrigation amount, mm	54.61	none	15.24	none
Irrigation events	4	none	1	none
Harvest	October 13th	October 1st	October 10th	October 1st

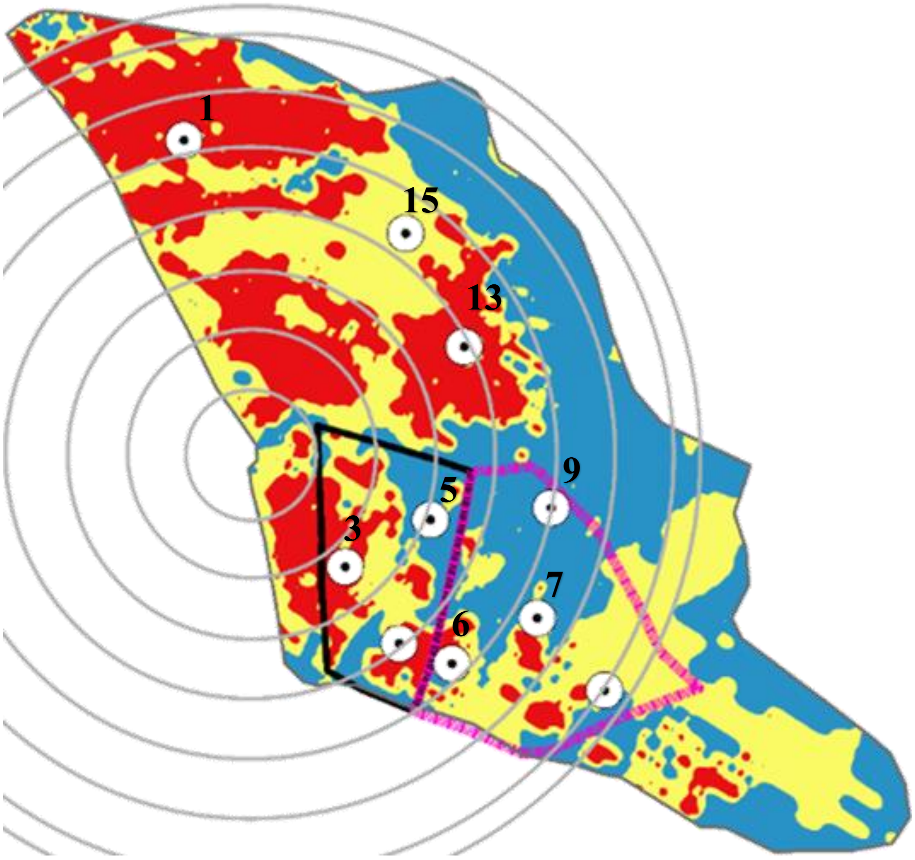


Figure 0.1 Sampling locations during the 2021 growing season showing the different management zones.

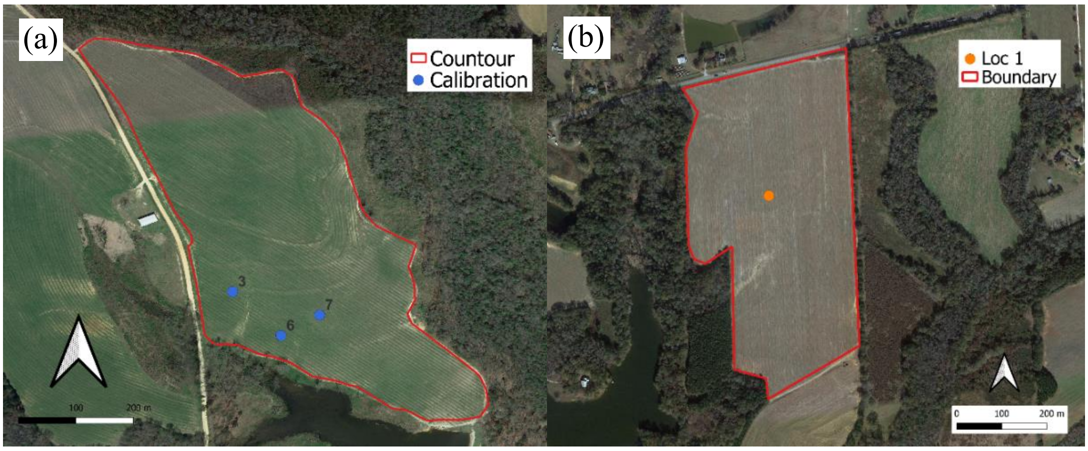


Figure 0.2 Fields and locations where peanut biomass and yield were collected for model calibration locations during the (a) 2021 growing season and (b) 2022 growing season.

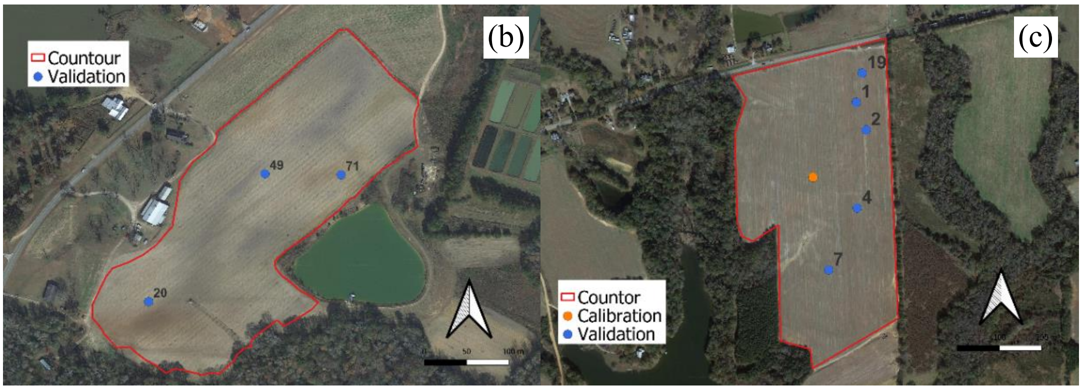


Figure 0.3 Sampling locations within two peanut fields used for model validation during the 2021 (b) and (c) 2022 growing seasons.

Table 0.2 Monthly average weather conditions during the study period (2021-2022).

2021	Minimum Temperature (°C)	Maximum Temperature (°C)	Solar Radiation (MJ m^{-2} day^{-1})	Accumulative Rainfall (mm day^{-1})
May	7	34	21	80
June	16	34	17	138
July	18	35	17	154
August	19	35	17	165
September	9	32	15	62
October	5	30	12	188
2022	Minimum Temperature	Maximum Temperature	Solar Radiation	Accumulative Rainfall
May	10	33	20	110
June	18	39	20	41
July	20	36	19	151
August	20	35	17	139
September	9	36	17	99
October	-1	30	15	57

Table 0.3 Simulated and observed pod weight and statistics of all locations collected throughout the 2021 and 2022 growing seasons.

Field/Year	Location Number	Simulated Pod Weight (kg ha^{-1})	Observed Pod Weight (kg ha^{-1})	d-stat[a]	RMSE[b]
Calibration					
1.2a - 2021	3	6022	4200	0.813	1620
	6	4092	3635	0.923	1046
	7	4072	3846	0.936	951
1.2b - 2022	1.1	5256	6658	0.947	1005
Evaluation					
1.3c - 2021	20	6306	5645	0.951	471
	49	5601	6022	0.943	555
	71	5443	4391	0.717	1081
1.3b - 2022	1	5187	5048	-	140
	2	5969	6395	-	430
	4	5031	4578	-	454
	7	5019	5678	-	698
	19	5575	5479	-	96

Table 0.4 Soil texture characteristics of the locations within Field 2(a) used for crop simulation modeling analyses.

Depth (cm)	Location 3			Location 6			Location 7		
	Clay (%)	Silt (%)	Soil Texture Class	Clay (%)	Silt (%)	Soil Texture Class	Clay (%)	Silt (%)	Soil Texture Class
5	6.2	12.2	Loamy Sand	4.2	14.2	Loamy Sand	6.2	14	Loamy Sand
15	10.3	12.2	Sandy Loam	6.2	16.2	Loamy Sand	8.2	15.9	Sandy Loam
23	12.2	10.2	Sandy Loam	12.2	18.2	Sandy Loam	10.2	16	Sandy Loam
30	18.3	10.2	Sandy Loam	20.2	18.2	Sandy Clay Loam	16.2	20	Sandy Loam
46	32.3	10.1	Sandy Clay Loam	30.2	16.2	Sandy Clay Loam	22.2	18	Sandy Clay Loam
61	34.3	8.1	Sandy Clay Loam	30.2	16.2	Sandy Clay Loam	26.3	16.3	Sandy Clay Loam
76	34.28	8.08	Sandy Clay Loam	32.16	14.2	Sandy Clay Loam	22.28	16.3	Sandy Clay Loam
91	36.3	8.1	Sandy Clay	38.2	12.2	Sandy Clay	22.2	14.3	Sandy Clay Loam
107	36.3	8	Sandy Clay	40.2	14.2	Sandy Clay	26.3	12.4	Sandy Clay Loam
122	42.3	6.1	Sandy Clay	44.2	14.3	Clay	30.3	12.3	Sandy Clay Loam

Table 0.5 Soil texture characteristics from Field 2(b) locations used for model validation.

Depth (cm)	Location 2022 Field 2b		
	Clay (%)	Silt (%)	Soil Texture Class
23	10.12	16.6	Sandy Loam
30	30.12	14.46	Sandy Clay Loam
68	31.08	13.38	Sandy Clay Loam
91	35.08	14.34	Sandy Clay Loam
122	37.08	13.24	Sandy Clay

Figure 0.4 Acclima TDR-315H sensor used for collection of real-time soil moisture data.

Table 0.6 Abundant and Well-Distributed Rainfall (AWDR) index values for 32 years of rainfall data (Society Hill, Alabama).

Year	AWDR Index value	
	Vegetative Period	Reproductive Period
2022	99	197
2021	66	110
2020	174	118
2019	118	137
2018	385	128
2017	250	202
2016	68	169
2015	197	118
2014	78	146
2013	327	138
2012	124	86
2011	70	80
2010	84	56
2009	143	95
2008	62	181
2007	103	49
2006	25	129
2005	182	194
2004	110	180
2003	275	137
2002	225	115
2001	188	117
2000	61	137
1999	247	50
1998	110	65
1997	220	76
1996	101	192
1995	78	96
1994	344	107
1993	53	152
1992	116	182
1991	217	86
1990	68	33

Vegetative period: Mid-May to mid-July.
Reproductive period: Mid-July to beginning of September.

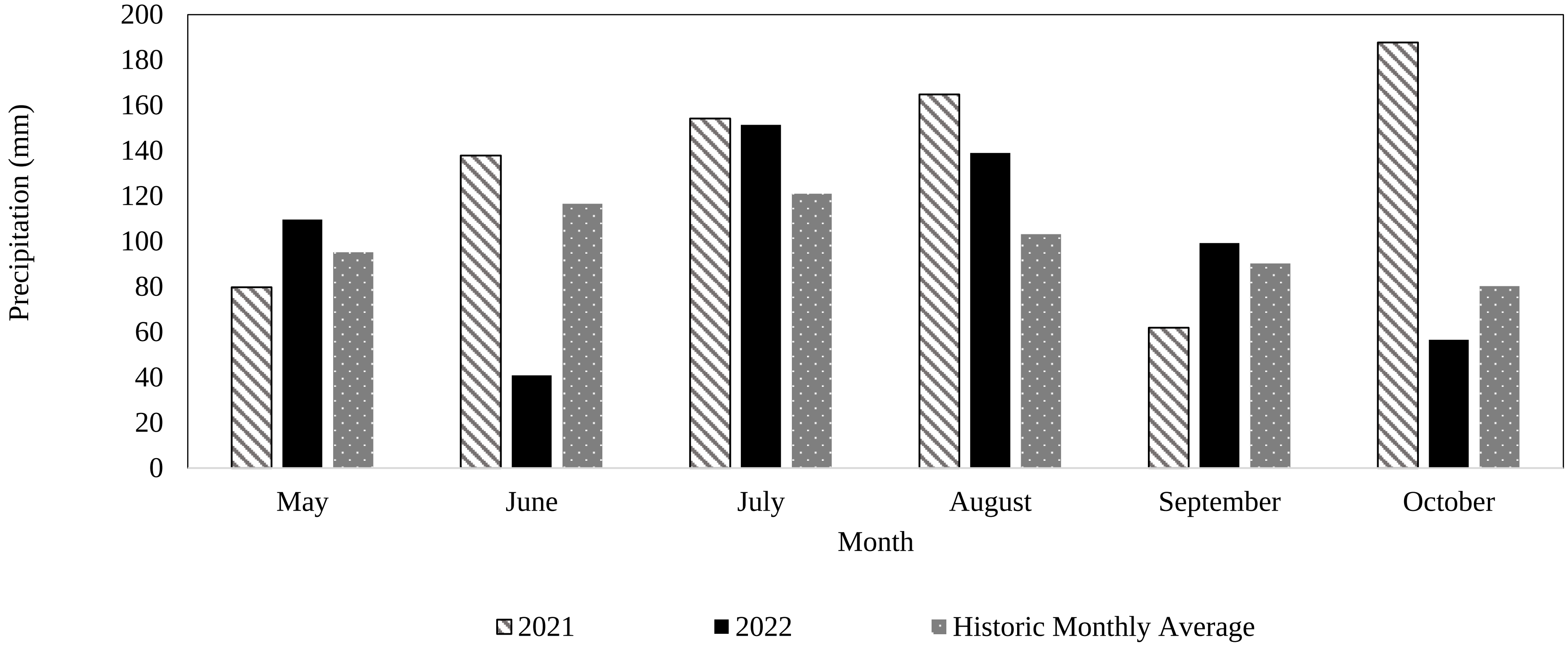


Figure 0.5 Monthly precipitation differences in 2021 and 2022 crop growing seasons concerning the historical monthly average (1990-2020).

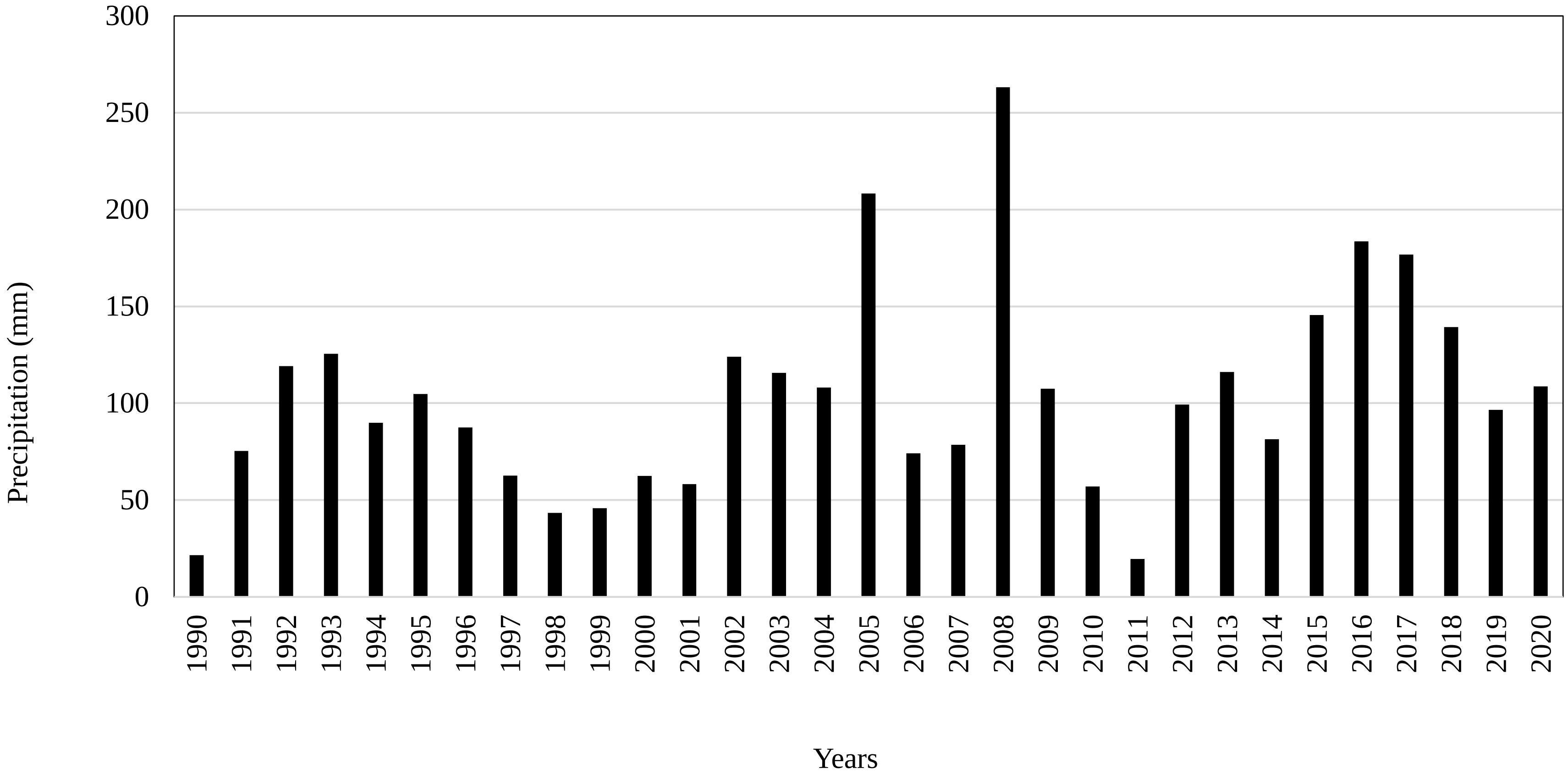


Figure 0.6 Historical August precipitation at Lazenby 1.2a field (Society Hill, Alabama).

Table 0.7 Cultivar coefficients of the peanut variety ACI 3321 in the CROPGRO-Peanut model – DSSAT-CSM v4.8.

Cultivar coefficients	Coefficient label	Unit	Initial Values	Final Values
Critical Short-Day Length (for short-day plants)	CSDL	hour	11.84	11.84
Slope response of development to photoperiod with time (positive for short-day plants)	PPSEN	1/hour	0	0
Time between plant emergence and flower appearance (R1)	EM-FL	photothermal days	21.2	25.8
Time between first flower and first pod (R3)	FL-SH	photothermal days	9.2	7.2
Time between first flower and first seed (R5)	FL-SD	photothermal days	18.8	20.5
Time between first seed (R5) and physiological maturity (R7)	SD-PM	photothermal days	77.3	78.59
Time between first flower (R1) and end of leaf expansion	FL-LF	photothermal days	85	85
Maximum leaf photosynthetic rate and high light	LFMAX	mg CO_2 m^{-2} s^{-2}	1.45	1.02
Specific leaf area under standard growth conditions	SLAVR	cm^2 g^{-1}	270	234
Maximum size of full leaf (three leaflets)	SIZLF	cm^2	18	16
Maximum fraction of daily growth (seed + shell)	XFRT	g	0.95	0.90
Maximum weight per seed	WTPSD	g	0.69	0.67
Seed filling duration for pod cohort at standard growth conditions	SFDUR	photothermal days	42	29
Average seed per pod under standard growing conditions	SDPDV	#/pod	1.65	1.49
Time to reach final pod load (optimal conditions)	PODUR	photothermal days	28	33
The maximum ratio of seed at maturity	THRSH	Seed (seed + shell) $^{-1}$	80	72
Fraction protein in seeds	SDPRO	g(protein) g(seed) $^{-1}$	0.27	0.27
Fraction oil in seeds	SDLIP	g(oil) g(seed)$^{-1}$	0.51	0.51

Table 0.8 Simulated and observed data for the model calibration using 2021 growing season data at Society Hill, Alabama (field 1.2a).

Variable	Simulated	Observed
Anthesis day (DAP)	41	39
Physiological maturity day (DAP)	135	145
Yield at harvest maturity (kg [dm]/ha)	4240	3072
Pod weight at maturity (kg [dm]/ha)	6014	4200
Tops weight at maturity (kg [dm]/ha)	11333	7459
Number at maturity (no/~~-~~m^2)	485	498.1
Unit weight at maturity (g [dm]/unit)	0.8737	0.615
Harvest index at maturity	0.374	0.412
Leaf area index, maximum	5.82	5.87

DAP: Days after planting.

Table 0.9 Simulated and observed data for the model calibration using 2022 growing season data at Society Hill, Alabama (field 1.2b).

Variable	Simulated	Observed
Anthesis day (DAP)	40	43
Physiological maturity day (DAP)	135	135
Yield at harvest maturity (kg [dm]/ha)	3796	4073
Pod weight at maturity (kg [dm]/ha)	5773	6658
Tops weight at maturity (kg [dm]/ha)	11467	15488
Number at maturity (no/-m^2)	510	369.4
Unit weight at maturity (g [dm]/unit)	0.7446	0.719
Harvest index at maturity	0.331	0.263
Leaf area index, maximum	6.12	6.315

DAP: Days after planting.

Table 0.10 Soil properties were calibrated using 2021growing season data at Society Hill, Alabama (field 1.2a).

Depth (cm)	Initial Lower Limit (LL) (cm^3 cm^{-3})	Final Lower Limit (LL) (cm^3 cm^{-3})	Initial Drained Upper Limit (DUL) (cm^3 cm^{-3})	Final Drained Upper Limit (DUL) (cm^3 cm^{-3})
5	0.59	0.068	0.12	0.153
15	0.113	0.088	0.207	0.176
23	0.98	0.097	0.166	0.183
30	0.128	0.124	0.201	0.211
46	0.195	0.183	0.273	0.277
61	0.205	0.192	0.28	0.284
76	0.201	0.192	0.273	0.284
91	0.211	0.201	0.284	0.294
107	0.212	0.201	0.285	0.294
122	0.242	0.229	0.315	0.324

Table 0.11 Soil properties were calibrated using 2022 growing season data at Society Hill, Alabama (field 1.2b).

Depth (cm)	Initial Lower Limit (LL) (cm^3 cm^{-3})	Final Lower Limit (LL) (cm^3 cm^{-3})	Initial Drained Upper Limit (DUL) (cm^3 cm^{-3})	Final Drained Upper Limit (DUL) (cm^3 cm^{-3})
23	0.095	0.095	0.183	0.183
45	0.183	0.13	0.268	0.19
68	0.186	0.186	0.267	0.21
91	0.204	0.204	0.288	0.288
122	0.216	0.216	0.299	0.299

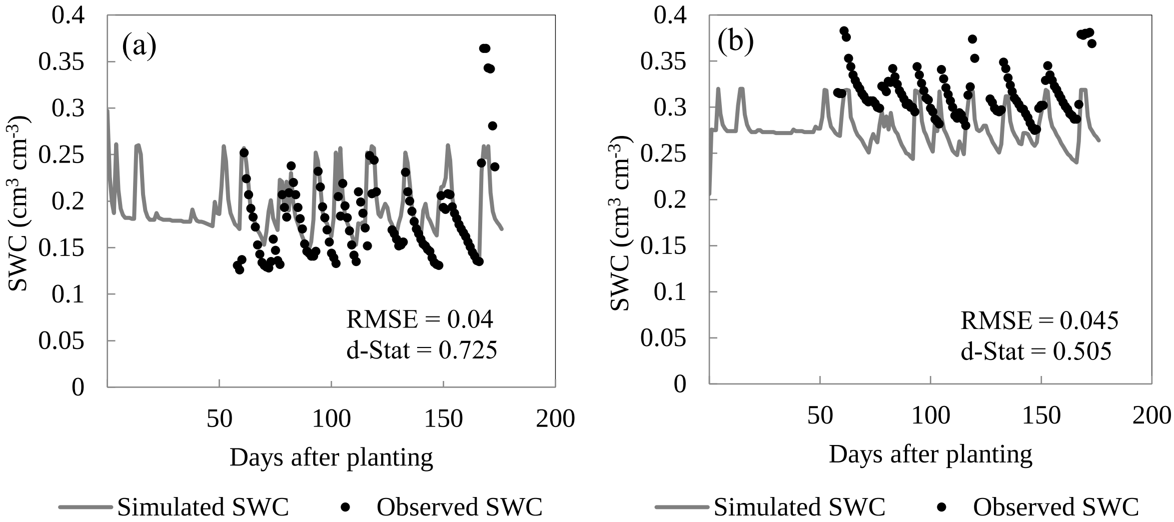


Figure 0.7 Simulated and observed soil water content at 15-30 cm depths (a) and 45 - 60 cm depths (b), at location 3, during the 2021 season (field 1.2a).

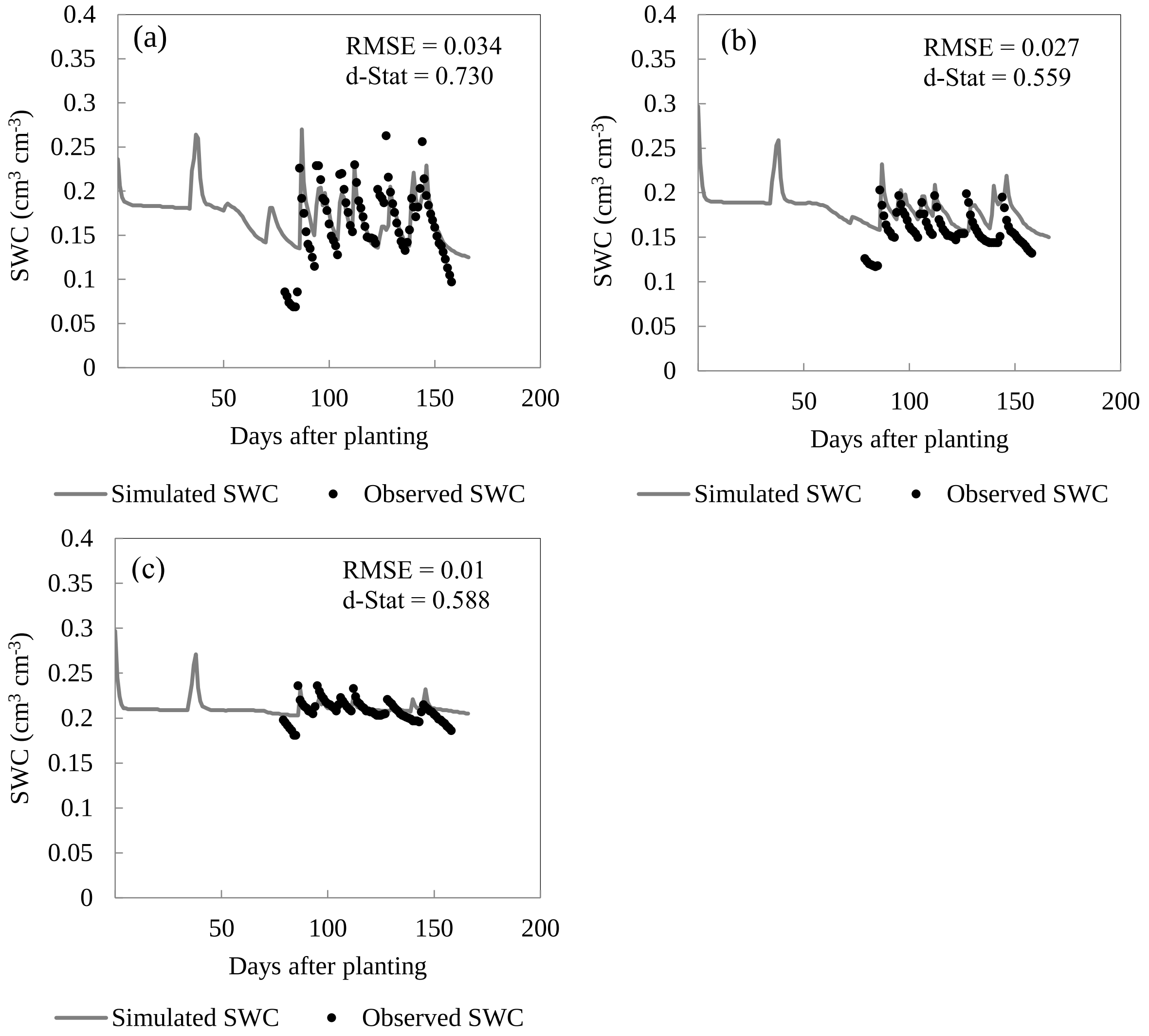


Figure 0.8 Simulated and observed soil water content at 15-30 cm depths (a), 30 - 45 cm depths (b), and 45 – 60 cm depths (c), at location 1, during the 2022 season (field 1.2b).

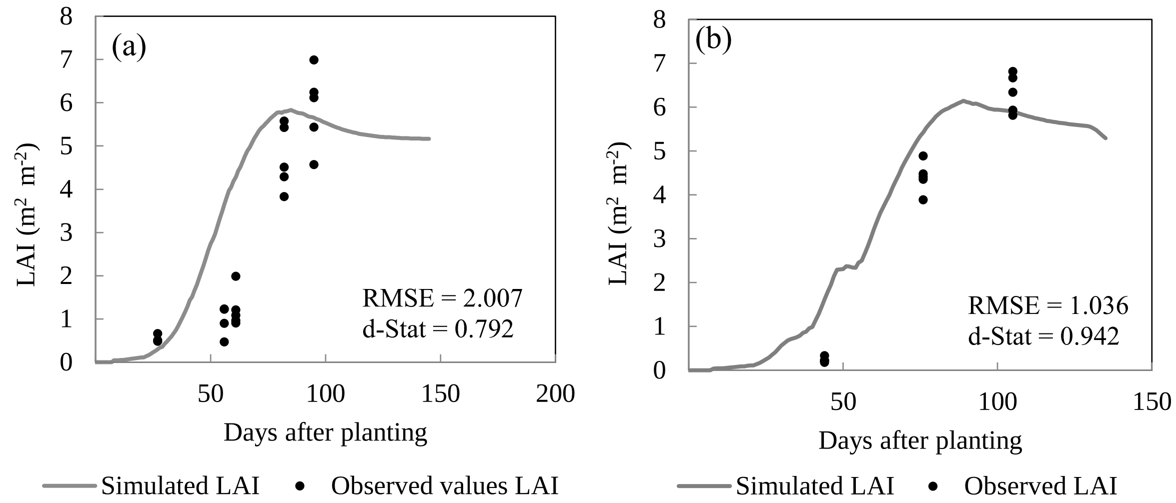


Figure 0.9 Observed and simulated leaf area index for the peanut ACI 3321 at field 1.2a in 2021 season (a), at location 3, and at field 1.2b in 2022 season (b), at location 1, in Society Hill, Alabama.

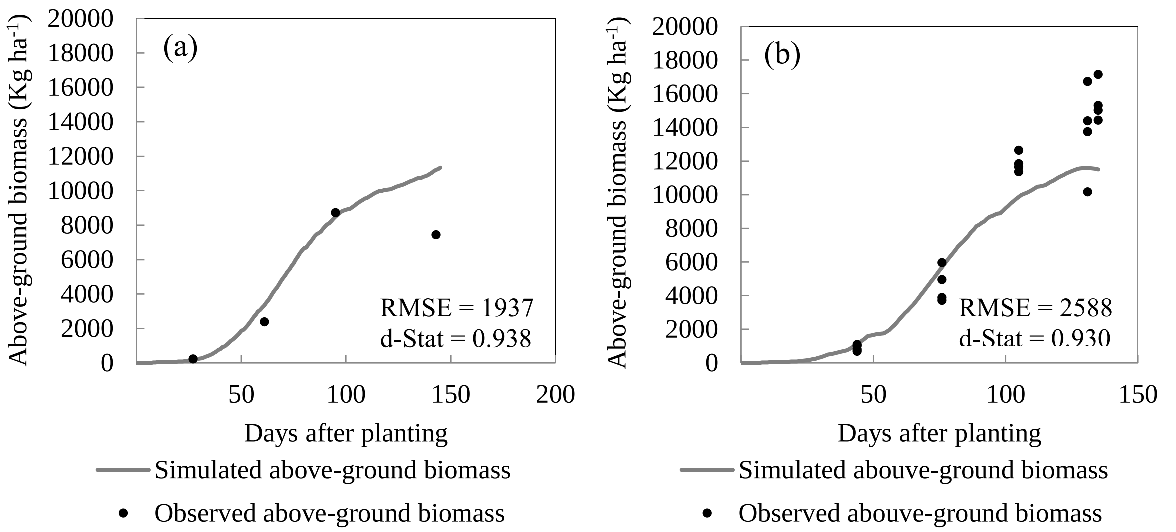


Figure 0.10 Observed and simulated above-ground biomass for the peanut ACI 3321 at field 1.2a in 2021 season (a), at location 3, and at field 1.2b in 2022 season (b), at location1, in Society Hill, Alabama.

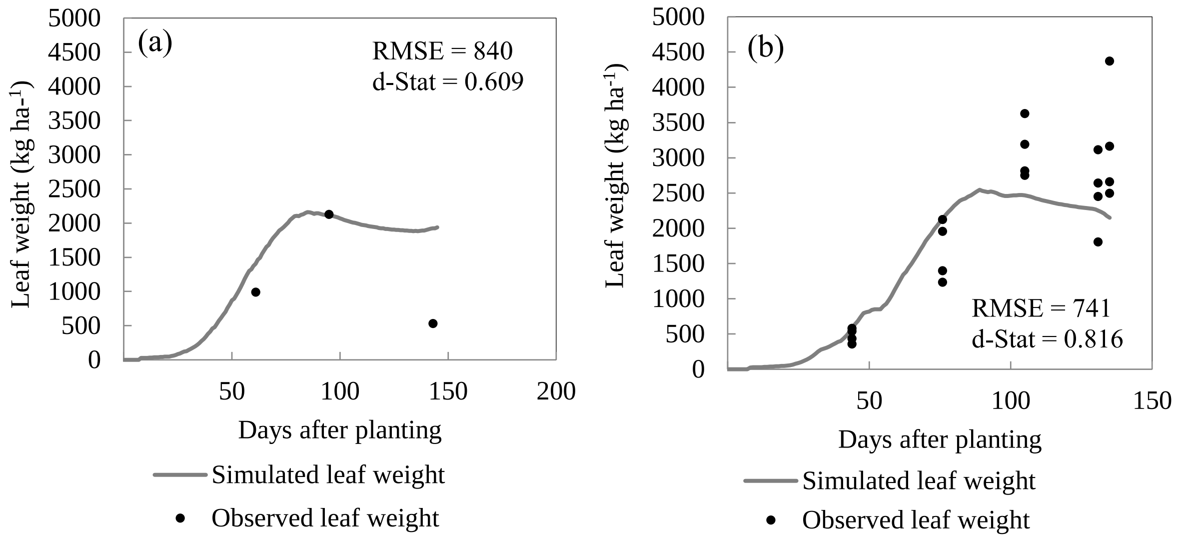


Figure 0.11 Observed and simulated leaf weight for the peanut ACI 3321 at field 1.2a in 2021 season (a), at location 3, and at field 1.2b in 2022 season (b), at location 1, in Society Hill, Alabama.

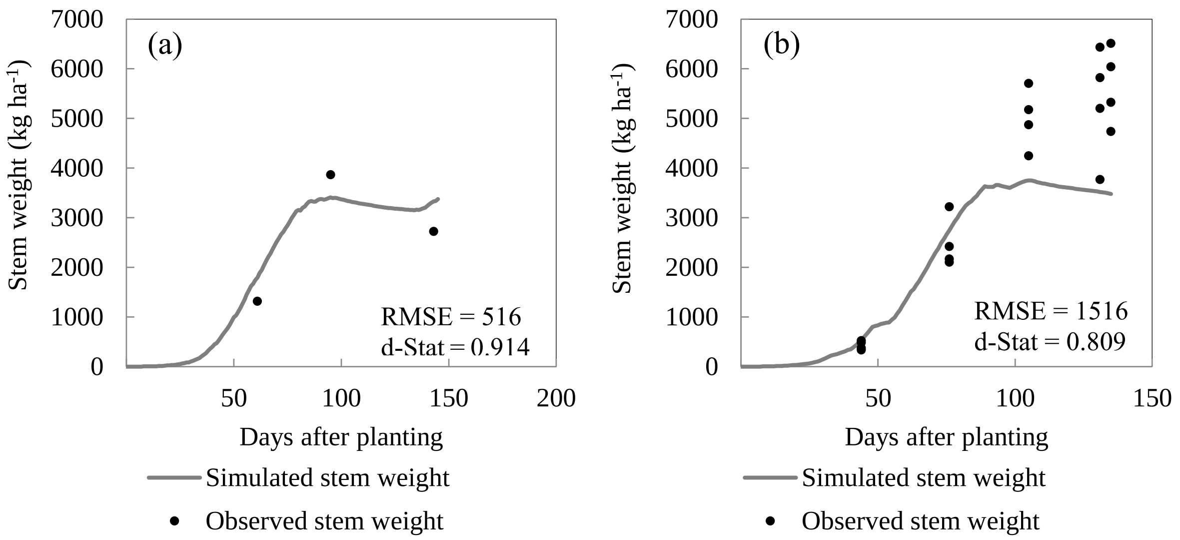


Figure 0.12 Observed and simulated the peanut ACI 3321 at field 1.2a in 2021 season (a), at location 3, and at field 1.2b in 2022 season (b), at location 1, in Society Hill, Alabama.

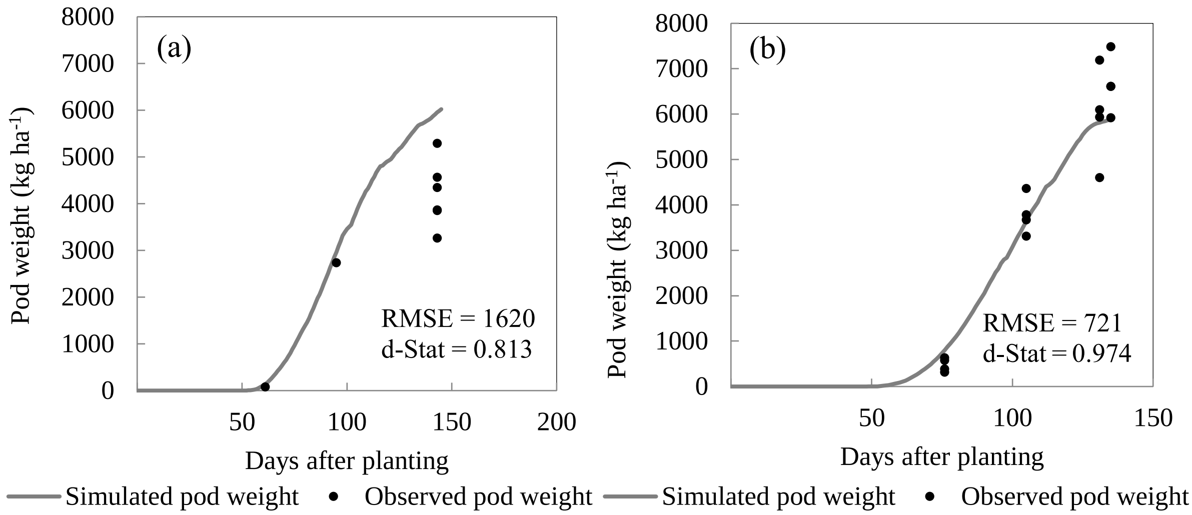


Figure 0.13 Observed and simulated pod weight for the peanut ACI 3321 at field 1.2a in 2021 season (a), at location 3, and at field 1.2b in 2022 season (b), at location 1, in Society Hill, Alabama.

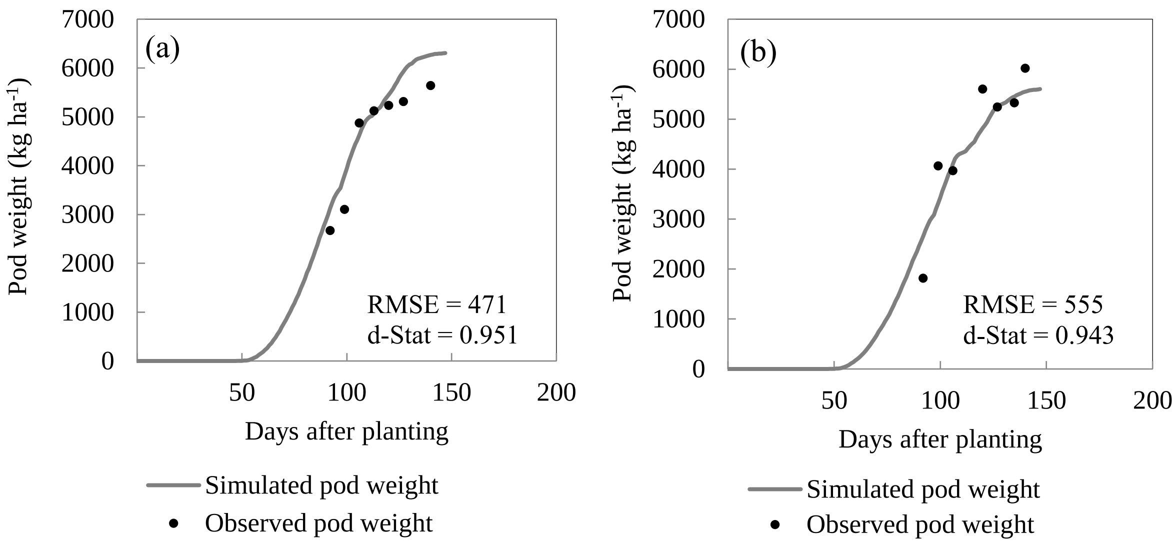


Figure 0.14 Validation pod weight for the peanut ACI 3321 at field 1.3c in 2021 at locations 20 (a) and 49 (b) at Society Hill, Alabama.

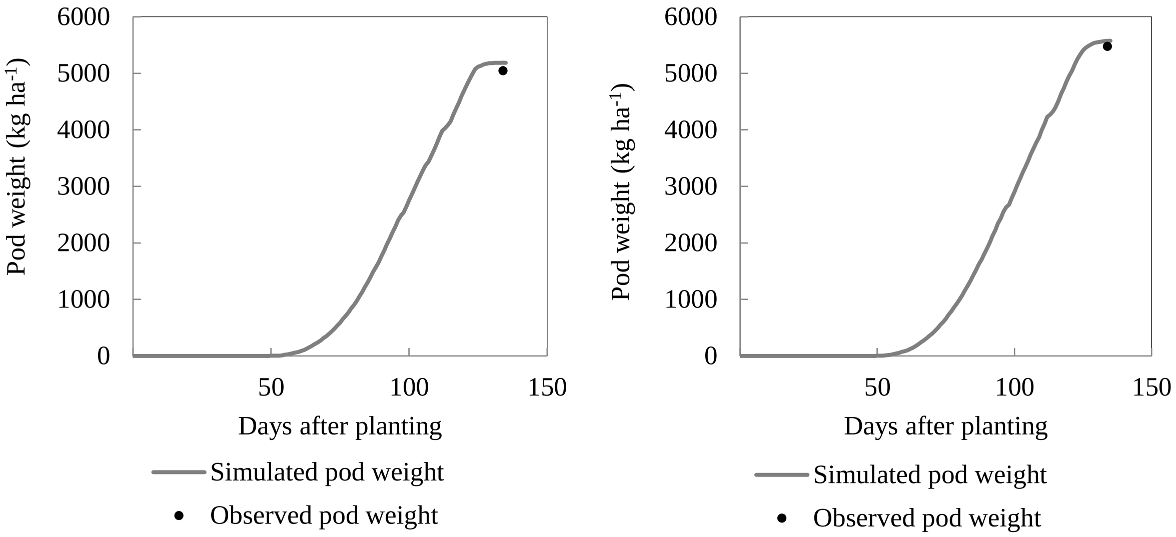


Figure 0.15 Validation pod weight for the peanut ACI 3321 at field 1.3b in 2022 at locations 1 (a) and 19 (b) at Society Hill, Alabama.

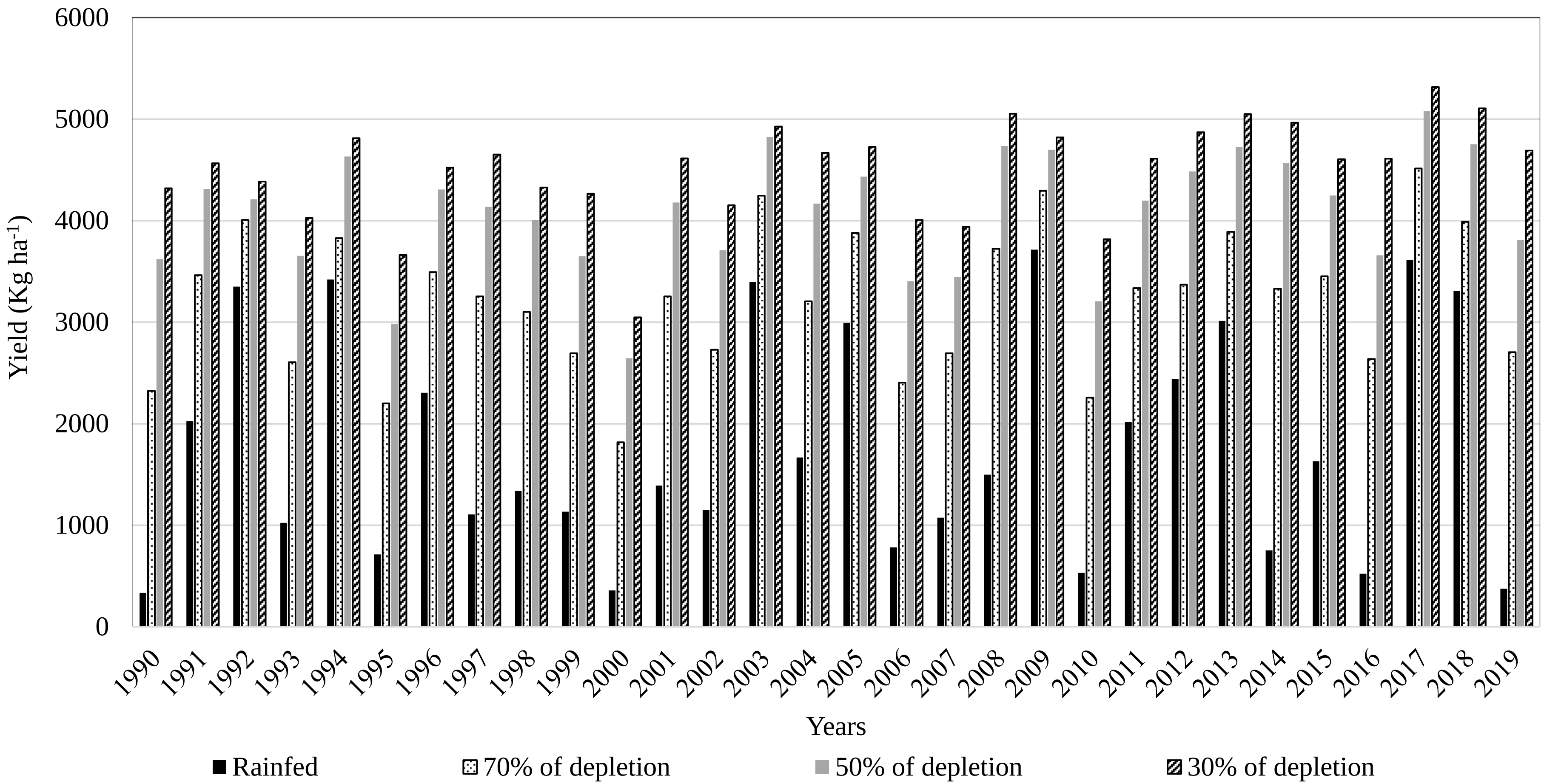


Figure 0.16 Yield (kg ha^{-1}) simulated with 30 years of weather data (1990-2019) and with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

Table 0.12 Tukey-Kramer Grouping for Least Squares Means of yield analysis, with respect to depletion levels versus AWDR, at a significance level of 0.05.

AWDR	Treatment	Estimate		
Wet	30	4778.33		A
Wet	50	4489.50		A
Dry	30	4219.67	B	A
Wet	70	3804.00	B	C
Dry	50	3677.17		C
Dry	70	2720.00		D

LS-means with the same letter are not significantly different.

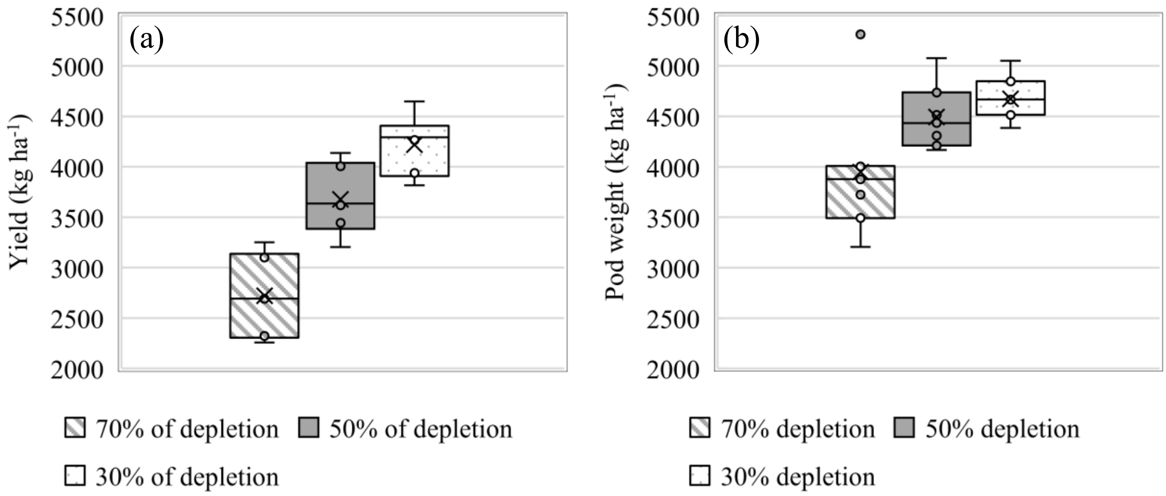


Figure 0.17 Yield (kg ha^{-1}) distribution and variability regarding AWDR driest years (a) and wettest years (b) with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

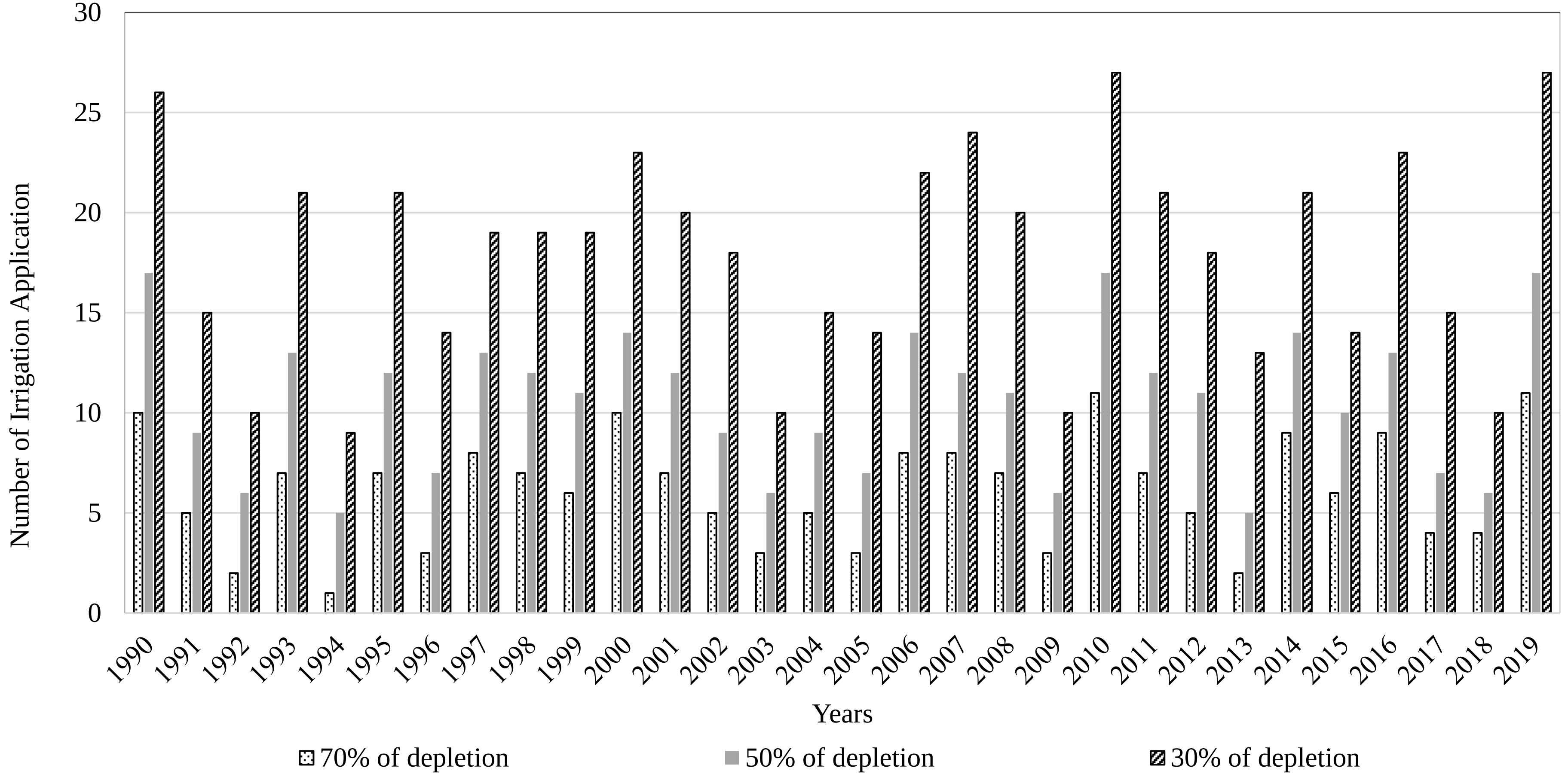


Figure 0.18 Number of irrigation applications simulated with 30 years of weather data (1990-2019) and with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

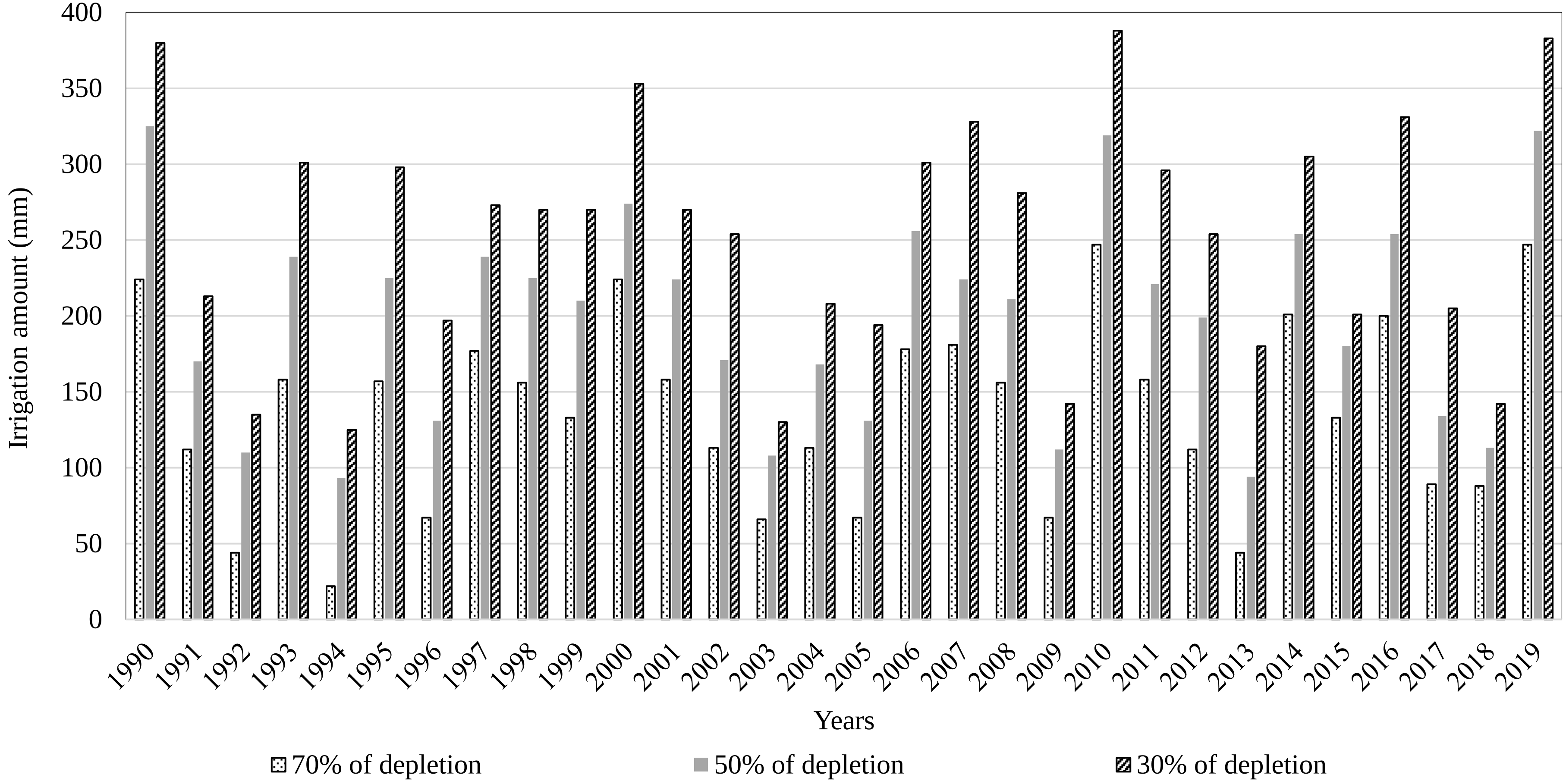


Figure 0.19 Irrigation amount (mm) simulated with 30 years of weather data (1990-2019) and with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

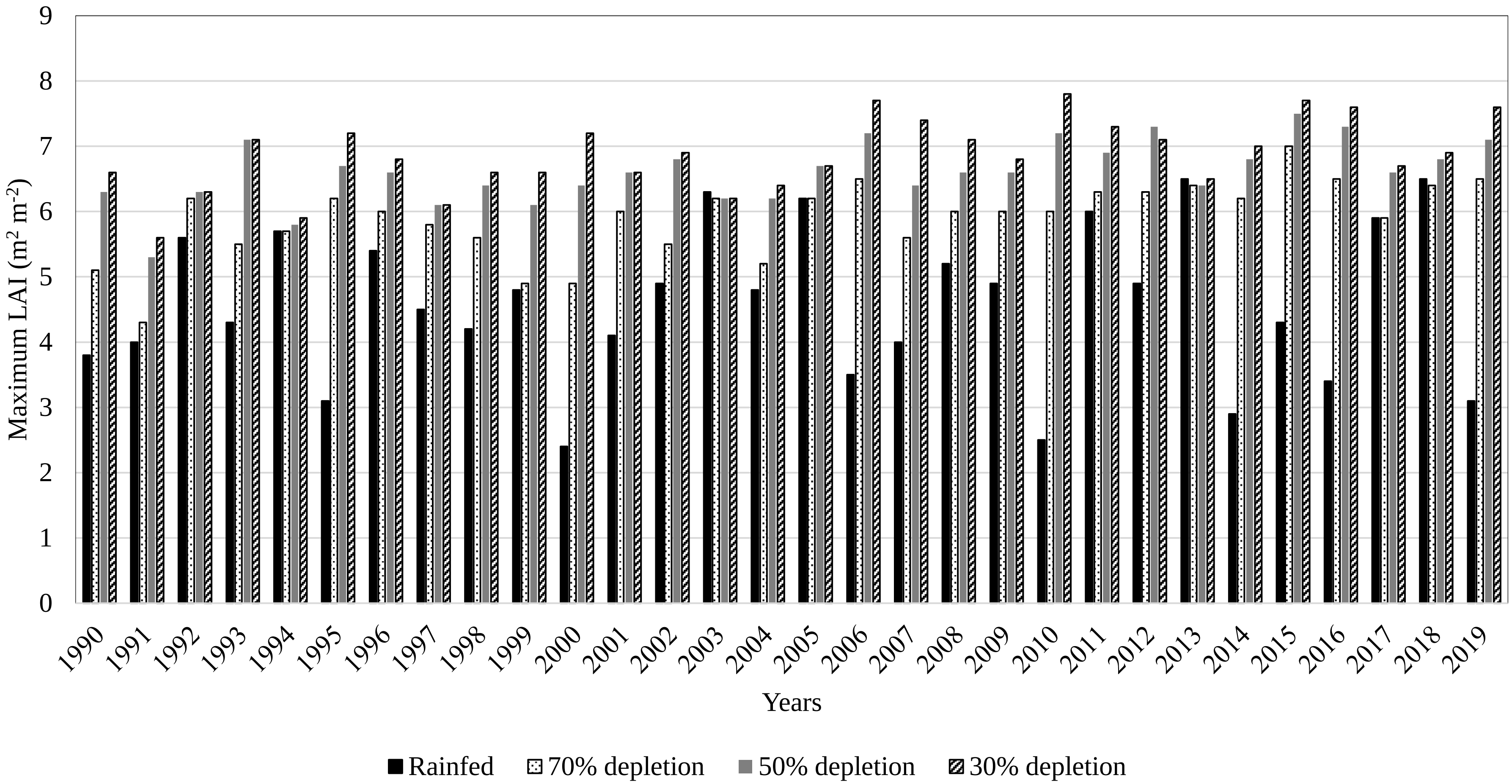


Figure 0.20 Maximum LAI (m^2 m^{-2}) simulated with 30 years of weather data (1990-2019) and with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

Table 0.13 Tukey-Kramer Grouping for Least Squares Means of LAI analysis, with respect to depletion levels versus AWDR, at a significance level of 0.05.

AWDR	Treatment	Estimate		
Dry	30	6.8500		A
Wet	30	6.6667		A
Wet	50	6.5000		A
Dry	50	6.4167	B	A
Wet	70	5.9167	B	C
Dry	70	5.5000		C

LS-means with the same letter are not significantly different.

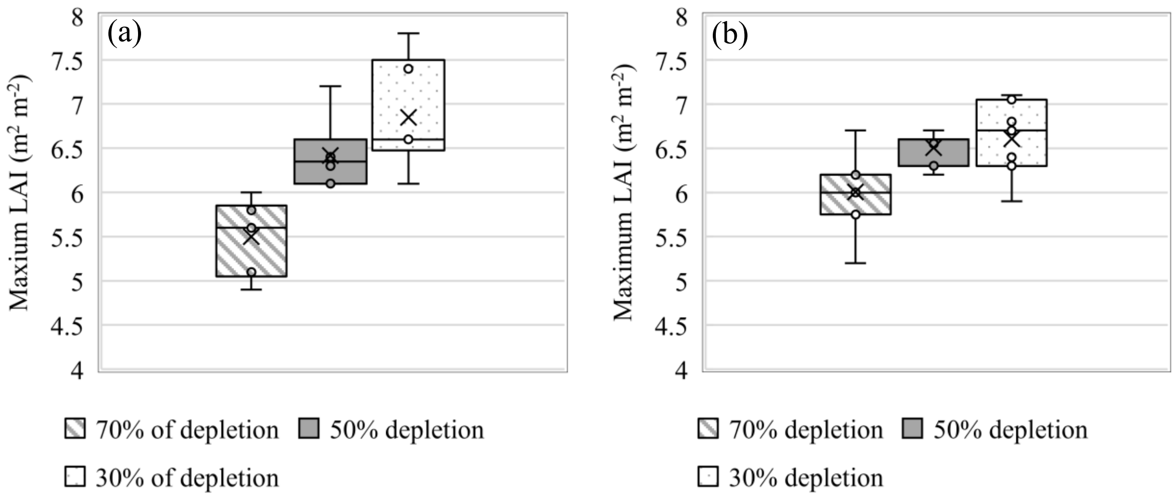


Figure 0.21 Maximum LAI (m^2 m^{-2}) distribution and variability regarding AWDR driest years (a) and wettest years (b) with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

Table 0.14 Tukey-Kramer Grouping for Least Squares Means of irrigation water productivity analysis, with respect to depletion levels versus AWDR, at a significance level of 0.05.

AWDR	Treatment	Estimate	
Dry	30	22.3333	A
Wet	30	14.6667	B
Dry	50	13.6667	B
Dry	70	8.3333	C
Wet	50	7.8333	C
Wet	70	4.0000	C

LS-means with the same letter are not significantly different

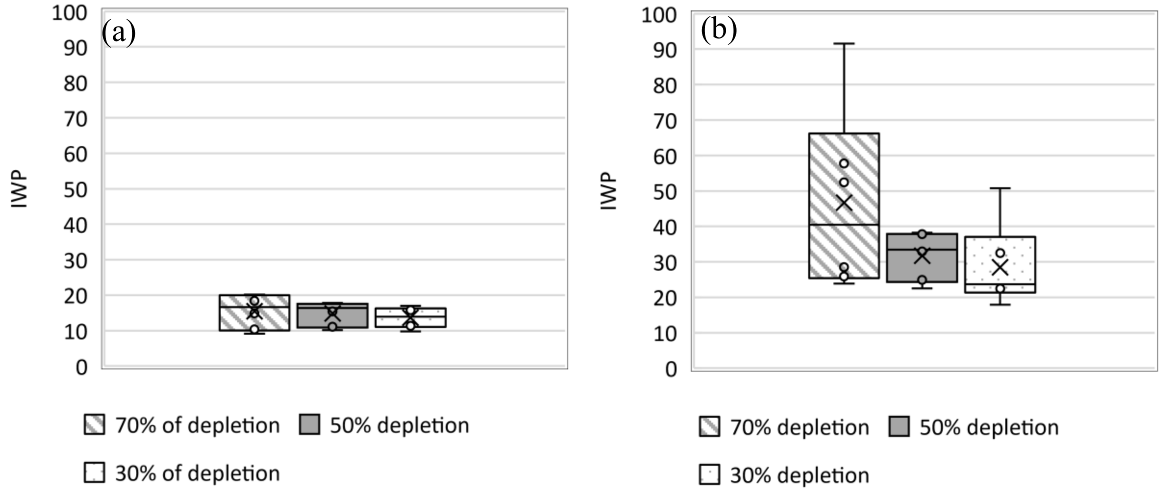


Figure 0.22 Irrigated water productivity (IWP) distribution and variability regarding AWDR driest years (a) and wettest years (b) with Marvyn Loamy Sand (location 01 Field 1.2b), with three deficit irrigation/soil water depletion treatments at Society Hill, Alabama.

III. EVALUATION OF THE FIELDPRINT CALCULATOR AS A TOOL TO ASSESS PROGRESS TOWARDS CONSERVATION AGRICULTURE AND TO PROMOTE BENCHMARKING AMONG FARMERS

ABSTRACT

Sustainable agriculture is crucial for environmental preservation and food security. This study, conducted in Alabama, USA, aimed to evaluate the application of sustainability indicators, particularly those in the Field to Market Fieldprint Calculator, to promote sustainable agricultural practices. The study's objectives involved understanding the current indicators' applications and benefits and identifying opportunities and barriers to their adoption. Five farmers were selected based on their crop rotation and conservation practices, and data was collected from 2019 to 2021. Comparative analyses were conducted by pairing farmers with the same crops and year but different management practices, which were then presented during two field days. The analysis aimed to evaluate the impact of farming practices on energy use, water quality, soil carbon, soil conservation, and greenhouse gas emissions indicators. The results revealed that Farmer 14 consumed more energy per acre than Farmer 22 due to the use of conventional tillage. Fertilizer energy, influencing overall energy use scores, was significantly higher for Farmer 14 due to increased fertilizer application. Higher fertilizer application by Farmer 14 led to a lower water quality score compared to Farmer 22. Conventional tillage resulted in a negative soil carbon score, indicating a higher risk of organic matter loss. In contrast, simulating strip tillage showed a positive soil carbon score, suggesting potential for improved soil carbon content. This transition also positively impacted soil conservation scores. In the greenhouse gas emission analysis, Farmer 71 emitted more CO_2e/acre than Farmer 17 due to conventional tillage and more trips to the field. Using sustainability indicators, such as the Fieldprint Calculator, for educating farmers, consultants, and NRCS personnel presented both challenges and opportunities. Some challenges identified included the understanding of the tool's complexity, interpreting the entry datasets, and acquiring a profound understanding of diverse agronomic practices used by farmers and their influence and contribution to the indicator

outputs. Opportunities include active participation within farmers' networks to promote conservation practices, while targeted educational programs can enhance basic knowledge and proficiency. In essence, this chapter emphasizes the importance of a comprehensive perspective of sustainable agriculture, focusing not only on implementing sustainable practices but also establishing a supportive atmosphere.

INTRODUCTION

Adopting sustainable agricultural methods is crucial in tackling global challenges such as food security and climate change. Achieving agricultural sustainability involves implementing cover cropping, crop rotation, reduced or no-till methods, integrated pest management, precision agriculture, and best management practices. However, these methods typically demand increased management efforts. In the United States, the adoption of conservation practices remains limited, with recent data indicating that for example, only 5.1% of U.S. cropland utilizes cover crops (Wallander et al., 2021). Cultural beliefs and values often hinder the widespread adoption of these sustainable practices (IPCC, 2022). Social pressures, including the desire for visually perfect fields, peer pressure, and negative views on sustainable agriculture, discourage farmers from adopting new methods (Rodriguez et al., 2008). Additionally, the lack of positive examples and successful cases hinders adoption. Traditional beliefs and the reluctance to change established practices, especially among older generations who control land, present significant barriers (Rodriguez et al., 2008).

Farmers face significant challenges when adopting these practices to maintain productivity (Foley et al., 2011). To achieve agricultural sustainability, it is essential to implement practices that are economically viable, environmentally, and socially responsible (Philip Robertson and Hamilton, 2015; Pretty, 2018). The barriers to adopting sustainable agricultural practices in the Southern United States are complex and multifaceted, involving issues related to finance, education, social perceptions, and institutional support. Overcoming these barriers requires targeted efforts in education, financial support, and changing social perceptions to encourage the widespread adoption of sustainable farming methods (Rodriguez et al., 2008). The adoption outcomes can vary significantly from year to year due to factors like crop type, climate, soil conditions, and management practices (Marcillo and Miguez, 2017; Laborde et al., 2020; Allam et al., 2021). Hence, balancing economic viability, environmental responsibility, and social sustainability becomes crucial in diverse agricultural contexts.

Although numerous sustainability assessment tools have been developed, questions arise regarding their practical implementation and contribution promoting change (de Olde et al., 2018). Promoting sustainable agricultural practices requires indispensable tools to help farmers comprehend the consequences of their actions and guide them towards adopting more sustainable approaches. Several factors, including economic incentives, farm characteristics, and risk perceptions, influence farmers' decisions regarding conservation practices (Rodriguez et al., 2008; Trujillo-Barrera et al., 2016; Bagnall et al., 2020; Hatanaka et al., 2022). Collaborative efforts and knowledge sharing with research and outreach specialists are pivotal in driving adoption (Fujisaka, 1994; Gielen et al., 2003; Kemp et al., 2014). Agricultural extension services, both public and private, have been shown to have a positive impact on adoption rates (Cole, 2010; Schirmer et al., 2012; Santiago et al., 2018; Nath et al., 2023). Connecting these programs with national extension systems can result in a notable change in agricultural sustainability. A study conducted by Laborde et al. (2020) revealed that using sustainability tools such as the Fieldprint Calculator led to the adoption of more sustainable practices by farmers.

In recent years, private industry initiatives and multi-stakeholder alliances have emerged as influential forces in promoting sustainability within the agriculture sector, often complementing governmental efforts (Ponte, 2014). Some multi-stakeholder initiatives have shifted from setting specific standards to using metrics to measure and evaluate sustainability. Prominent U.S. food and agriculture companies, grower associations, and environmental groups endorse the metrics and data approach to boost agricultural sustainability (Freidberg, 2017, 2020; Konefal et al., 2019; Hatanaka et al., 2022). This approach is embraced by Multi-

Stakeholder Initiatives (MSIs) like Field to Market, the Sustainability Consortium (TSC), the Stewardship Index for Specialty Crops (SISC), and the U.S. Cotton Trust Protocol. Metrics provide farmers with the means to measure and evaluate their performance, enhancing their sustainability efforts (de Olde et al., 2016).

Using sustainability indicators to assess the environmental impact of agricultural practices represents a crucial step toward bolstering sustainability efforts. One notable initiative in this realm is the Alliance for Sustainable Agriculture, also known as Field to Market, a nonprofit organization in the United States that promotes sustainable agricultural practices across the entire food and agriculture value chain. It is a diverse collaboration of stakeholders, including farmers, agricultural retailers, food companies, conservation groups, and universities. Field to Market works to unite the agricultural supply chain to create a more sustainable food system by providing resources, tools, and initiatives that help farmers, businesses, and organizations measure and improve their environmental and social performance. The Fieldprint Calculator tool measures and compares sustainability performance from several crops using NRCS tools to calculate eight indicators: biodiversity, energy use, greenhouse gas emissions (GHG), irrigated water use, land use, soil carbon, soil conservation, and water quality (Field to Market, 2023). Another prominent example, besides Field to Market, is the Cool Farm Tool, developed by the Cool Farm Alliance. This non-profit organization enables farmers to measure and reduce their carbon footprint and environmental impact (Haverkort and Hillier, 2011). It originated in the United Kingdom and was developed collaboratively by experts, including researchers, farmers, and agricultural organizations. It is not limited to a specific region or country; instead, it is applicable globally, allowing farmers from different parts of the world to assess and improve the environmental sustainability of their farming operations (Cool Farm Alliance, 2021). Similarly, companies like Indigo Ag have introduced innovative sustainability calculators to assess environmental impacts and promote sustainable farming practices. Among their initiatives is carbon farming, operated through the Indigo Carbon program. The carbon farming approach was designed to sequester carbon dioxide from the atmosphere and store it in the soil, thus mitigating climate change (Indigo Ag., 2022).

Benchmarking is a vital strategy adopted by various industries, including agriculture, to improve performance by learning from others. In agriculture, especially since the late 20th century, this approach has been pivotal in bolstering productivity and sustainability efforts. Tools like the Fieldprint Calculator have significantly contributed to benchmarking sustainability in agriculture, empowering agribusinesses (Field to Market, 2023). Despite the widespread acceptance of the Fieldprint Calculator, concerns have been raised regarding its benefits, data accuracy, and the practical interpretation of benchmarking reports (Hoffelmeyer et al., 2022). Parrish's (2016) study, focusing on establishing benchmarks for the environmental impact of cotton production, showcased that, on average, Georgia cotton producers outperformed the national Fieldprint Calculator average in sustainability. Another research by (Robertson et al., 2020) demonstrated the positive impacts of conservation practices on soil carbon and soil conservation, emphasizing the need for documenting sustainable practices, a crucial aspect for brands and retailers seeking sustainable products. Black (2018) highlighted the Fieldprint Calculator's utility in encouraging resource conservation, efficient water management, and analyzing profitability metrics. Several universities have integrated this tool into their practices, such as Tennessee University (Gibson and Buschermohle, 2013), University of Georgia (Parrish, 2016; Reagin and Porter, 2021, 2022; Reagin et al., 2022), University of Arkansas (Robertson et al., 2020), and Texas A&M University (Gillum and Johnson, 2015, 2016; Gillum et al., 2016; Black, 2018), showcasing the tool's versatile application in promoting sustainable agriculture practices.

Although the Fieldprint Calculator has been effectively employed in other regions, its usability, and benefits towards increasing adoption of conservation practices by Alabama farmers must be explored. This study aims to identify opportunities and challenges in using sustainability indicators within the Field to Market Platform to document environmental conditions related to the adoption of conservation practices. The objectives include identifying applications and benefits of sustainability indicators and exploring potential opportunities and barriers to their adoption, particularly tracking environmental management practices and emphasize the importance of stakeholder engagement. Actively involving stakeholders, including farmers, consultants, and relevant agricultural organizations, we aimed to explore potential opportunities and barriers to the adoption of these indicators. This inclusive approach seeks to establish connections between the sustainability indicators and the perspectives of those actively involved in using environmental management practices. Ultimately, the study aims to contribute to the knowledge base of sustainable agriculture and offers insights into enhancing understanding of the relationship between agronomic practices and their impact or contribution towards sustainability among farmers.

MATERIAL AND METHODS

This section is divided into several parts. Firstly, it starts with a description of how participating farmers were chosen and identified. The next part details the selection of the sustainability indicators tool, emphasizing why the Fieldprint Calculator was chosen and its widespread use in different regions of the USA. The following subsection goes into a detailed description of the Fieldprint Calculator, providing information on each indicator metric. After this, the steps for learning how to use the indicators' tool and understanding the report outputs are explained. The process of collecting data, analyzing it, and presenting and discussing the results is then outlined. Finally, the section concludes with insights into the sharing and engagement activities with farmers, crop consultants, NRCS personnel, and other stakeholders, especially during two field days in the summer of 2023.

1. Selection/Identification of Participating Farmers

The study was part of the Future of Farming project, funded by the Natural Resources Conservation Service (NRCS), spanning five years (from 2020 to 2025). The interdisciplinary team leading the project involved experts from Auburn University and the Alabama Cooperative Extension System, along with graduate students and Postdoctoral scientists from Crop, Soil, and Environmental Science department. This collaborative effort spanned various vital areas, including precision irrigation, nutrient management, soil health, rural sociology, and economy. The project encompassed three components: farmer-owned demonstration sites in different regions of Alabama, "Farmer-Focused Learning Groups" composed of local farmers, crop consultants, Extension agents, and NRCS representatives, and an incentive payment program to implement cover crops. Therefore, with the assistance of a local extension agent, five farmers were selected from the Central Alabama focus group. The farmers' selection criteria included crop rotation type (cotton, peanut, or corn), use of irrigation, use or not use of conservation practices. After identifying the potential cooperating farmers, each farmer was contacted by phone, and a brief description of the study's goal was provided. After the conversations, some farmers and a few declined the invitation, which resulted in identifying a few more. This study is part of a six-year NRCS funded project and then, pseudonyms are used for all project participants. The cooperating farmers included in this specific study were F14, F17, F22, F40, and F71. The Fieldprint Calculator analyzes year-to-year crop management data on a field-level basis. Therefore, just one or two fields from their farm were selected for the study. Crop management data from the period 2019 to 2022 was input into the calculator with the expectation that during those years farmers would have made changes in their management practices that could have resulted into advances towards conservation and could be used as study cases to other farmers.

2. Selection of the Sustainability Indicators Tool

The study started with the goal of using the sustainability indicators as benchmarking tools to facilitate dialogues and knowledge exchange among farmers concerning their experiences and challenges related to conservation practices. Field to Market comprises diverse organizations representing the entire supply chain, including universities, agribusinesses, grower organizations, conservation groups, and public sector partners. In 2023 Field to Market are boasting over 190 organizations in the Field to Market community (Field to Market, 2023). Field to Market also has a partnership to integrate NRCS tools and models into the Fieldprint Platform (Field to Market, 2022a). Currently available for various crops, including alfalfa, barley, corn (grain and silage), cotton, peanuts, potatoes, rice, sorghum, soybeans, sugar beets, and wheat. The Fieldprint Calculator has been extensively used by universities, including Tennessee, Georgia, Arkansas, and Texas A&M, to promote conservation practices. Its widespread use along with its user-friendly interface, led to the selection of the Fieldprint Calculator for this study.

Moreover, the calculator generates scores based on the practice implemented and the potential impact (positive or negative) on the environment (Field to Market, 2022b). This enables growers to compare their sustainability scores with enrolled project benchmarks and state and national benchmarks. Many agribusiness industries, such as the cotton industry, have already embraced this tool. For instance, in the cotton industry, producers can compare their current management techniques with growers from different areas, regions, and states. This functionality enables them to modify scenarios within the system, thereby understanding how they can reduce inputs and enhance sustainability (Parrish, 2016). Such practical applications underscore the effectiveness and versatility of the Fieldprint Calculator in driving sustainable agricultural practices.

2.1 Fieldprint Calculator Description

The Fieldprint Calculator offers a comprehensive suite of sustainability indicators, including measures for biodiversity, energy use, greenhouse gas emissions (GHG), irrigated water use, land use, soil carbon, soil conservation, and water quality. The report of those eight indicators is presented in two ways, a written report with tabular results and suggest management practices that should be considered for improvement and in the form of a spidergram (Figure 2.1) to visually present the agricultural footprint with respect to state and national benchmarks for each indicator. These comparisons aid producers in determining which practices are best suited for their operation. Smaller values, closer to the center of the spidergram, indicate more efficient resource use and more progress towards sustainability. The spidergram allows user to easily visualize the impact of crop management and how that compares to other farmers in the state and national level.

2.2 Group of Sustainability Indicators available in the Fieldprint Calculator

Indicators measure environmental outcomes based on individual farm field operations data and environmental factors like soil, landscape, and weather. These indicators are created collaboratively through a multi-stakeholder process to establish a common framework for measuring environmental progress in the U.S. commodity crop production. The metrics generated by these indicators represent measurable sustainability outcomes calculated using algorithms within the Fieldprint Platform. These calculations can be simple or complex, resulting in either quantitative (efficiency) or qualitative (risk) assessments (Field to Market, 2022c). Factors that affect the sustainability metrics are described in Table 2.1, and Tools/models used to estimate the metrics are described in Table 2.2.

2.2.1 Land Use

The land use metric quantifies the number of acres used to produce a single unit of crop yield (acres/unit of crop production), which is influenced by the farmer's operational efficiency. A lower score indicates more efficient land use, influenced by crop yield, operational efficiency, variety selection, and management decisions such as irrigation and pest control. Increasing crop yield could decrease land use score and therefore, increase land use efficiency. Although weather events significantly affect yields, farmer decisions play a significant role in optimizing productivity.

2.2.2 Irrigation Water Use

Irrigation water use metric accounts for the volume of water applied per unit of increased production compared to dryland cultivation. A lower metric indicates superior water efficiency. This metric is calculated as the volume of irrigation applied in acre-inches divided by the yield from irrigated land minus the yield from non-irrigated land. Factors affecting irrigation water use are crop species, variety and crop development stage, evapotranspiration, soil texture, structure, and salinity. Although a grower cannot change the soil texture, its impacts can be mitigated using management practices that improve water holding capacity and infiltration.

$$IWU = \frac{Irrigation\ Amount\ (acre\ inches)}{Irrigated\ Yield - Non\ Irrigated\ Yield}$$

2.2.3 Energy Use

Energy use measures all energy consumed throughout the growing season, represented in gallons of diesel per production unit. It is also quantified in British thermal units (BTU) per unit of crop production, such as bushels, pounds, or hundredweights. A lower value signifies more efficient energy use in producing a unit of crop. To illustrate, one BTU can increase the temperature of one pound of water by 1°F, and a single gallon of diesel generates 137,452 BTU (Field to Market, 2017). The metric encompasses the entire crop cultivation process, from pre-planting to the first sale or transfer to a processing facility. Direct energy accounts for various fuel types (diesel, electricity, gasoline, natural gas, and liquefied petroleum gas), while indirect energy includes embedded energy in inputs like fertilizers and crop protectants. National-level data from sources like the USDA Agricultural Resources Management Survey (ARMS) and the Irrigation and Water Management Survey are used to calculate irrigation energy based on operating pressure and water lift factors. Management energy related to tillage and residue management is estimated using data from ARMS and other sources. Manure application energy is calculated using application rates and treated acreage data. The energy associated with equipment used for fertilizer and crop protectant applications is also considered, incorporating factors such as the number of applications and energy conversion values. Post-harvest treatment energy, including grain drying and transportation, is factored in up to the first point of sale. Energy from synthetic fertilizers is calculated based on application rates and energy conversion factors, considering improvements in production efficiency over time. Crop protectant energy is determined using active ingredient data and energy factors. Seed energy is estimated based on industry judgment and expert input, considering the intensive management and input use involved in seed production. The analysis focuses on various crops, adjusting energy components based on specific crop characteristics and agricultural practices, providing a comprehensive overview of the energy inputs across various stages of crop production.

2.2.4 Greenhouse Gas Emissions

The Greenhouse gas emissions (GHG) indicator within the Fieldprint platform assesses emissions from various sources in agricultural activities. Significant sources include energy use, residue burning emissions, nitrous oxide emissions from soils, and methane emissions from flooded rice production. Emissions from energy use are converted to GHG emissions using factors considering energy sources. Emissions from equipment operation for different tillage systems are calculated, with conventional tillage producing the most emissions. Emissions from irrigation water pumping and application are estimated based on energy use data, accounting for different fuel sources. Greenhouse gas emissions embedded in seeds, crop protectants, and synthetic fertilizers are calculated using established models and emission factors. Nitrous oxide emissions from soils are estimated considering nitrogen application, application method, and soil conditions. Emissions from field burning and residue removal are accounted for, with residue burning contributing a small portion of total emissions. Methane emissions from flooded rice fields are calculated based on available data, with emissions varying due to changes in rice acreage. Methane emissions from other crops due to flood irrigation are not considered due to limited data.

2.2.5 Soil Conservation

The soil conservation metric within the Fieldprint platform measurement is computed using the USDA NRCS Integrated Erosion Tool (IET), which consists of two models: WEPP (Water Erosion Prediction Program) and WEPS (Wind Erosion Prediction Service) and is reported as tons of soil lost per acre. It utilizes USDA NRCS models, specifically the Integrated Erosion Tool (IET), which integrates two models: Water Erosion Prediction Program (WEPP) for water erosion and Wind Erosion Prediction Service (WEPS) for wind erosion (Flanagan et al., 2007). To calculate the Soil Conservation metric value, users provide information on field characteristics (slope, slope length, and soil properties) and crop management practices like tillage, cover crop and crop rotation. Data is sourced from various databases, including USDA SSURGO (SSURGO, 2023) for soil profile properties and PRISM Climate Group (PRISM, 2023) for climate data. Users select field characteristics, confirm drainage systems, and enter management details using the rotation builder tool. High in clay and silt, fine soils are more prone to erosion than sandy soils (Field to Market, 2018). The soil disturbance coverage, like plants and residue, also affects the metric values. Soil that has been disturbed is easily picked up by wind and water and carried away. Soil covered reduces erosion potential as the plant roots hold soil in place.

2.2.6 Soil Carbon

The Fieldprint Platform assesses soil carbon, a crucial factor supporting water infiltration, nutrient retention, crop productivity, and carbon storage. Soil carbon and organic matter are closely related. Organic matter, being rich in carbon, is a key component of soil carbon (Bhattacharyya et al., 2022). So, the decomposition of organic matter directly affects the soil's carbon levels. Due to the challenge of measuring yearly changes in soil carbon, the platform employs a qualitative and directional measure represented by the Soil Conditioning Index (SCI). The outcome varies based on the crop and ranges from -1.0 to +1.0, with values closer to +1.0 signifying a higher likelihood of management practices enhancing soil organic matter over time (Field to Market, 2018). Both the soil carbon and conservation metrics necessitate information about field activities affecting the soil, like tillage, and how crop residue and crop rotation are managed. Tillage and other practices that disturb soil stimulate decomposition and change the location of organic matter in the soil profile. While soil characteristics are derived from the USDA SSURGO database, users can modify specific inputs, such as organic matter content, based on soil tests conducted in their fields.

2.2.7 Water Quality

This metric assesses nutrient loss from a farm field to nearby waterways, focusing on four pathways: Surface Nitrogen, Subsurface Nitrogen, Surface Phosphorous, and Subsurface Phosphorous. For each pathway, two scores are assigned: the Field Sensitivity Score (FSS), indicating field sensitivity to nutrient loss based on location, climate, soil, and topography, and the Risk Mitigation Score (RMS), indicating the effectiveness of management practices in preventing loss. The final metric score is divided into four pathways which indicate whether mitigation scores exceed sensitivity scores for each pathway or not. The goal is to mitigate all four nutrient loss pathways. A pathway is mitigated if the pathway ratio (RMS/FSS) is equal to or greater than 1 (Field to Market, 2021). The RMS is influenced by the nutrient management techniques used, nitrification inhibitors and precision application, cover crop, tillage type, and nutrient management techniques (right rate, right time, right location, right source, defined as 4Rs).

The water quality metric uses the NRCS Stewardship Tool for Environmental Performance (STEP) to calculate the score. The STEP tool utilizes complex biophysically-based crop and water quality models, Agricultural Policy / Environmental Extender (APEX) (Gassman et al., 2010) and The Soil and Water Assessment Tool (SWAT, 2023), along with detailed survey results from the National Resources Inventory (NRCS/NRI, 2023) to assess nutrient loss potential and conservation practice effectiveness. The Fieldprint platform accesses USDA models and data services through the Cloud Services Integration Platform (CSIP) hosted by Colorado State University (CSU) to calculate STEP scores.

2.2.8 Biodiversity

The biodiversity metric assesses a farm's ability to support a diverse community of plants and animals using the Habitat Potential Index (HPI). This metric is unique as it evaluates all lands on a farm, whereas other metrics focus on individual crop fields. The HPI determines the potential biodiversity capacity by considering land properties, ecoregion (structural score), and land management practices (management score). The structural score is influenced by land types and any conversions that occurred in the previous five years. Different land types (cultivated fields, forests, wetlands) have varying ecological values based on their region-specific ecoregion classification. The management score is determined by user inputs, encompassing activities like tillage, cover crops, grazing, and invasive species management. The management score contributes two-thirds to the ecological quality score, while the structural score contributes one-third. Each land type receives a separate HPI score, and a full-farm HPI score is calculated, indicating the percentage of potential habitat realized. Scores below 50% present significant opportunities for enhancing habitat potential, while values between 50% and 80% indicate moderate realized potential. Scores exceeding 80% demonstrate farms that have fully exploited opportunities for biodiversity to thrive.

3. Steps followed to learn how to use the indicators' tool and understand the indicator report outputs

Before identifying applications and benefits of sustainability indicators and exploring potential opportunities and barriers to their adoption using the Fieldprint Calculator tool, a series of steps were taken. First, contact with the Field to Market team was made to gain access to the tool and associated resources. Collaborative meetings with specialists from the University of Georgia and the University of Tennessee were conducted to facilitate the learning process and share insights on data collection and input procedures. Self-guided learning was used to ensure a deep understanding of the tool's functionalities and capabilities and continuous contact with the Field to Market team to understand metrics and the meaning of the outputs, disparities, and problems with the outputs.

Although the Fieldprint Calculator’s documentation includes information on how to input data, that was not enough to fully understand some of the data needed by the tool to generate an accurate report of each field and how to interpret the outputs. After creating the account into the platform, individual interviews with the cooperating farmers were initiated to collect the data, with each interview being on average two hours in length. During each interview, a better understanding about the crop and the most common management practices used in each farm was gained. One of biggest challenge in collecting the data required by the tool was the lack of farm records on the crop management practices, then we relayed on the farmers' memories. Therefore, any unclear questions were reevaluated and rephrased so growers would better understand the concept, or the type of data needed. All the data necessary for the Fieldprint Platform and the respect metrics associated with it as shown in Table 2.3.

4. Data Collection

Data collection involved conducting in-person semi-structured interviews with farmers selected for this study, who were participants in the Future of Farming Project. During these interviews, growers were explained the study's purpose and how the collected information would be used. An Excel spreadsheet with a questionnaire of the basic data required by the Fieldprint calculator was created, then enabling data collection even without internet access. Individual interviews to gather data from 2019 to 2021 typically occurred at one of the farmers' fields or barns, lasting around two hours to inquire about all their management practices, which were documented in the Excel spreadsheet. The initial goal was to assess farmers' performance and changes over time. Questionnaire topics include crop rotation, use of cover crops, tillage and irrigation practices, nutrient and fertilizer methods and application rate, chemical applications, and annual harvest yield (Table 2.3). Parrish' (2016) and Reagin et al. (2022) studies used the same data collection format. Following the interview, the responses were entered into the Fieldprint Calculator for each field that was collected.

The process of inputting the data creating a field in the Fieldprint Calculator involves the following steps: it initiates with the field creation by providing basic information, such as the field's location, size, and the specific crops grown. Subsequently, detailed information on management practices is entered, encompassing aspects like crop rotation, tillage methods, irrigation practices, fertilizer usage, and other relevant factors. Additionally, a rotation template is required, necessitating detailed data from at least two growing seasons; however, for this study, three years of data were entered. This template involves recording crop management data over multiple years to evaluate changes and trends in management practices, including crop types, rotation sequences, tillage, and specific practices adopted each year. The accuracy of data is very important, as adding or missing on travel to the field, for example, already affects the outcome. The time needed to generate a rotation template depends on factors like the complexity of management data, the number of fields, and the user's familiarity with the platform. Typically, this process may take a few hours to input data over a three-year period. Given the complexity involved, additional contact with the farmer was often necessary during data entry into the calculator to ensure comprehensive and precise information. Follow-ups were typically conducted via phone calls, and occasionally, multiple follow-up calls were necessary, caused by the identification of discrepancies upon reviewing the outcomes.

5. Data Analysis

Once data was entered into the Fieldprint Calculator, sustainability metric scores were calculated and presented in a report. Scores in the report are offered as a spidergram (Figure 2.1), a graph shows the farmer’s field, state, and national indicator values for each one of the eight sustainability metrics. This graph could be used as a benchmarking tool to compare farmer’s management with respect to other farmers at the state and national level. Each field’s score was analyzed to interpret the sustainability level of each of the eight metrics. On the spidergram, each sustainability indicator can receive values from zero to one hundred. If the values are closer to one hundred, they are further away from the center of the spidergram and indicate that the management practices used on a field are more resource-intensive and less environmentally sustainable. In addition to showing the indicator values of a farmer's field, the spidergram shows the scores at the state and national allowing comparison and benchmark. Comparative analyses were performed to assess variations among fields and farming practices, which included comparing metrics. These benchmarks give the grower an insight into how their scores compare to growers across the state and nation. These spidergram comparisons help farmers see how their own metrics change from year to year, giving them a clear picture of their progress.

The Fieldprint Calculator report includes the individual scores for the different factors that comprise the metrics. Among the farmers selected for this project and based on the knowledge gained from their operations and practices used, data analyses and comparisons were done by "pairing" farmers with the same crop and year, but different management practices. This strategic pairing resulted in divergent outcomes, intended to foster discussions and engagement (Table 2.5). Comparisons among each pair of farmers were done with respect to the impact of their management practices on indicators such as energy use, water quality, soil carbon, soil conservation, and greenhouse gas emissions. Three case studies were created: Case Study 1 examined energy use and water quality between corn fields from Farmers 14 and 22 on 2021 growing season. Case Study 2 focused on soil carbon and soil conservation between cotton field of Farmer71 in 2019 simulating the field on conventional tillage versus strip tillage. And Case Study 3 analyzed greenhouse gas emissions between cotton fields from Farmers 71 and 17. These case studies were selected to represent different practices used not only by the five farmers selected for this study, but the practices used by farmers in Central Alabama.

A simulation using just one field was done for soil carbon and conservation, changing from conventional tillage to strip-till. This approach allowed for more accurate comparisons as soil and weather conditions fundamentally shape soil carbon levels and erosion rates. It is essential to consider local and temporal variations to make meaningful comparisons and analyses using soil carbon and conservation indicators. This consideration ensures that the results and recommendations are context-specific and obtainable for farmers and land managers in their unique agricultural settings.

6. Sharing and Engagement with Farmers and Field to Market Team

The metrics results from the case studies were presented during two field days in the summer of 2023, aimed at introducing sustainable practices and indicators to farmers, crop consultants, NRCS personnel and other relevant stakeholders in Central and Southeast Alabama (AL). The first field day took place in Ashford, AL, on June 26th, covering topics such as fertigation, variable rate irrigation, soil sensors for irrigation scheduling, and conservation practices' impact on profitability and environmental sustainability. The second field day, held in Society Hill, AL, on July 19th, focused on the effects of conservation practices on profitability and environmental sustainability, the impact of optimal irrigation practices on productivity and profitability, and variable rate irrigation methods. It is worth noting that the identities of participating farmers in the Fieldprint Calculator study were kept confidential to uphold their privacy.

Farmers were expected to engage with the presented data during these field days, fostering discussions about sustainability initiatives. The results were visually presented, using large posters to illustrate comparisons of the impact of agronomic practices on the sustainability indicators and metrics. To further engage the farmers and facilitate understanding of the indicator outputs and differences among crop management practices used by each farmer, an economic expert from the Future of Farming Project conducted analyses to highlight the differences between various practices. The sessions with farmers where the results of the sustainability indicators' analyses were presented started with an interactive game designed to promote peer-to-peer knowledge exchange regarding crop management practices and their impacts. Farmers, representatives from the NRCS, and industry professionals were divided into two groups, each tasked with evaluating farming practices (sustainable or not) and selecting practices to create a whole-season crop management and rotation. Throughout the game, participants had the opportunity to collaborate and share insights. A representative from Field to Market was also invited to discuss the tool briefly. These field days were designed to facilitate knowledge exchange, offering valuable information to farmers and project stakeholders, and aiding in developing sustainable farming practices.

RESULTS AND DISCUSSION

The coming section describes the results and discussions derived from pair-comparisons of farmers' fields, particularly focusing on the impact of different crop management practices on the sustainability indicators provided by the Fieldprint calculator. The sequence of topics included below corresponds to the potential impact of agronomic practices performed at pairs of farmers' fields on the sustainability indicators of Energy Use, Water Quality, Soil Carbon, Soil Conservation, Greenhouse Gas Emissions. The opportunities and barriers in engaging farmers through the use of each indicator are also discussed. Each indicator will be presented through case studies, comparisons, and implications of crop management and conservation practices.

1. Energy Use

In Case Study 1 a comparative analysis of two corn farmers, F22 practicing strip tillage on the study field and F14 using conventional tillage, revealed differences with respect to energy use (Table 2.6). Besides the difference in tillage method, they present difference in fertilizer rate too. With farmer 14 applying 320.4 lbs/ac of N, 117 lbs/ac of P and 108 lbs/ac of K, while farmer 22 applied 191.8 lbs/ac of N, 138lbs/ac of P and 91 lbs/ac of K. The simulation suggested that farmer 14 consumed a total of 11,178,782 BTU per acre, higher than the 9,490,989 BTU per acre used by farmer 22. Analyzing the components of energy use (Table 2.7 and Figure 2.2), fertilizer energy, which means the energy used to manufacture fertilizers, had a substantial contribution towards the final energy budget. Farmer 14 had a higher fertilizer energy score due to the use of a higher fertilizer rate (320.4 lbs/acre) than farmer 22 (191.8 lbs/acre). Protectant energy, which refers to the energy used to manufacture the protectants, also influenced the total energy score, with farmer 14 utilizing 942,698 BTU per acre, higher than the 591,425 used by farmer 22. The energy use score is also affected by the number of trips over a field done with farm machinery with a higher number of trips increasing the energy use score (Reagin and Porter, 2022). Additionally, management energy, including diesel fuel usage for various operations, was noteworthy. Farmer 22, despite practicing strip-till and theoretically requiring fewer trips, registered a higher management energy score of 1,389,055 BTU/acre. However, unlike farmer 14, he planted cover crops and applied lime, which involved additional trips to the field and could have explained the higher score.

Upon analyzing both reports in preparation for the field days, concerns arise about the high nitrogen applied by farmer 14. Therefore, to comprehend this better, one more call was made to this farmer. The farmer explained that this variation in nitrogen was due to field variability, requiring variable rate nitrogen application across the field. This change in nitrogen rate promoted discussions among fellow farmers during the field day, with some suggesting that this adjustment in nitrogen might have been made to compensate for fertilization in another year. Results showed that the data provided by the energy use indicator provides an opportunity to discuss with farmers and consultants the role and impact various crop management practices have not only on energy but the environment. Consultants collaborating with farmers could employ conversations adhering to the principles of 4R nutrient stewardship (right source, right rate, right time, right place of nutrient application) to guarantee efficient fertilizer absorption and decrease indirect energy consumption.

On the first field day, the focus of the presentation of the energy use indicator highlighted the fertilizer and protectant energy components. The facilitate comprehension of the energy scores, the energy indicator output, BTU, was converted into gallons of diesel fuel, units of measure farmers are more familiar with. The goal with presenting the fertilizer and protectant energy outputs using the metric of gallons of fuel per acre was to use metrics and concepts more familiar to farmers, common expenses, and then facilitate comprehension of the impacts current practices might have to their fixed costs and how that could translate into the environment. The choice aimed to bridge the gap between abstract BTU values (the unit used in the Calculator report) and tangible, relatable concepts. Despite the efforts of simplification of the metric, the challenge understanding it persisted, prompting discussions with peers and experts.

In retrospect, the initial aim was not merely to present numbers but to foster a deeper understanding of conservation practices. The indicators, exercises, presentations, and feedback promoted discussions not just about the results but also the opportunities these indicators offered in teaching the essence of best management practices in conservation agriculture.

2. Water Quality

In Case Study 1, farmer 14, who had moderate-high field sensitivity and a 2.3 (RMS/FSS) pathway ratio, managed one pathway (surface P). On the other hand, farmer 22, with pathway ratios of 2.38 for surface P and 1.25 for N, effectively managed two pathways.

Field sensitivity determined by factors like soil texture and slope, and pathway ratios, are influenced by practices such as nutrient management and tillage, are key factors influencing this metric. A pathway ratio equal to or higher than 1 indicates successful pathway management.

Therefore, farmer 14, opting for a higher fertilizer rate, fewer nitrogen splits, not using cover crops and doing conventional tillage reflected on a lower simulated water quality score compared to farmer 22. Differently, farmer 22 does strip tillage, does the use of cover crop, apply a lower rate of N, and split it more times during the growing season. Strategic fertilizer application (4R - right time, right place, right source, and right rate) aligned with strip tillage and cover crop use, significantly mitigated the risk of nutrient loss and positively influencing water quality (Bijay-Singh and Craswell, 2021) (Table 2.8).

Comparisons of how those different practices that can impact water, during field days, where farmers observe a side-by-side comparison, can provide opportunities to discuss best nutrient management practices of farms. Moreover, the study highlighted the significant influence of management practices on these sustainable indicators. Adopting NRCS conservation practices, such as riparian forest buffers, tailwater recovery systems, and vegetative barriers, emerged as strategic approaches. Optimizing nutrient applications through the 4R Nutrient Stewardship and minimizing soil disturbance was essential to reduce nutrient losses and enhance water quality.

3. Soil Carbon

Case Study 2 examined the cotton farming methods of farmer 71, who initially practicing conventional tillage. The study simulated a transition from conventional tillage to strip tillage, enabling a comparison of their potential effects on soil carbon buildup or depletion (Table 2.9). During conventional tillage, the farmer made 16 trips to the field, including disking two times, hipper, planting, harvesting, and stalking chopper operations. In contrast, with strip tillage, the farmer reduced field trips by 3, omitting the disk and hipper operations.

Under conventional tillage, the simulation of soil carbon score was -0.47, indicating a high risk of soil carbon loss, and of organic matter loss. Transitioning to strip tillage raised the simulated score to 0.23, meaning a significant potential for soil carbon gain. This metric score ranges from -1 to +1, with negative scores indicating potential carbon loss and positive scores indicating potential carbon gain. Therefore, this transitioning from conventional to strip tillage reversed the field's carbon dynamics, highlighting the impact of different tillage methods on soil carbon levels and conservation.

Results from simulations using the FieldPrint Calculator Tool suggested that farmers using traditional tillage methods were approximately two times less effective in maintaining simulated soil carbon levels and nearly five times less successful in mitigating simulated soil erosion than alternative methods (Parrish, 2016). This highlights the substantial enhancement in soil carbon levels through the implementation of strip tillage and underscores the importance of minimizing soil disturbance. Some of the practices that reduce soil carbon losses that farmers and consultants need to have in mind are the integration of cover crops and minimizing soil disturbance by considering strip-till or no-till. Keeping the soil covered and preventing erosion are factors that increase organic matter and, however, soil carbon.

This information is a valuable tool for informing fellow farmers about the consequences of different tillage practices on their overall sustainability scores. The observability and trialability of new practices have been recognized to reduce perceived risks (Serebrennikov et al., 2020). It also aids consultants in comprehending the challenges farmers face when changing their management practices. Improving farmers' knowledge of soil carbon and related management practices is crucial as there is a lack of scientific understanding among farmers regarding sustainable soil management (Joona et al., 2022). To achieve understanding of soil organic matter and develop management strategies, strategies like training, on-farm trails, and field days with farmers are suggested (Gentry et al., 2018). These strategies are essential for the adoption of these indicators and, ultimately, the adoption of conservation practices.

Although not asking the farmer during the in-person interview regarding his conventional tillage practice, the farmer voluntarily expressed, "I know this is not the best practice, but I already tried strip-till, and it did not work on my soil type." Soil health is just one element within the complex decision-making process for agricultural practices (Andersson and D'Souza, 2014). Other socioeconomic factors significantly influence this decision-making (Hermans et al., 2021). It is crucial to understand whether farmers perceive this improvement.

4. Soil Conservation

Studying the transition from conventional tillage to strip tillage in case study 2, allows to highlight the role of tillage management on soil conservation. The simulated soil conservation score for conventional tillage was 2, decreasing to 0.7 when strip tillage was used. This metric is described by tons of soil loss, so decreasing the score is desirable. Farmer 71 planted cover crops, then the only change on the soil conservation score was attributed to the change on tillage practice which directly decreased the risks for soil erosion. This change underscores the importance of tillage methods in preserving soil integrity and then reducing the movement of nutrients, pesticides, and agricultural chemicals into water sources (Gallaher and Hawf, 1997).

The residue management practices employed, specifically in strip tillage or no tillage methods, not only preserve but also enhance soil health. Residues left on the soil surface degrade over time, increasing soil organic matter and carbon levels. This increase in soil carbon not only fortifies the soil structure but also amplifies water and nutrient retention, aids in improved infiltration, and ultimately reduces erosion significantly.

Improving soil health is essential for sustainability in agriculture and to mitigate climate risks. Despite the familiarity most farmers have with the term soil conservation, the diverse interpretations they have of soil health cannot be ignored. This variability in understanding among farmers underscores the critical need for conservation strategies. Farmers' understanding of soil health is pivotal, yet it is often misrepresented or misunderstood by organizations (Wirth-Murray and Basche, 2020; Wade et al., 2021).

To establish sustainable practices, it is imperative to develop extension programs that not only educate but truly understand farmer's need (Irvine et al., 2023). This approach ensures that the scientific objectives are not only communicated effectively but are also rooted in practical realities. Specialized programs that consider what farmers think act as an essential link between scientific plans and making them work on farms.

5. Greenhouse Gas Emissions

From Case Study 3, farmer 71 used conventional tillage, irrigated the crop, made 15 trips across the field, and applied potash, simulating emissions of 2,200.90 lbs-CO2e/ac. In contrast, farmer 17, who did not apply potash, emitted 1,909.60 lbs-CO2e/ac. The main difference in their emissions were primarily due to application energy and soil nitrous oxide (N2O), followed by post-harvest and management energy (Figure 2.3). The primary differences between farmers 71 and 17 are their tillage system, irrigation methods, field trips, and post-harvest energy emissions (Table 2.10). Post-harvest emissions are influenced by factors such as mileage from the field to the first point of sale, type of fuel used by transportation vehicle, and drying process. Since farmer 71 used conventional tillage, applied more fertilizer, and had more field trips, the GHG emissions were expected to be higher. Implementing practices that reduce soil tillage decreases soil disturbance and microbial activity and lowers CO_2 and N_2O emission rates (Lemke et al., 1999; Drury et al., 2006; Mosier et al., 2006).

Greenhouse gas emissions (GHG) are influenced by various factors such as tillage, irrigation, and nitrogen fertilization (Sainju et al 2012). In the past decade (2010-2019), GHG emissions reached record levels. Agriculture, forestry, and land-use activities contributed to 22% of these emissions in 2019 (IPCC, 2022). Although this metric was not included in the field day presentation to avoid overwhelming farmers with information, it is crucial for analysis.

Irrigation influences GHG emissions due to the energy required for water pumping and application. In the case of farmer 17, the irrigation used to growth cotton contributed to the higher total GHG emissions compared to farmer 71. While some practices are beyond farmers' control, others can be improved. Reducing energy use linked to GHG emissions is crucial. Adhering to the 4Rs of nutrient stewardship ensures optimal fertilizer uptake and reduces nutrient loss. Thoughtful crop rotation planning and the incorporation of cover crops can help fix nitrogen, offering environmentally friendly alternatives. These strategies can significantly impact GHG emissions and promote sustainable farming practices.

6. Opportunities and barriers engaging farmers

Using sustainability indicators, such as the Fieldprint Calculator, in educating farmers, consultants, and NRCS personnel presents both limitations and opportunities in crop management's environmental impact. The limitations are diverse such as challenges in understanding the complexity of the tools, interpreting intricate datasets and reports, collecting the management practices data effectively, and acquiring a profound comprehension of diverse farming practices and their impact. Learning and utilizing these tools demand significant effort and expertise from individuals, especially considering the complexity of agricultural systems. Extension services are pivotal in facilitating the learning process as highlighted in several studies (Altalb et al., 2015; Sewell et al., 2017; de Olde et al., 2018; Piñeiro et al., 2020). However, these challenges also suggest opportunities for growth and improvement. Active participation within farmers' networks leads to more adoption of conservation practices (Takahashi et al., 2020; Asprooth et al., 2023). Creating targeted educational programs and resources tailored to farmers' and consultants' needs can bridge knowledge gaps and enhance tool proficiency. Additionally, these indicators could serve as valuable resources for NRCS personnel, aiding them in providing more precise and informed guidance to farmers.

Furthermore, using benchmarks, combined with farmer commitment, stakeholders, and industry dedication, offers a unique opportunity for engagement (De Snoo, 2006; De Snoo et al., 2010; Lokhorst et al., 2010). These tools provide concrete insights into environmental impacts, motivating farmers to embrace sustainable practices when they can compare their performance with peers. With this knowledge, consultants can provide more targeted and practical advice, fostering a deeper understanding of the environmental consequences of various farming choices. Incorporating these tools into extension services and consultancy practices is essential. Workshops, training sessions, and collaborative learning environments empower farmers and consultants to use these indicators effectively. Moreover, NRCS personnel can integrate these tools into their advisory services, offering farmers concrete data to inform their decisions. Partnerships between researchers, extension services, consultants, and NRCS can enhance tool accessibility, simplifying guides and workshops, reducing the learning curve.

However, challenges persist. Older farmers resist change, believing in traditional methods (Rodriguez et al., 2008). Social barriers, like peer pressure and the lack of successful examples, hinder adoption (Rodriguez et al., 2008). It is crucial to understand that in crop farming initiatives, sustainability usually precedes social and economic aspects due to increased consumer awareness, media attention, and stakeholder consensus (Konefal et al., 2023). Overcoming these challenges means addressing practical obstacles and understanding social dynamics within farming communities.

Such comparative analyses actively engage farmers and serve as educational tools, showcasing the real-world impact of agricultural choices (Rodriguez et al., 2008). Tools like the Fieldprint Calculator empower farmers, consultants, and industry, introduce a sense of responsibility and encourage proactive engagement in sustainable agricultural practices (Whitehead et al., 2020). Through collaborative efforts and tailored education, the path to sustainable farming becomes not only clearer but also more accessible for everyone involved.

CONCLUSION

In conclusion, this chapter searches through the complexities of promoting sustainable agricultural practices, particularly in the context of the Southern United States. Despite the critical need to address global challenges like food security and climate change, adopting sustainable methods in agriculture faces multifaceted barriers. Social, cultural, financial, and educational factors intertwine, hindering the widespread acceptance of practices crucial for sustainability. This study analyzed the applications and implications of sustainability indicators, notably the Fieldprint Calculator, in enhancing sustainable agricultural practices in Alabama.

Through case studies, various aspects of sustainability were explored, including energy use, water quality, soil carbon levels, soil conservation, and greenhouse gas emissions. These analyses provided nuanced insights into the challenges faced by farmers in adopting more sustainable practices. Key findings underscored the critical role of factors like fertilizer application, tillage methods, irrigation practices, and field trips in shaping environmental impacts.

Utilizing tools like the Fieldprint Calculator highlighted the potential of benchmarking sustainability performance. While these tools offer valuable metrics, challenges such as data entry and understanding the accuracy of the data required, analyses, and practical interpretation persist. Additionally, this study highlighted the positive impact of collaborative efforts, agricultural extension services, and multi-stakeholder initiatives. Collective attempts facilitate knowledge sharing and bridge gaps in understanding and implementing analyses and the best way to present them to farmers.

Key Insights:

Energy Efficiency: Fertilizer energy emerged as a significant factor influencing overall energy consumption. Utilizing technologies such as irrigation scheduling and optimizing grain drying processes can further enhance energy efficiency in agriculture.

Water Quality: Strategic fertilizer application adhering to the 4 Rs (right time, right place, right source, and right rate) significantly impacted water quality. Farmers embracing NRCS conservation practices and optimizing nutrient applications can effectively mitigate water contamination, ensuring environmental integrity and agricultural sustainability.

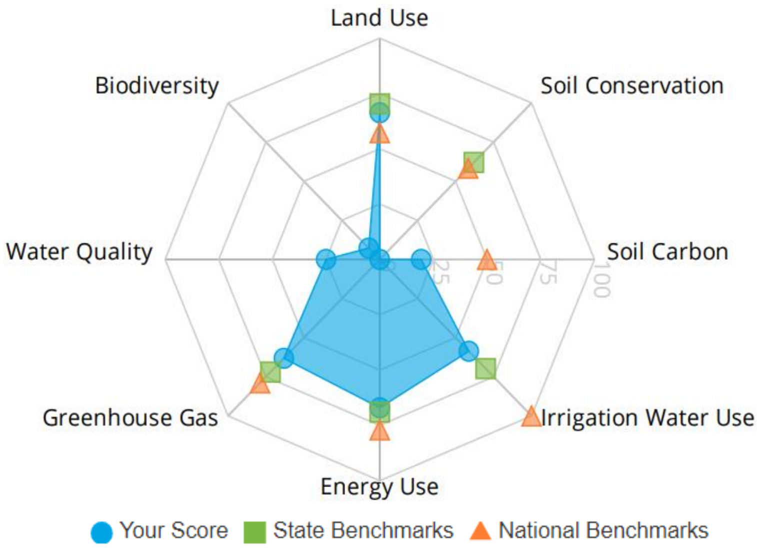
Soil Health: Minimizing soil disturbance, integrating cover crops, and managing planting and harvest dates emerged as vital strategies for preserving soil carbon levels and minimizing soil loss. Transitioning from conventional tillage to strip tillage presents a substantial opportunity for improving soil health and preventing erosion.

Greenhouse Gas Emissions: Implementing reduced tillage methods and optimizing irrigation practices are crucial avenues for reducing greenhouse gas emissions. These strategies not only promote environmental sustainability but also enhance the overall efficiency of agricultural practices.

Engaging Farmers: The study identified challenges in understanding complex tools and interpreting data but also illuminated avenues for growth. Active participation within farmers' networks, targeted educational programs, and collaborative learning environments were recognized as powerful tools for engagement. Benchmarking, when combined with commitment, served as a motivator for change, enabling farmers to embrace sustainable practices when presented with clear benchmarks.

In addressing these challenges and leveraging these opportunities, this study advocates for a multifaceted approach. Integrating sustainability indicators into extension services, consultancy practices, and NRCS advisory services is essential. Workshops, training sessions, and collaborative learning environments can empower farmers and consultants, bridging the gap between scientific knowledge and on-field implementation. Moreover, addressing social barriers and practical obstacles within farming communities is crucial. By fostering a deeper understanding of the environmental consequences of various farming choices and providing concrete data-driven insights, this research sets the stage for a more sustainable agricultural future in Alabama.

In essence, this chapter emphasizes the importance of a comprehensive perspective. It is not only about implementing sustainable practices but also about establishing a supportive atmosphere. Education, financial support, community involvement, and innovative tools are the foundation of sustainable agriculture. Achieving agricultural sustainability requires ongoing discussions, cooperative initiatives, and a dedication to transformation. A more sustainable agricultural environment can be achieved by tackling challenges and utilizing stakeholders' strengths.



2. Two

Figure 2.1 Example of the spidergram from Fieldprint Calculator results, with metric scores on a scale of 1-100. Lower scores indicate reduced resource use and environmental impact. Benchmarks, based on USDA data from 2008-2012.

Table 2.1 Variables influencing the sustainability indicators within the Fieldprint Calculator.

Metric	Yield	Crop type	Irrigation systems	Tillage systems	Irrigation management	Environmental factors	Production inputs	Soil type	Topography
Land use	Yes	No	No	No	No	No	No	No	No
Irrigation water use	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Energy use	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No
Greenhouse gas emissions	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No
Soil conservation	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Soil carbon	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Water quality	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Biodiversity	No	Yes	No	No	No	Yes	Yes	No	No

Table 2.2 Models and metrics used in each of the Fieldprint Calculator Indicators.

Metric	Model/calculation
Land Use	Math (acre/unit of production)
Irrigation Water Use	Math (acre-inches/unit of production)
Energy Use	Argonne National Labs GREET Model + Field to Market Calculations (btu/unit of production)
Greenhouse Gas Emission	DayCent/Empirical Hybrid (pounds-CO_2e/pounds)
Soil Conservation	NRCS WEPPS Models (ton/acre/year)
Soil Carbon	NRCS Soil Conditioning Index
Water Quality	NRCS STEP Model
Biodiversity	Habitat Potential Index + Field to Market calculations

Table 2.3 Data necessary for the Fieldprint Platform and its respective metrices.

Category	Input	Biodiversity	Energy Use	GHG emissions	Irrigation water use	Land use	Soil carbon	Soil conservation	Water quality
Location	• State	x	x	x			x	x	x
	• County	x	x	x			x	x	x
	• Area	x	x	x			x	x	
	• Field boundary		x	x			x	x	x
Soil	• Slope						x	x	x
	• Slope length			x			x	x	x
	• Surface soil texture		x	x			x	x	x
	• Wind barrier							x	
	• Organic matter content						x		x
Crop rotation	• Crop	x	x	x		x	x	x	
	• Seeding rate		x	x					
	• Tile drainage system	x							x
	• Irrigation		x	x	x				x
	• Yield (irrigated and/or non-irrigated)		x	x	x	x		x	
	• Irrigation method	x							x
	• Water applied		x	x	x				

Category	Input	Biodiversity	Energy Use	GHG emissions	Irrigation water use	Land use	Soil carbon	Soil conservation	Water quality
Management	• Pump pressure		x	x					
	• Pumping depth		x	x					
	• Tillage system	x	x	x			x	x	x
	• Management system		x	x			x	x	
	• Crop residue removal			x					
	• Irrigation water source	x							
	• Irrigation water recapture	x							
	• Irrigation pump energy source		x	x					
	• Integrated pest management	x							x
	• Nutrient application rate		x	x					x
	• 4R practices	x							
	• Soil condition at								x

Category	Input	Biodiversity	Energy Use	GHG emissions	Irrigation water use	Land use	Soil carbon	Soil conservation	Water quality
	the time of N application								
	• Dominant application method								x
	• Fertilizer application type								x
	• Fertilizer application timing		x	x					x
	• Number of fertilizer applications		x	x					x
	• Fertilizer products		x	x					
	• Lime application								x
	• Herbicides		x	x					
	• Insecticides		x	x					
	• Fungicides		x	x					
	• Growth regulation		x	x					
	• Fumigants		x	x					
	• Manure application		x	x					

Category	Input	Biodiversity	Energy Use	GHG emissions	Irrigation water use	Land use	Soil carbon	Soil conservati on	Water quality
	• Timing/Split application								x
	• Manure amount		x	x					
	• Manure N applied		x	x					
	• Distance to sale		x	x					
	• Transportati on backhauls		x	x					
	• Transportati on fuel type		x	x					
Drying	• Drying system		x	x					
	• Energy source		x	x					
	• Points of moisture removed		x	x					
	• Fuel amount		x	x					
	• Electric amount		x	x					
Conservation practices	• Conservatio n practices adopted	x							x

Table 2.4 Description of farmers' fields included in the study.

Specifications	F14	F17	F22	F71
Rotation (2019, 2020, 2021)	Cotton, Corn, Corn	Cotton, Cotton, Peanuts	Cotton, Cotton, Corn	Cotton, Peanuts, Cotton
County	Macon County, AL	Lee County, AL	Autauga County, AL	Russel County, AL
Plantable Acre	398	66	27	105.1
Soil Type	Silty Clay	Loamy Sand	Silt Loam	Fine Sandy Loam
Tillage	Reduced Tillage	Strip-till	Strip-till	Conventional
Cover Crop	No	Yes	Yes	Yes
Irrigation	No	No	No	Yes

Table 2.5 Description of soil type and management practices of farmers F14 and F22 growing corn during 2021. Case Study 1.

Specifications	F14	F22
Crop	Corn	Corn
Soil Type	Silty Clay	Silt Loam
Tillage	Conventional	Strip-till
Cover Crop	No	Yes
Total Nitrogen (lbs/ac)	320.4	191.8
Total Phosphorus (lbs/ac)	117.3	183
Total Potassium (lbs/ac)	108	91
Final Yield	190 bushes/acre	180 bushes/acre

Table 2.6 Case Study 1. Description of soil type and management practices on a corn field of farmers F14 and F22 during 2021 and economic values related to their practices.

	F14	F22
Soil type	Silt Clay	Silt Loam
Tillage	Conventional tillage	Strip-till
Cover crop	No	Yes
Fertilizer application	Split 2x	Split 3x
Total N (lbs/ac)	320.4	191.8
Total P (lbs/ac)	117	138
Total K (lbs/ac)	108	91
Crop protectants	4 passes – 8 products	2 passes – 5 products
Yield (yield goal)	190 bu/ac	180 bu/ac
Total energy use	11,178,782 btu/acre	9,490,989 btu/acre
Surface P & N loss sensibility	Moderately high	Low
Economics		
Nitrogen value ($1.05 / lb N)	$336.4	$197.5
Phosphorus value (0$0.70 /lb of P)	$82.1	$96.6
Potash value ($0.60 / lb K)	$64.1	$54.6
Total value (not including application)	$438.3	$348.7
Yield equivalent ($6/bu)	80.6	58.1

Table 2.7 Energy components from farmers F14 and F22 from a corn field in 2021.

	F14		F22	
Component	(BTU/acre)	(BTU/bushel)	(BTU/acre)	(BTU/bushel)
Management Energy	322,682	1,98	1,389,055	11,112
Application Energy	10,668,643	56,151	7,957,279	63,658
• Seed Treatment Energy	24,790	130	24,790	198
• Fertilizer Energy	9,594,380	50,497	6,216,157	49,729
• Protectant Energy	942,698	4,962	591,425	4,731
• Field Operations Energy	106,776	562	88,980	712
• Lime Energy	0	0	1,035,929	8,287
Manure Loading Energy	0	0	0	0
Seed Energy	21,154	111	17,308	138
Irrigation Energy	0	0	0	0
Post-Harvest Energy	0	0	0	0
Transportation Energy	166,303	875	127,347	1,019
Total Energy	11,178,782	58,836	9,490,989	75,928

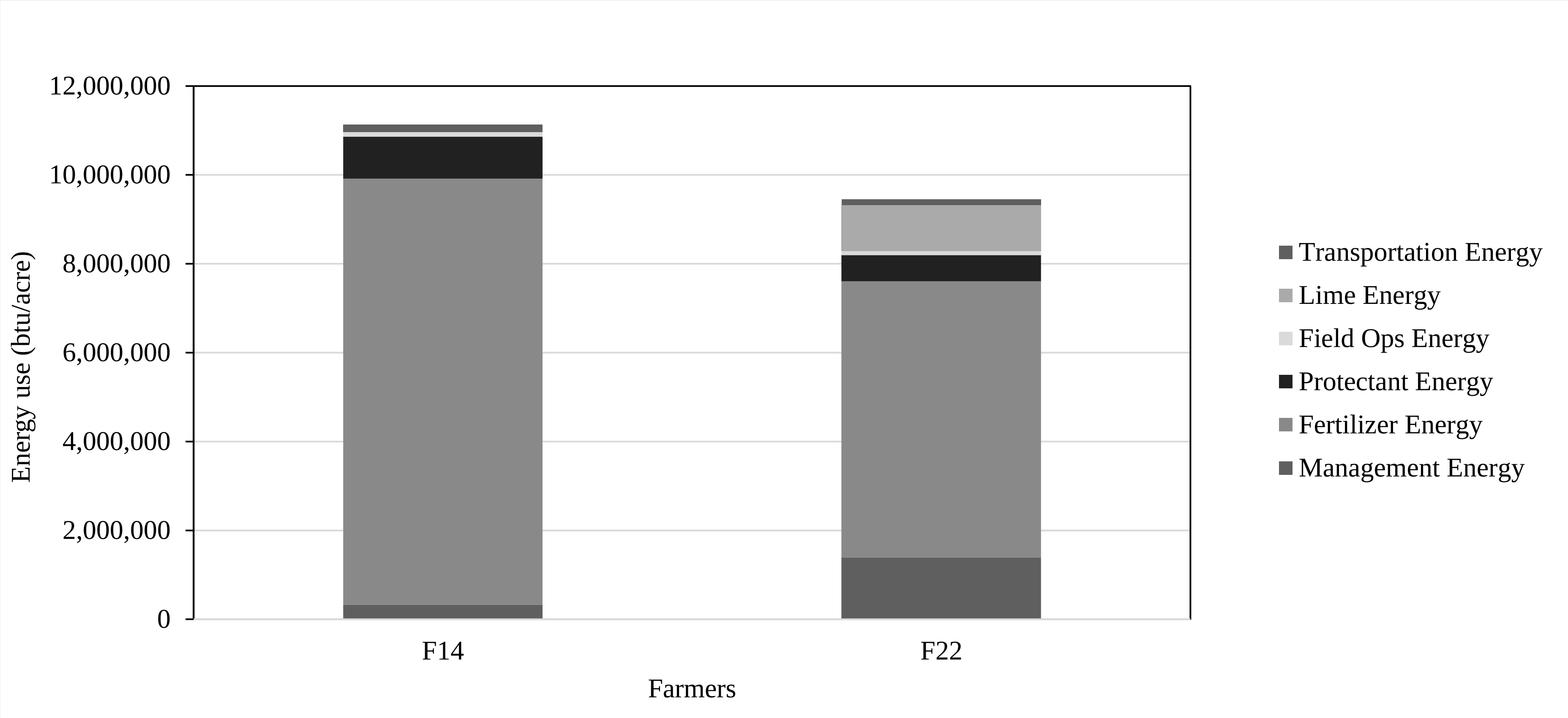


Figure 2.2 Energy use components in btu/yield unit from farmers 14 and 22 - Corn 2022.

Table 2.8 Water quality metric to assess how likely a field is to lose nutrients to waterways on farmers' 14 and 22 fields in the 2021 crop season.

Farmer 14	Loss pathway	Field sensibility category	Pathway ratio (RMS/FSS)	Pathway mitigation
	Surface P	Moderately high	2.3	Mitigated
	Subsurface P	Moderate	0.46	Improve
	Surface N	Moderately high	0.58	Improve
	Subsurface N	Moderate	0.2	Improve
Farmer 22				
	Surface P	Low	2.38	Mitigated
	Subsurface P	Moderate	0.15	Improve
	Surface N	Low	1.25	Mitigated
	Subsurface N	Moderate	0.2	Improve

RMS: risk mitigation score.
FSS: field sensitivity score.
RMS/FSS > 1: basic risk mitigation level for surface nutrient loss met.
RMS/FSS < 1: excessive nutrient loss likely.

Table 2.9 Case Study 2. Description of soil type and management practices on a cotton field of farmer F71 in 2019.

	Farmer 71	
Soil type	Fine Sandy Loam	Fine Sandy Loam
Tillage	Conventional tillage/Disk 2 times	Strip tillage
Cover Crop	Yes	Yes
Trips to the field	16	13
Soil carbon	-0.47	0.23
Soil conservation	2	0.7

Table 2.10 Case Study 3. Description of soil type and management practices on farmers F71 and 17 cotton fields during 2019.

	Farmer 71	Farmer 17
Soil type	Fine Sandy Loam	Loamy Sand
Tillage	Conventional tillage	Strip-till
Irrigation	Yes	No
Cover crop	Yes	Yes
Trips to the field	15	11
Total N (lbs/ac)	90	81.6
Total P (lbs/ac)	30	120 (2 tons of chicken litter)
Total K (lbs/ac)	170	0
Yield (yield goal)	1250 lbs/ac	1250 lbs/ac
Greenhouse gas emission (lbs-CO_2 e/ac)	2,200.9	1,909.6
Economics		
Nitrogen Value ($1.05 / lb N)	$94.50	$85.68
Phosphorus Value (0$0.70 /lb of P)	$21	$84
Potash Value ($0.60 / lb K)	$102	$0
Total Value (not including application)	$217.50	$169.68
Yield Equivalent ($0.75/bu)	290	226

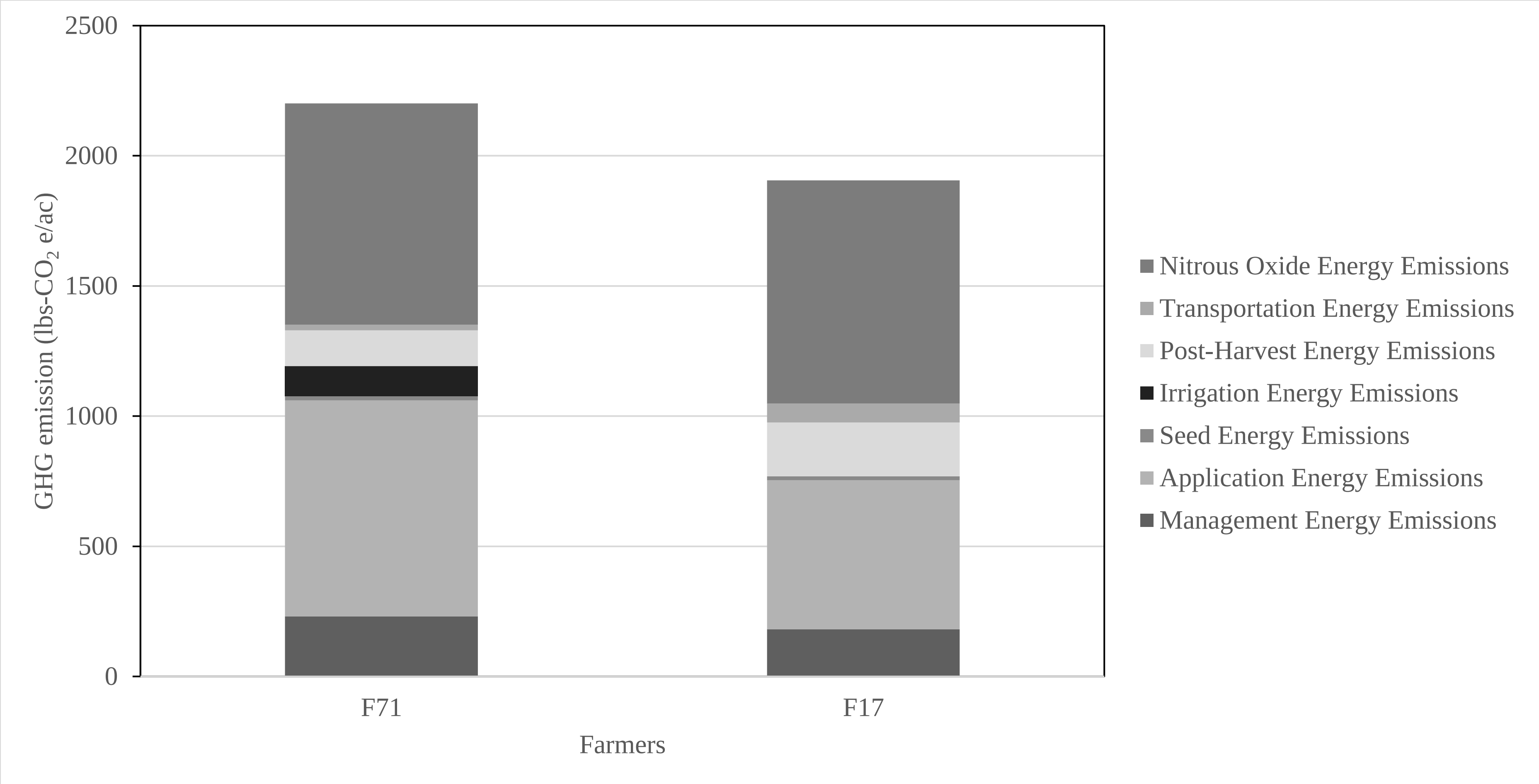


Figure 2.3 Greenhouse gas emission components in lbs-CO2 e/ac from farmer 71 and 17 – Cotton 2019.

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DSSAT files calibration

```
@PEOPLE
Marina and B. Ortiz
@ADDRESS
201 Funchess Hall
@SITE
Auburn University

*TREATMENTS                        -------------FACTOR LEVELS------------
@N R O C TNAME.................... CU FL SA IC MP MI MF MR MC MT ME MH SM
 1 1 1 0 loc3                       4  1  0  1  1  1  1  0  0  0  0  1  3
 2 1 1 0 loc6                       4  2  0  2  1  1  1  0  0  0  0  1  3
 3 1 1 0 loc7                       4  3  0  3  1  1  1  0  0  0  0  1  3
 4 1 1 0 loc9                       4  4  0  4  1  1  1  0  0  0  0  1  3
 5 1 1 0 GeoG AU(Loc7)70%           4  3  0  3  1  1  1  0  0  0  0  1  4
 6 1 1 0 GeoG AU(Loc7)50%           4  3  0  3  1  1  1  0  0  0  0  1  5
 7 1 1 0 GeoG AU(Loc7)30%           4  3  0  3  1  1  1  0  0  0  0  1  6
 8 1 1 0 GeoG AU 2022 70%           4 16  0 16 16  0  0  0  0  0  0 16  7
 9 1 1 0 GeoG AU 2022 50%           4 16  0 16 16  0  0  0  0  0  0 16  8
10 1 1 0 GeoG AU 2022 30%           4 16  0 16 16  0  0  0  0  0  0 16  9
11 1 1 0 loc6 2022 cultivar         4  2  0  2  1  1  1  0  0  0  0  1  3
12 1 1 0 loc9 2022 cultivar         4  4  0  4  1  1  1  0  0  0  0  1  3
13 1 1 0 loc7 2022 cultivar         4  3  0  3  1  1  1  0  0  0  0  1  3
14 1 1 0 loc3 2022 cultivar         4  1  0  1  1  1  1  0  0  0  0  1  3
16 1 1 0 2022 location              4 16  0 16 16  0  0  0  0  0  0 16 16
```

Soil profile information in DSSAT - Location 3. Field 1.2a 2021

```
*AULanze3_2  NRCS-UGALab LS       122  Malboro Loamy sand
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 Lazenby     USA             32.42 -85.416 -99
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .6    73     1    .8 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
     5   -99  .068  .153  .402     1  6.11  1.39  .058   6.2  12.2   -99   .01   6.1   -99   -99   -99
    15   -99  .088  .176  .391     1  2.59  1.76 1.309  10.2  12.2   -99   .11   6.1   -99   -99   -99
    23   -99  .097  .183   .38     1  2.59  1.78  .389  12.2  10.2   -99   .03   5.6   -99   -99   -99
    30   -99  .124  .211   .38     1  2.59  1.91  .389  18.3  10.2   -99   .03   5.6   -99   -99   -99
    46   -99  .183  .277  .387     1   .43  1.85  .282  32.3  10.1   -99   .02   5.4   -99   -99   -99
    61   -99  .192  .284  .387  .657   .43   1.9  .282  34.3   8.1   -99   .02   5.4   -99   -99   -99
    76   -99  .192  .284  .387  .583   .43  1.88  .131  34.3   8.1   -99   .01   5.6   -99   -99   -99
    91   -99  .201  .294  .387  .517   .12   1.7  .131  36.3   8.1   -99   .01   5.6   -99   -99   -99
   107   -99  .201  .294  .387  .458   .12  1.77  .159  36.3     8   -99   .02   5.1   -99   -99   -99
   122   -99  .229  .324  .391  .407   .12  1.68  .159  42.3   6.1   -99   .02   5.1   -99   -99   -99
```

Soil profile information in DSSAT - Location 6. Field 1.2a 2021

```
*AULazen6_2  UGA         LS       122  Malboro Loamy Sand
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 Lazenby     USA            32.42 -85.415 -99
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .6    73     1    .8 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
     5   -99  .058  .144  .413     1  6.11  1.57 1.235   4.2  14.2   -99    .1   6.3   -99   -99   -99
    15   -99  .069  .161  .413     1  6.11  1.82  .504   6.2  16.2   -99   .03     6   -99   -99   -99
    23   -99  .097  .194  .398     1  2.59  1.81  .312  12.2  18.2   -99   .02   5.5   -99   -99   -99
    30   -99   .13   .23  .395  .589   .43  1.75  .312  20.2  18.2   -99   .02   5.5   -99   -99   -99
    46   -99  .173  .275  .395  .468   .43  1.81  .202  30.2  16.2   -99   .02   5.1   -99   -99   -99
    61   -99  .173  .275  .395  .343   .43  1.69  .202  30.2  16.2   -99   .02   5.1   -99   -99   -99
    76   -99  .182  .282  .395  .254   .43  1.54   .13  32.2  14.2   -99   .02     5   -99   -99   -99
    91   -99   .21  .312  .395  .188   .12  1.54   .13  38.2  12.2   -99   .02     5   -99   -99   -99
   107   -99   .22  .328  .405  .138   .12  1.51  .136  40.2  14.2   -99   .02   4.8   -99   -99   -99
   122   -99  .242  .353  .413  .101   .06  1.49  .136  44.2  14.3   -99   .02   4.8   -99   -99   -99
```

Soil profile information in DSSAT – Location 7. Field 1.2a 2021

```
*AULazen7_2  UGA         LS       122  Malboro Loamy Sand
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 Lazenby     USA            32.42 -85.415 -99
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .6    73     1    .8 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
     5   -99  .068  .157  .405     1  6.11  1.15 1.554   6.2    14   -99   .12   6.9   -99   -99   -99
    15   -99  .079  .171  .405     1  2.59  1.86  .574   8.2  15.9   -99   .03   7.1   -99   -99   -99
    23   -99  .088  .182  .398     1  2.59  1.87  .383  10.2    16   -99   .02   6.6   -99   -99   -99
    30   -99  .114  .215  .398  .589  2.59  1.81  .383  16.2    20   -99   .02   6.6   -99   -99   -99
    46   -99  .138  .239  .395  .468   .43  1.92    .2  22.2    18   -99   .02   6.1   -99   -99   -99
    61   -99  .156  .256  .395  .343   .43  1.94    .2  26.3  16.3   -99   .02   6.1   -99   -99   -99
    76   -99  .139  .237  .395  .254   .43  1.54   .09  22.3  16.3   -99   .01   7.1   -99   -99   -99
    91   -99  .139  .234  .391  .188   .43  1.55   .09  22.2  14.3   -99   .01   7.1   -99   -99   -99
   107   -99  .157  .251  .391  .138   .43  1.55   .08  26.3  12.4   -99   .01     5   -99   -99   -99
   122   -99  .174   .27  .391  .101   .43  1.55   .08  30.3  12.3   -99   .01     5   -99   -99   -99
```

Soil profile information in DSSAT – Location 1.1 Field 1.2b 2022

```
*AULazMarvy  UGA         SL       122  Marvyn Sandy Loam
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 Lazenby     USA            32.42 -85.437 -99
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .6    73     1    .9 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    23   -99  .095  .183  .414     1  2.59  1.48   .69  10.1  16.6   -99   .04   5.2   -99   2.9   -99
    45   -99   .13   .19  .385  .589   .43  1.57   .24  30.1  14.5   -99   .04   5.1   -99   4.4   -99
    68   -99  .186   .21  .379  .375   .43  1.59   .16  31.1  13.4   -99   .04   4.7   -99   7.5   -99
    91   -99  .204  .288  .383  .204   .12  1.58    .1  35.1  14.3   -99   .02   4.6   -99   8.6   -99
   122   -99  .216  .299  .386  .119   .12  1.57   .15  37.1  13.2   -99   .03   4.6   -99   9.1   -99
```

Example of the weather file in DSSAT. 2021 growing season. Society Hill, AL.

```
@ INSI      LAT     LONG  ELEV   TAV   AMP REFHT WNDHT
  AULZ   32.417  -85.400   300  18.1  19.0 -99.0 -99.0
@  DATE  SRAD  TMAX  TMIN  RAIN  RHUM
2021001   1.6  20.1  15.4  23.9  95.9
2021002   4.4  17.0   8.8   0.0  92.9
2021003  11.5  12.9   1.2   0.0  79.3
2021004  11.5  15.6  -1.1   0.0  79.6
2021005  12.0  16.8   1.2   0.0  76.8
2021006   9.2  12.6  -2.3   0.0  77.9
2021007   1.8   7.7   2.3   7.1  89.4
2021008   1.8   6.9   3.4   0.8  91.0
2021009   2.5   3.6   1.3   0.0  80.9
2021010   8.1   7.3  -3.3   0.0  79.5
2021011   2.3   8.3   3.4   6.3  91.0
2021012   2.3   6.8   3.3   0.0  90.8
2021013   7.8  10.2  -1.2   0.0  80.9
2021014  12.7  15.3  -3.1   0.0  76.7
2021015  11.1  13.6   0.7   0.0  63.5
2021016  12.9   9.2  -2.2   0.0  65.2
2021017  10.7  12.3  -4.3   0.0  74.0
2021018  13.1  13.9  -3.0   0.0  68.7
2021019  11.8  18.4  -2.6   0.0  65.0
2021020  10.9  16.9   7.3   0.0  64.1
2021021   1.6  15.9   7.7   5.1  91.5
2021022   2.8  13.3   8.3  20.1  95.4
2021023  13.4  17.7   2.5   0.0  68.8
2021024   9.2  17.5   7.4   0.0  78.1
2021025   8.5  24.4  13.9   0.0  83.0
2021026   6.3  21.2  14.7   1.5  83.8
2021027   6.0  16.8   7.1   0.0  81.0
```

Example of the weather file in DSSAT. 2022 growing season. Society Hill, AL

```
@ INSI      LAT     LONG  ELEV   TAV   AMP REFHT WNDHT
  AULZ   32.417  -85.400   300  18.1  19.0 -99.0 -99.0
@  DATE  SRAD  TMAX  TMIN  RAIN  RHUM
2022001   6.9  27.5  19.4   0.0  23.0
2022002   2.1  23.0   5.3   7.6  17.3
2022003   5.3   6.6  -1.3   0.3   2.7
2022004   9.1  13.2  -2.0   0.0   4.7
2022005   8.0  15.8   2.7   0.0   9.1
2022006   9.8  21.4   2.9   2.5  10.5
2022007  12.8   3.9   3.8   0.0   3.9
2022008  10.5  15.3  -0.6   0.0  73.8
2022009  11.1  22.5   9.4  41.9  66.5
2022010   5.6  14.8   0.1   0.0  89.4
2022011  11.2  11.8  -2.3   0.0  57.5
2022012  11.7  14.0  -1.6   0.0  70.3
2022013  11.0  17.1  -0.7   0.0  76.7
2022014  11.0  16.0  -1.3   0.0  75.2
2022015  10.9  15.7   3.1  13.2  75.3
2022016   5.0   8.5   1.1  15.2  80.2
2022017   2.0   4.6  -2.3   0.0  93.5
2022018   2.9  13.1  -3.6   0.0  86.4
2022019  12.0  18.2   0.9   0.0  82.0
2022020  11.6  13.4   1.9  10.2  76.7
2022021   1.8   4.1   0.8   0.3  92.5
2022022   2.1   7.6  -2.9   0.0  90.8
2022023   7.9  10.4  -5.8   0.0  84.9
2022024  13.0  15.3  -3.1   0.0  73.8
2022025  11.5  15.9   4.8   0.0  75.3
2022026   7.5  14.9   1.7   0.0  75.6
2022027  13.2  14.3  -0.3   0.0  53.5
2022028  12.8  11.7   1.6   0.0  61.3
```