DigitalAg@Farms

Efforts to put digital technologies and site-specific crop management practices in the hands of the farming community (2020 & 2021 report)

► The Alabama Precision Agriculture Extension team is committed to working with stakeholders on digital agriculture applications to increase farm profitability, efficiency, and environmental sustainability.

Introduction

Adopting technologies such as sensors and controls on farm machinery, remote sensing, or big-data–driven decision support systems to aid site-specific crop management has often been slow. Some reasons could be attributed to farmers' perception of their effectiveness, usability, comparative advantages, compatibility, and complexity. Easy-to-use technologies such as GPS-autosteer guidance systems or swath control for farm machinery are widely adopted among farms. In contrast, adopting practices that require collecting, processing, and analyzing digital data are still behind. The goal of the DigitalAg@Farms program is to work with farmers on their farms in evaluating, demonstrating, and training in the use of digital technologies in agriculture.

Although digital agriculture involves the use of communication, sensing, smart machinery, electronics, computing technologies, and algorithms to support farm operations and practices, "sense-making" of data and derived management approaches resides in the involvement of multiple disciplines such as agronomy, engineering, computer and data science, biology, and many others. All the projects included in this report result from collaboration with faculty from various disciplines and colleges within Auburn University, other universities in the region, state and federal agencies, crop consultants, and private industry.

Training is a big component of this program. Demonstration sites are currently the nodes of a training network. Around each demonstration site, neighboring farmers are invited to learn and discuss the technologies being demonstrated and interact with fellow farmers using the technology, Extension agents, and private industry representatives. Field days and workshops are also hosted at or near demonstration sites. The data collected from each demonstration site is a crucial part of the technology evaluation and training efforts.

2020–2021 Demonstration, Evaluation & Training Locations

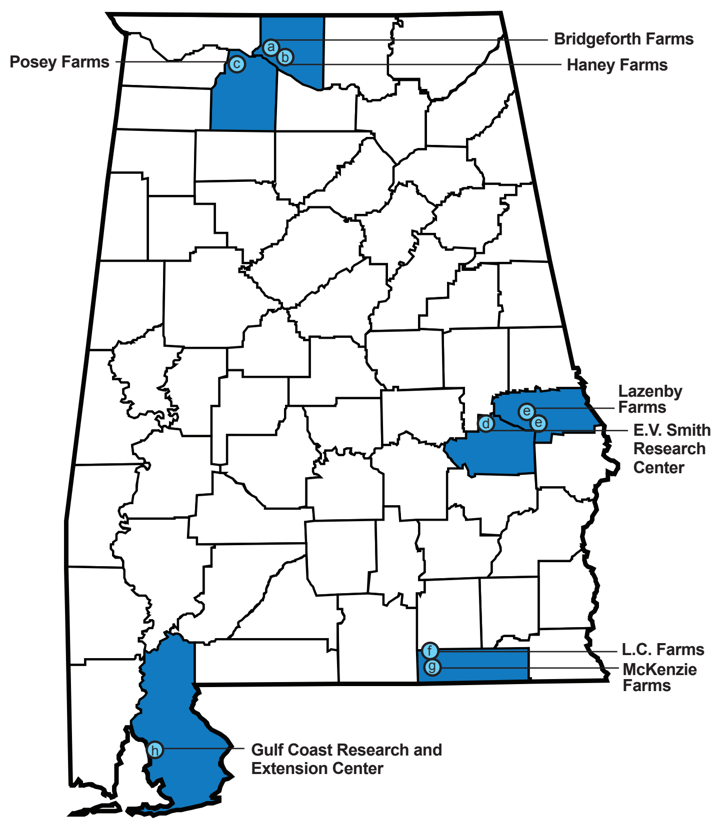

Figure 1. Demonstration and training sites.

- (a) Tanner, Alabama – Limestone County
- (b) Athens, Alabama – Limestone County
- (c) Town Creek, Alabama – Lawrence County
- (d) Shorter, Alabama – Macon County
- (e) Society Hill, Alabama – Macon & Lee Counties
- (f) Samson, Alabama – Geneva County
- (g) Kingston, Alabama – Geneva County
- (h) Fairhope, Alabama – Baldwin County

ANR-2918

DigitalAg@Practice

During the 2021 growing season, seven sites across Alabama were selected to evaluate, demonstrate, and train various stakeholders in the use of digital technologies in agriculture (figure 1). Preliminary results of six other studies conducted between 2020 and 2021 are included.

In collaboration with farmers and research stations, several technologies from multiple companies were evaluated for the implementation of site-specific management practices. These included irrigation scheduling, variable rate irrigation, smart planting, seed spacing and seed depth control, and segregation of harvest using remote assessment of crop maturity.

The data and preliminary results included in each report are not only the effect that the technology and practice might have on crop growth and final yield but also the impact abiotic (weather, soil) and biotic (insects) factors have on the crop. In 2021, cotton and peanut farmers in Baldwin County had issues with planting because of drought conditions. Rainfall above historic average values was common to all crops (sites) during the reproductive growth stages.

The data and results presented here should be considered preliminary results. A final assessment of the agronomic and economic benefits of a technology or associated practice requires at least 2 years of evaluation. Producers should not make final conclusions based on a single year of data.

2021 DigitalAg Demonstration Topic Areas

Our demonstration projects covered ten digital agriculture topic areas (figure 2). Some projects covered more than one topic. We have color-coded each topic area to help you identify the use of each on every project and location.

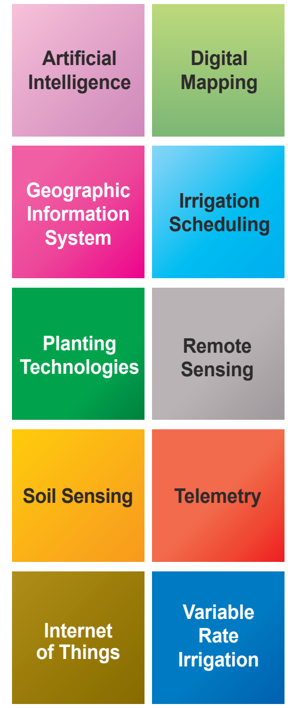

Figure 2. Digital agriculture areas covered in the 2020–2021 demonstration and training project.

Each project report covers two pages in this document. The various topic areas involved in each project are identified by colors at the top of the first page. The first page provides planting and site characteristics, treatments, project design, and a box highlighting three technologies used in each demonstration. The second page includes a brief description of the major results. The Food for Thought sections identify the significant take-home messages from each project. The list of personnel involved and their contact information are also included.

This document is for educational purposes only. Auburn University and the Alabama Cooperative Extension are not endorsing any specific product or company.

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Evaluation of Canopy Temperature as an Irrigation Scheduling Tool

Objective

- Evaluate the sensitivity of the crop water stress index (CWSI) derived from canopy temperature data as a method for irrigation scheduling.

Project Justification

Irrigation scheduling based on canopy temperature is advantageous compared to soil sensor–based irrigation because of the potential for capturing early plant water deficits and improving irrigation triggering decisions. However, information about this technology is lacking for the subtropical humid regions of the United States.

Planting Details

Location: Shorter, AL	**Planting:** 04/02/20 and 04/21/21
Crop: Corn	**Hybrid:** DKC62-08
Test size: 45 acres	**Row width:** 36 inches
Seeding rate: 36,000/acres	**Irrigation system:** Valley–7000 Series
Tillage: Conventional	**Predominant soil map unit:** Altavista silty loam

Treatments

T_{100}	Full rate to bring soil (24 inches) back to field capacity
T_{66}	66% of the rate calculated for T_{100}
T_{33}	33% of the rate calculated for T_{100}
T_0	Rainfed condition

Project Design

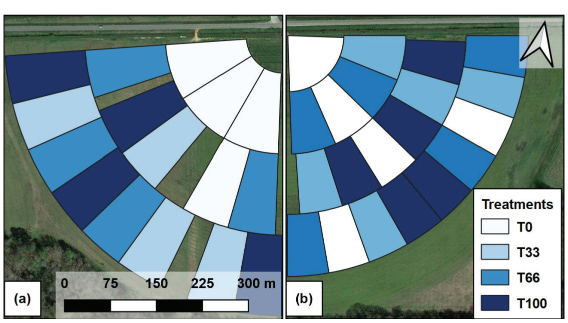

Figure 1.1. Layout of irrigation plots (1.2 to 2 acres/plot). SapIP-Infrared Thermal (IRT) Dynamax sensors were installed on each plot. The T_{100} plots were instrumented with Acclima 315LTM sensors installed at 6-, 12-, and 24-inch soil depths.

Precision Ag Toolbox

SapIP-IRT Canopy Temperature Sensor
(Dynamax Inc., Houston, Texas, USA)

Figure 1.1TB. Infrared temperature sensor used to collect canopy temperature data and calculate CWSI.

Acclima True TDR-315LTM Sensor
(Acclima, Inc., Meridian, Indiana, USA)

Figure 1.2TB. Acclima TDR 315LTM soil sensors used to collect soil volumetric water content.

Valley–7000 Series Center Pivot Irrigation
(Valley, Lincoln, Nebraska, USA)

Figure 1.3TB. Center Pivot Irrigation System with a variable rate irrigation system used to apply different irrigation rates.

Observations & Preliminary Results

Canopy temperature data collected with infrared thermal sensors (IRTs) was used to calculate the crop water stress index (CWSI). This index ranges from 0 (plants fully watered, no stress) to 1 (plants under full water stress).

CWSI was sensitive to changes in soil water levels (Figure 1.2). A trend of increasing CWSI values was observed as rainfall frequency decreased. When irrigation was applied to supply crop water demand, soil water levels increased, which in turn resulted in smaller CWSI values in the irrigated treatments (T_{100}, T_{66}, and T_{33}) in comparison with the rainfed treatment (T_0). This is represented by the separation of CWSI values between the irrigated and rainfed treatments shown in Figure 1.2.

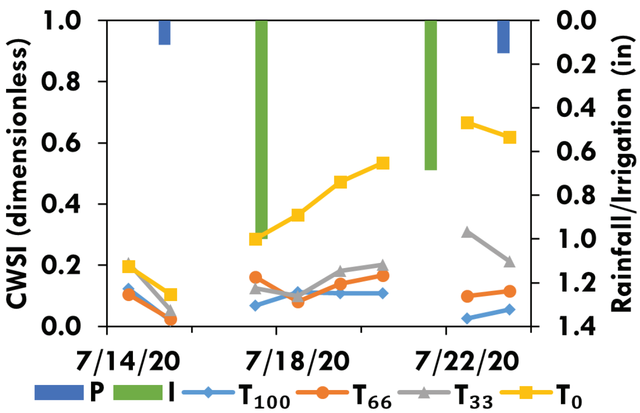

Figure 1.2. Crop water stress index (CWSI) differences among the full irrigation rate (T_{100}), 66% from full irrigation (T_{66}), 33% from full irrigation (T_{33}), and rainfed (T_0) treatments during a selected period in the 2020 corn growing season. Irrigation (I) and precipitation (P) events are also indicated.

Because seasonal rainfall was smaller in 2020 (17.5 inches) than in 2021 (25 inches), total irrigation amount was higher in 2020 (7.6 in applied on T_{100}) than in 2021 (2.7 in applied on T_{100}). The rainfall pattern during the growing season also affected the fluctuation of corn yield and seasonal CWSI values among the treatments. In 2020, corn yield ranged from 176 (T_0) to 244 bu/ac (T_{66}) and seasonal CWSI ranged from 0.07 (T_{100}) to 0.24 (T_0). In 2021, on the other hand, corn yield and seasonal CWSI among treatments averaged 210±9 bu/ac and 0.06±0.01, respectively, and very small treatment differences were measured. The low CWSI values observed in 2021 are explained by the high amount of well-distributed rainfall, which resulted in a low number of irrigation events and small soil moisture level differences among the treatments.

Figure 1.3 shows the relationship between seasonal corn yield and seasonal CWSI for 2020 and 2021 growing seasons. Because this is a long-term project, the dataset collected in 2018 and 2019 was also added to Figure 1.3. A strong inverse relationship between corn yield and CWSI was observed, whereas yield increased the CWSI decreased. Maintaining the plants under low soil water availability (T_{33} deficit irrigation and rainfed), resulted in larger CWSI values and low corn yield. In contrast, when soil water availability was maintained high due to irrigation, corn yield increased and CWSI approached zero. Results from the last 4-year's study show that CWSI is sensitive to crop water stress levels and, therefore, is a promising irrigation scheduling tool that could be used to support irrigation decisions. Identification of the CWSI threshold values at which irrigation should be initiated is still a work in progress, and their determination could increase the opportunities for adoption of this irrigation scheduling method.

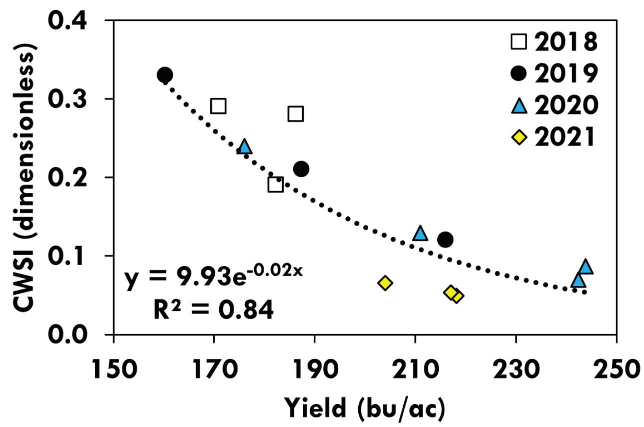

Figure 1.3. Relationship between seasonal average CWSI and corn yield using data from the 2018, 2019, 2020, and 2021 growing seasons.

Food For Thought

- Crop water stress index (CWSI) is sensitive to various soil water levels. The greater the soil water deficit, the higher CWSI values, and the lower the corn yield.
- Once CWSI-based irrigation scheduling thresholds have been identified through research, farmers or consultants could use CWSI data values estimated from data of individual canopy temperature sensors or thermal images to determine when to start irrigation.

Project Team: Bruno P. Lena, Brenda V. Ortiz, Alvaro Sanz-Saez, Greg Pate, Nicholas Stockdale.

Project Contacts: Bruno P. Lena, Postdoctoral Fellow. (brunoplena@gmail.com) or Brenda V. Ortiz, Extension Specialist, Professor, Crop, Soil, and Environmental Sciences (bortiz@auburn.edu).

Irrigation Scheduling | Remote Sensing | Telemetry | Internet of Things

Real-Time Mapping of Canopy Temperature Using a Wireless Network of Infrared Thermometers Mounted on a Central Pivot

Objective

- Develop a real-time canopy temperature mapping system that uses infrared leaf temperature sensors mounted on a center pivot irrigation system.

Project Justification

Mapping canopy temperature allows the assessment of plant water status or signs of crop water stress caused by lack of water or crop diseases. For the purposes of this project, canopy temperate data is used to estimate crop water stress indices that can be used to determine irrigation timing at different parts of crop fields.

Planting Details

Location: Shorter, AL	**Planting:** 04/21/21
Crop: Corn	**Hybrid:** DKC62-08
Test size: 37 acres	**Row width:** 36 inches
Seeding rate: 36,000/acres	**Irrigation system:** Valley–7000 Series center pivot
Tillage: Conventional	**Predominant soil map unit:** Altavista silty loam

Project Design

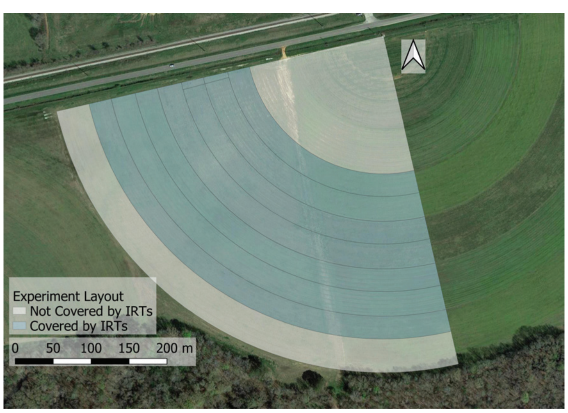

Figure 2.1. Area covered by the infrared thermometers (IRTs). The width of each ring-shaped polygon represents half pivot span length. IRTs were mounted in the center of each half-span, covering an area of three and a half pivot spans.

Precision Ag Toolbox

SapIP-IRT Canopy Temperature Sensor
(Dynamax Inc., Houston, Texas, USA)

Figure 2.1TB. Infrared thermometer (IRT) sensor mounted on the center of a half-span along four pivot spans. The sensors were used to map canopy temperature as the irrigation system traversed the field.

GPS Garmin GLO
(Garmin Ltd. Olathe, Kansas, USA)

Figure 2.2TB. Global positioning system (GPS) installed at the last center pivot tower used to determine the geographic position of each IRT sensor as the irrigation system travels across the field.

Python3
(Python Software Foundation, Wilmington, Delaware, USA)

Figure 2.3TB. Python programming language used to develop the real-time canopy temperature mapping software.

Observations & Preliminary Results

Seven infrared thermometer (IRT) sensors were mounted along the pivot main line covering 3½ spans. The sensors recorded canopy temperature as the center pivot irrigation system moved across the research area. A GPS receiver was installed at the last pivot span, allowing the estimation of the geographic coordinates of each IRT at any point in time. Figure 2.2 shows the layout of the components and processes included in the mapping system. The sensors, central station, communication, and cloud subsystem were integrated into the design of the automated irrigation system. Sensor data and the geographic coordinates were transmitted using the radio connection to the central station in a 1-minute reading interval. The central station was connected to an LTE/4G network, so the data was automatically uploaded to the cloud for later data processing and analysis. Also, the system can be accessed remotely using a web browser.

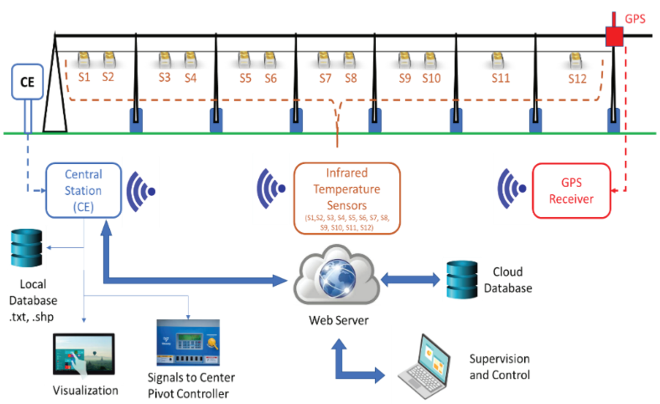

Figure 2.2. Real-time canopy temperature mapping system layout.

Four times during the growing season, the pivot traveled over the study area applying water, and those events were used to collect canopy temperature data. Figure 2.3 shows one example of data collected with the real-time canopy temperature mapping system. The different color dots on the map correspond to corn leaf temperature data collected on June 18, 2021 (corn at V12 growth stage). Each data point represents a reading taken from one IRT sensor at a given time of the day. Note that data points are arranged along seven concentric lines that correspond to the travel path of the center pivot irrigation system. Data in figure 2.3 shows spatial variability on infrared temperature data that might indicate differences in plant water status at different locations or more bare soil due to poor crop growth. Plants under lesser water stress will show lower canopy temperatures (blue data points) than those plants under high water stress (red data points).

In 2021, the corn growing season was very wet, with total seasonal rainfall of 25 inches being recorded at this site. The abundant rainfall affected plant emergence; therefore, there were few spots within the study area where poor or no crop emergence was observed. Because the soil was exposed at these spots, soil surface temperature recorded a larger infrared temperature compared to the area where corn developed well. The concentration of red data points highlighted in figure 2.3 matches the area where the plants did not emerge, showing that the IRTs recorded higher temperatures on the bare soil surface compared to the corn canopy temperature. The system developed works in real-time. Then as the pivot travels across the cropped area, the systems collect instantaneous readings, which are sent to the internet and an algorithm converts data into CSWI to provide an irrigation scheduling recommendation for on-the-go implementation.

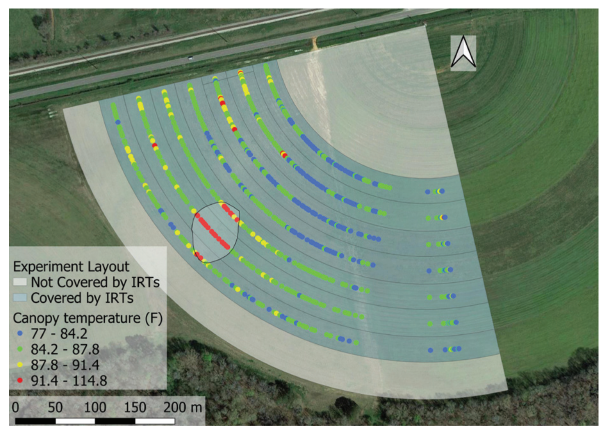

Figure 2.3. Canopy temperature data points collected from seven IRTs on June 18, 2021.

Food for Thought

- An automatic real-time mapping system that gathers data from infrared leaf temperature sensors mounted along the center pivot irrigation system main line could be used to implement dynamic variable rate irrigation.
- Infrared canopy temperature data reflects crop water and transpiration status at the time of collection, which can be described as an integrator of plant health.

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Evaluation of Corn Yield Response to Different Irrigation Levels

Objective

- Determine the corn yield response to different irrigation rates and the net returns of each irrigation strategy.

Project Justification

Better irrigation scheduling and reducing the total amount of water applied to a crop could help farmers increase water use and energy efficiency, reduce yield variability, and prevent yield losses. Information on the economic impact of those strategies is provided to support adoption by farmers.

Planting Details

Location: Shorter, Alabama	**Planting:** 04/02/20 and 04/21/21
Crop: Corn	**Hybrid:** DKC62-08
Test size: 45 acres	**Row width:** 36 inches
Seeding rate: 36,000/acres	**Irrigation system:** Valley–7000 Series
Tillage: Conventional	**Predominant soil map unit:** Altavista silty loam

Treatments

T_{100}	Full rate to bring 24 inches of soil back to field capacity
T_{66}	66% of the rate calculated for T_{100}
T_{33}	33% of the rate calculated for T_{100}
T_{0}	Rainfed condition

Project Design

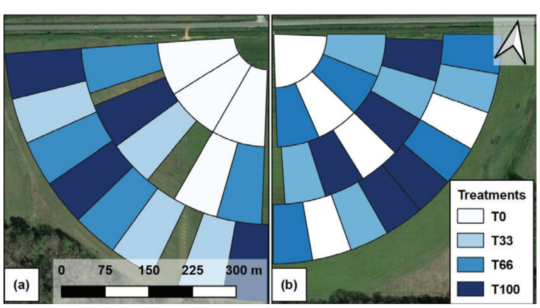

Figure 3.1. Layout of irrigation plots (1.2 to 2 acres/plot). The T_{100} plots were instrumented with Acclima TDR-315LTM sensors installed at 6-, 12-, and 24-inch soil depths.

Precision Ag Toolbox

Acclima True TDR-315LTM Sensor

(Acclima, Inc., Meridian, Idaho, USA)

Figure 3.1TB. Acclima TDR 315LTM soil sensors used to real-time collect soil volumetric water content.

Valley–7000 Series Center Pivot Irrigation

(Valley, Lincoln, Nebraska, USA)

Figure 3.2TB. Center pivot irrigation system with a variable rate irrigation system used to apply different irrigation rates across the field.

Weather Station Vantage Pro2 Plus

(Davis Instruments, Hayward, California, USA)

Figure 3.3TB. Weather station measuring agrometeorological parameters such as minimum and maximum air temperature and relative humidity, solar radiation, wind speed, and precipitation at 15-minute intervals. Solar-powered telemetry for remote access of data.

Observations & Preliminary Results

Total rainfall during the 2020 and 2021 growing seasons was 17.5 and 25 inches, respectively, which was 5 percent and 50 percent above the historic average for the region (16.7 inches), respectively. Because the rainfall during the 2021 growing season was more abundant and less sparse than in 2020, irrigation requirements were much smaller in 2021 than in 2020, as shown in figure 3.2. In 2021, a total of 2.8, 2.3, and 1.6 inches of irrigation water was applied in the T_{100}, T_{66}, and T_{33} treatments, respectively. In 2020, on the other hand, the T_{100}, T_{66}, and T_{33} treatments received 7.6, 5.2, and 3.1 inches of irrigation water application, respectively. Early in the growing season, one inch of irrigation was applied across the test area to guarantee a uniform development, therefore the T_0 treatment received one inch of irrigation during both growing seasons.

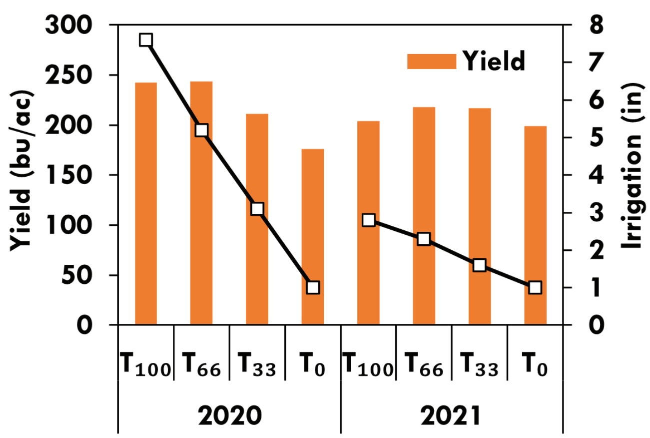

Figure 3.2. Corn yield and total irrigation differences among treatments in 2020 and 2021 growing seasons.

Corn yield in 2020 was similar between T_{100} and T_{66} (~243 bu/ac); however, decreasing irrigation amount 66 percent (T_{33}) with respect to the full irrigated (T_{100}) treatment resulted in a yield reduction of 13 percent (33 bu/ac and 27 percent (67 bu/ac) for the rainfed treatment (figure 3.2). The abundant and well distributed rainfall observed in 2021 resulted in small corn yield differences among the treatments, with the largest difference of 19 bu/ac (8 percent) occurring between T_{66} and T_0. Although in 2020 the treatments with the highest irrigation rate (T_{100}) promoted substantial yield gain compared to the T_{33} and T_0 treatments, corn yield at the T_{100} during the 2021 growing season was lower than the T_{33} and about the same than the T_0. Additionally, the T_{66} treatments showed the best corn yield results in both growing seasons. Among several other factors, rainfall pattern during the growing season was the main factor influencing the corn yield response to irrigation rates. A 66 percent irrigation water application (T_{66}) could be a feasible irrigation management strategy for corn growing under conditions similar to the ones on this test in Alabama. Except for the T_{100} treatment in 2021, irrigation water application resulted in revenue gain with respect to the rainfed treatment (T_0) ranging from 30.9 to 44.7 \$/ac-inch in 2020, and from 10 to 17.7 \$/ac-inch in 2021. The loss in revenue on T_{100} in 2021 of -25.7 \$/ac-inch was explained by the excessive amount of rainfall observed in this growing season, suggesting that full irrigation is not a recommended strategy for rainy years. Additionally, the different irrigation treatments resulted in revenue gain on both growing seasons. These findings show that the rainfall pattern during the growing season should be considered when defining which irrigation strategy should be used. If rainfall is abundant (as in 2021), T_{33} (66% deficit with respect to full irrigation) will yield profit, however when rainfall is not abundant, as in 2020, T_{66} (33% deficit) water application is recommended.

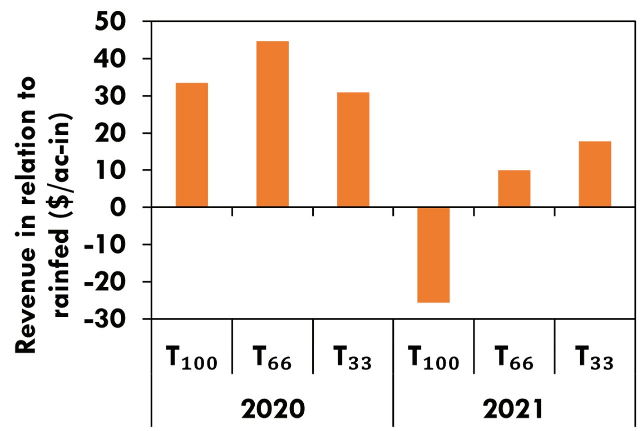

Figure 3.3. Net returns above variable treatment cost (NRAVTC) for the full irrigation rate (T_{100}), 66% from full irrigation (T_{66}), and 33% from full irrigation (T_{33}) treatments in relation to the rainfed treatment.

Food for Thought

- Deficit irrigation, a reduced amount of water with respect to full irrigation (replenishing soil back to field capacity), could maintain yield and reduce irrigation amount and energy cost. This practice should be implemented with caution on soils with low water storage capacity (e.g., sandy soils) or during periods of high crop water demand.
- On soils with high soil water holding capacity, like the silt loam soil on this test, and corn growing seasons with frequent rainfall events in Central, AL; farmers could consider reducing irrigation rate up to a 33% (66% of full irrigation treatment).

Project Team: Bruno P. Lena, Brenda V. Ortiz, Alvaro Sanz-Saez, Greg Pate, Nicholas Stockdale, Leah Duzy.

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Identification of Irrigation Tension Threshold for Common Soil Types in Alabama

Objective

- Identify irrigation tension threshold values that can be used to determine irrigation timing and rate for Decatur silt loam and Alpin sand soils in Alabama.

Project Justification

Irrigation decisions based on soil sensor data could improve irrigation use efficiency (right rate and the right place and time), which might translate into better crop growth and high or less variable yield. Adoption of soil sensor–based irrigation scheduling could increase if soil water tension data is presented in the form of irrigation triggering thresholds and rates.

Planting Details

	Site 1	Site 2
Location	Town Creek, Alabama	Samson, Alabama
Planting Date	04/10/18	03/17/18
Crop Rotation	Corn–Soybean	Corn–Peanut –Cotton
Tillage	Conventional	Conventional
Soil Map Unit	Decatur silt clay loam	Alpin sand

Treatments

Site 1	Decatur Silt Clay loam soil series (SSURGO survey). An in-situ soil textural analysis reported a Clay Loam soil texture.
Site 2	Alpin sand soil series

Project Design

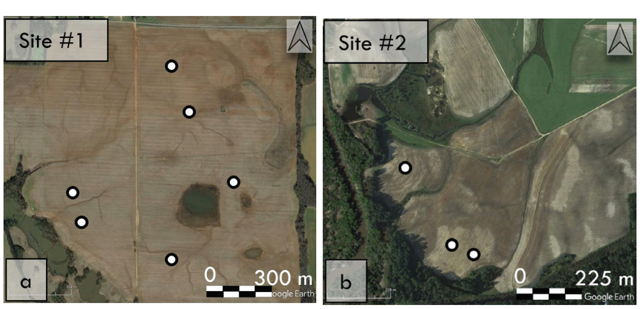

Figure 4.1. Soil sampling locations at site 1 (a) and site 2 (b) where the soil physical and hydraulic parameters were assessed and the irrigation tension thresholds determined.

Precision Ag Toolbox

Soil Water Tension Sensor
(Trellis, Atlanta, Georgia, USA)

Figure 4.1TB. Soil water tension sensor used to track daily changes in soil water during the growing seasons and to support irrigation decisions.

Hydraulic Proper Analyzer
(HYPROP 2, Meter Group, Pullman, Washington, USA)

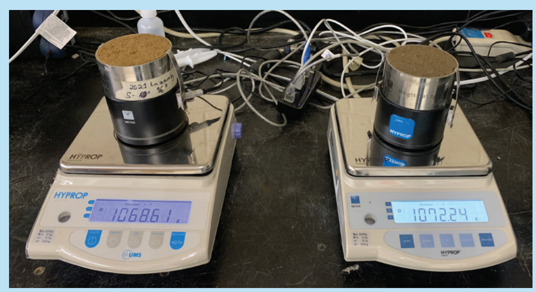

Figure 4.2TB. Hydraulic proper analyzer used to assess soil hydraulic properties from undisturbed soil cores. This instrument allows collection of data to generate a soil water retention curve. Data was later used to determine the irrigation tension thresholds.

Soil Water Potential Instrument—WP4
(WP4, Meter Group, Pullman, Washington, USA)

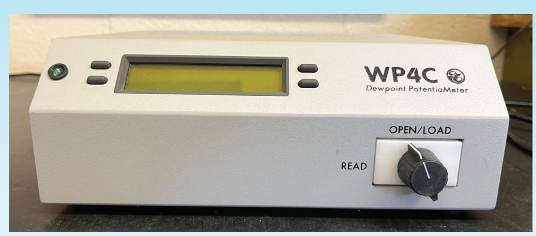

Figure 4.3TB. WP4 measures soil water potential in the range of 0 to -300 MPa. This instrument was used to determine the permanent wilting point values for each soil type.

Observations & Preliminary Results

Data from soil water tension (SWT) sensors correlates with soil water status and, therefore, plant water stress, as it is analogous to the force needed by plants to extract water from the soil. SWT is usually measured in kilo Pascal (kPa) or centibar (cb). Irrigation scheduling based on SWT sensors requires actual real-time soil sensor data, estimated values of field capacity (FC), and permanent wilting point (PWP). It also requires the maximum amount of water the irrigation operator allows the crop to extract from the active root zone or managed allowable depletion (MAD) (figure 2). Some irrigation specialists consider MAD as 50 percent, but this value should be adjusted based on crop type, climate, soil type, and the irrigator's knowledge. Soil sensor data allows the irrigation operator to track SWS so it can be maintained above the irrigation threshold (MAD level) to prevent crop water stress and subsequent yield losses. As a rule of thumb, initiate irrigation when SWT reaches a maximum allowable soil water depletion (SWD). Then irrigation depth is calculated to replenish the soil moisture to field capacity.

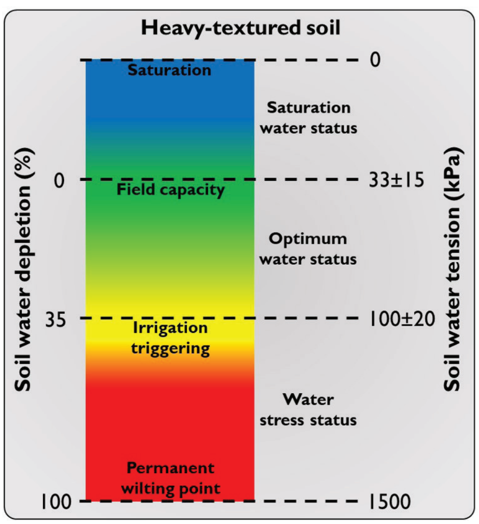

Figure 4.2. Different soil water status used in irrigation to determine when and how much to irrigate. Values are presented in terms of soil water depletion and its corresponding soil water tension.

Because the relationship between SWT and SWD changes with soil type, the irrigation trigger point or irrigation initiation time and the correspondent irrigation depth varies among soil types and field conditions. Several soil samples were collected from two common soil types in Alabama to determine SWT irrigation initiation thresholds and the corresponding irrigation depth. Table 4.1 recommended irrigation depths in relation to a range of SWT values. Considering a maximum allowable 35 percent SWD and a 24-inch soil profile depth, results from this study suggested that the SWT irrigation initiation triggering threshold for the Decatur soil loam and Alpin sand soil type should be around 100 and 35–40 kPa, respectively. These differences in SWT irrigation trigger values among soil types are mainly due to the differences in plant available water associated with soil texture. Alpin soil type has a higher sand content that holds less water than Decatur soil type with less sand contact and clay content. The values shown in table 4.1 are examples of why irrigation should be managed differently among soil types to prevent over- or under-irrigation.

Table 4.1. Recommended Irrigation Depth and Correspondent Soil Water Depletion (in parenthesis) for Various Soil Water Rension (SWT) Values

SWT	Decatur (Clay Loam)	Alpin (Sand)
kPa	Irrigation Depth (inches)	
20	-	0.28 (20)
30	0.06 (4)	0.53 (34)
40	0.18 (10)	0.68 (41)
50	0.31 (15)	0.79 (47)
60	0.42 (20)	0.86 (51)
70	0.52 (24)	0.93 (54)
80	0.61 (28)	0.99 (56)
90	0.69 (31)	1.03 (59)
100	0.76 (35)	1.08 (61)
110	0.83 (36)	1.12 (62)
120	0.89 (39)	1.15 (64)
Recommended SWT (kPa)[a]	100	35-40

[a] Recommended SWT triggering value was based on 35 percent soil water depletion and a 24 -inch soil profile depth.

Food for Thought

- Irrigation triggering thresholds based on soil water tension sensors could allow farmers and consultants to precisely determine the time to start irrigation, avoiding over- or under-irrigation.
- Farmers or consultants can access soil water characteristics online through the NRCS web soil survey. The information on this website could facilitate the implementation of soil sensor–based irrigation scheduling methods.

Project Team: Bruno P. Lena, Brenda V. Ortiz, Guilherme T. Morata, Luca Bondesan, Hemendra Kumar.

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Irrigation Scheduling | Soil Sensing

Evaluation of Irrigation Scheduling Tools on a Peanut Crop

Objective

- Evaluate two irrigation scheduling tools (IrrigatorPro and FieldNET Advisor) for on-farm irrigation management use in Coastal Plain soils of the southeastern United States.

Project Justification

Smart irrigation applications (SIAs), both sensor-based and crop evapotranspiration–based, can be used to provide irrigation recommendations based on current crop water needs and soil available water. Many commercially available SIAs are designed for use in the midwestern United States. Thus evaluation and demonstration are needed to facilitate their adoption across the southeastern region.

Planting Details

Location: Hacoda, Alabama	**Planting:** 05/18/21 and 05/21/21
Crop: Peanuts	**Hybrid:** FloRun 331
Test size: 105 acres	**Row width:** 36 inches
Seeding rate: 124,000/ac	**Irrigation system:** Lindsay Growth Smart
Tillage: Conventional	**Predominant soil map unit:** Dothan sandy loam

Treatments

T_{FNA}	Irrigation-based on recommendations from FieldNET Advisor
T_{IP}	Irrigation based on recommendations from Irrigator Pro
T_F	Farmer-determined irrigation

Project Design

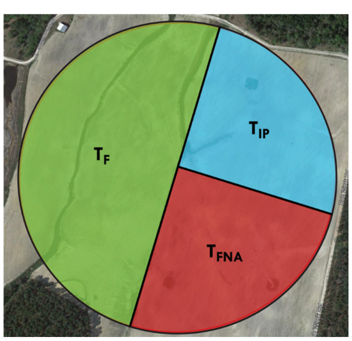

Figure 5.1. Layout of comparison plots for T_F, T_{IP}, and T_{FNA} treatments. A soil water tension sensor probe was installed in each treatment area.

Precision Ag Toolbox

Irrigator Pro (Version 2.0)

(National Peanut Research Laboratory, USDA-ARS)

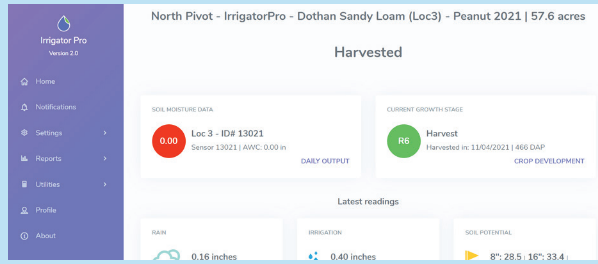

Figure 5.1TB. A web-based irrigation scheduling application that generates irrigation recommendations based on the crop evapotranspiration method combining soil water tension sensors to determine soil available water. This tool is also available through a phone application and can run with or without soil sensor data.

FieldNET Advisor

(Lindsay Corporation, Omaha, Nebraska, USA)

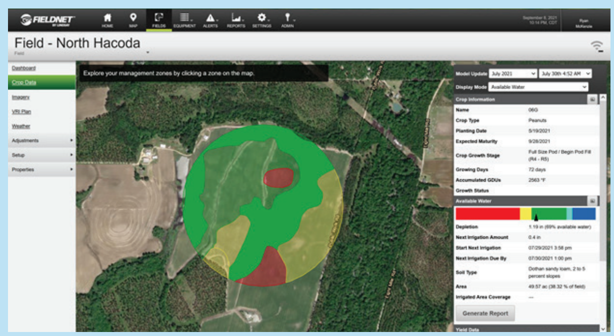

Figure 5.2TB. A cloud-based smart irrigation application that uses a crop growth model to provide irrigation recommendations based on crop growth, soil type, crop available water, and weather conditions. The tool generates daily irrigation prescription maps that are uploaded automatically to the variable rate irrigation (VRI) control panel of the irrigation system.

Soil Water Tension Sensor Probe

(Trellis, Atlanta, Georgia, USA)

Figure 5.3TB. Soil water tension sensor probe (Watermark sensors at 8, 16, and 24-inch depths) used to estimate soil moisture data, an input to the daily evapotranspiration-based soil water balance.

Observations & Preliminary Results

Daily water use (DWU) and available water content estimated from the two SIAs varied throughout the 2021 growing season. These differences were most apparent from late June to the middle of August, particularly at the peak of peanut water demand. During this period of greatest water use, FieldNET Advisor (FNA) estimated a slightly lower DWU as compared to Irrigator Pro (IP) (figure 5.2). Throughout the growing season, the FNA model generally provided a finer resolution of DWU, better capturing the daily DWU changes, which changed due to frequent rainfall events. In contrast, the IP model determined DWU exclusively based on the estimated crop growth stage. Due to this rigid approach to estimating DWU, the IP model tended to estimate higher values of DWU. This overestimation could be compensated by the ability of this tool to estimate daily available water content (AWC) from data recorded by soil water tension sensors. Both AWC and DWU are used by IP to determine irrigation timing and rate.

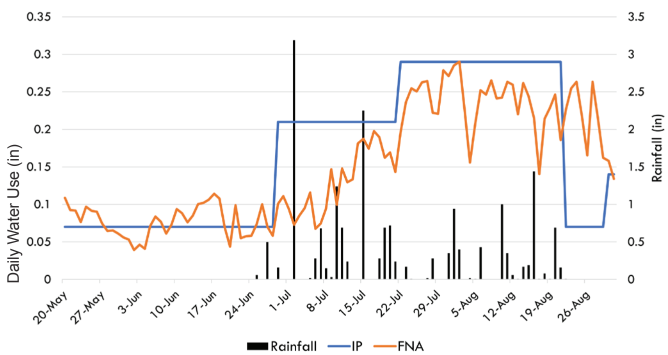

Figure 5.2. Daily water use (DWU) estimates from the FieldNET Advisor (FNA) and Irrigator Pro (IP) models during the period of peak water demand in the 2021 peanut growing season.

As discussed above, irrigation prescriptions are also expected to differ between different daily crop water use estimates between models. In the study field, these expected differences were observed, especially during the peak of crop water demand from late June to the middle of August. Figure 5.3 shows the differences in the irrigation prescriptions alongside rainfall events. Of note in this observation is the relatively low response the IP had to rainfall events. Two things could explain these differences: (a) the IP model estimates DWU exclusively on the projected growth stage and (b) it calculates available water content from soil water tension values that are converted into volumetric water content using a soil water retention curve (SWRC). If the SWRC does not represent well the characteristics of the soil where the sensor is installed or the sensor does not provide accurate readings because of installation problems, the estimation of the water content could be inaccurate.

Figure 5.3 shows an increased sensitivity to rainfall and irrigation events with the FNA model. This is likely due to the model's more complex methods to calculate DWU. The models included in FNA lead to a more dynamic DWU estimate, as seen in figure 5.2 and more accurate soil available water.

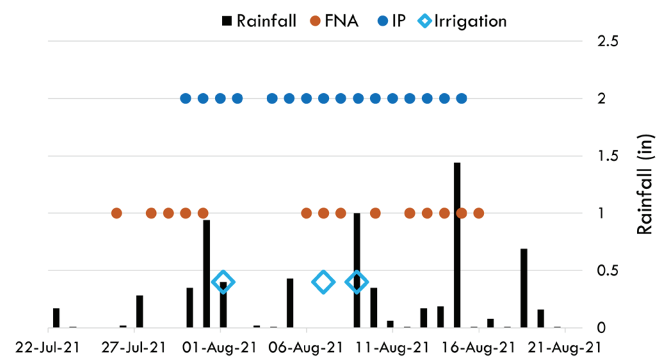

Figure 5.3. Dates on which either the Irrigator Pro (IP) or FieldNET Advisor (FNA) models recommended irrigation. For each model, irrigation was recommended at a uniform rate of 0.40 inches.

Food for Thought

- Irrigation scheduling—when and how much to irrigate—on peanut fields could easily be implemented using smart irrigation tools such as Irrigator Pro or FieldNet Advisor.
- Smart irrigation applications can be useful for accurately monitoring crop water needs and available water content, thus increasing irrigation water use efficiency and crop yield.
- FieldNET Advisor provides daily crop water use information and available soil water content. It also runs daily soil water balance and provides irrigation scheduling recommendations.
- Irrigator Pro, when used in tandem with soil moisture sensors in the field, provides daily available water content data incorporated into the evapotranspiration-based water balance. It could be used as an entry- level tool for irrigation scheduling in peanuts. The tool is available as a web interface or through a phone application.

Project Team: C. Pierce McClendon, Brenda V. Ortiz, Guilherme Morata.

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Irrigation Scheduling | Telemetry

Evaluation of the SmartIrrigation Corn App as an Irrigation Scheduling Tool

Objective

- Evaluate the irrigation scheduling recommendations of the SmartIrrigation Corn app, a free phone app that uses the evapotranspiration-based soil water balance method to recommend irrigation.

Project Justification

Many irrigation scheduling tools are available on the market that can be used to support decisions for irrigation timing and rate. One example is the SmartIrrigation Corn app, a free mobile app still in beta. It helps farmers implement irrigation scheduling using the soil water balance approach. Little information is available on the performance of this app under Alabama corn growing conditions, which suggests the need for evaluating it before being widely used by the farmers.

Planting Details

Location: Fairhope, Alabama	**Planting:** 03/19/21
Crop: Corn	**Hybrid:** P2042 VYHR
Test size: 25 acres	**Row width:** 38 inches
Seeding rate: 34,000/acres	**Irrigation system:** Valley–7000 Series
Tillage: Strip till	**Predominant soil map unit:** Marlboro very fine sandy loam

Irrigation Application

Five irrigation events, each of 0.5 inches, were applied on May 24, 26, 28, and June 3 and 16, 2021.

Field Location

Figure 6.1. Center pivot with three spans covering 25 acres in Fairhope, Alabama.

Precision Ag Toolbox

SmartIrrigation Corn App (Beta)
(University of Georgia, Tifton, Georgia, USA)

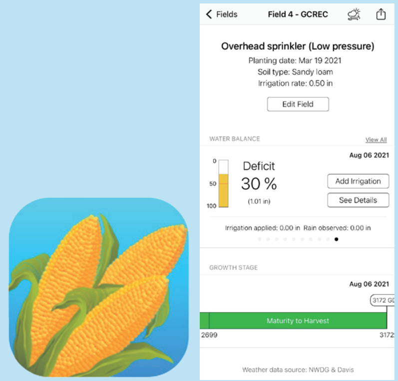

Figure 6.1TB. Corn evapotranspiration-based irrigation scheduling tool that uses daily weather data and soil information to estimate soil water deficit and irrigation rate. Users should manually input irrigation rates applied.

Weather Station
(Davis Instruments, Hayward, California, USA)

Figure 6.2TB. Weather station used to collect rainfall and agrometeorological data (air temperature, air relative humidity, solar radiation, and wind speed) during the growing season.

Valley–Center Pivot Irrigation
(Valley, Lincoln, Nebraska USA)

Figure 6.3TB. Center pivot irrigation system with three spans used to irrigate the corn field of this study.

Observations & Preliminary Results

The total rainfall for the growing season (March to August) was 30 inches, which was 4 percent below the historic rainfall average for the region (31.2 inches). Figure 6.2 shows the rainfall distribution (left Y-axis) and irrigation events (right secondary Y-axis) during the season. While the rainfall was abundant and well distributed during the growing season, a mini drought occurred during the period covering the V9 and tasseling growth stages. Therefore, five irrigation events were required to meet the corn water demand. The irrigation rate chosen by the grower was 0.5 inches each event due to the irrigation system capacity.

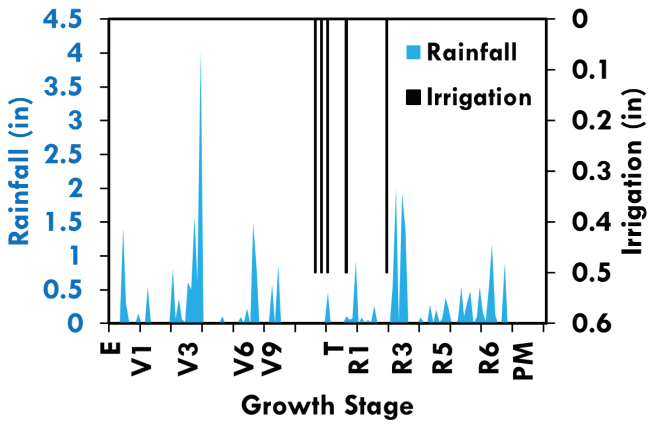

Figure 6.2. Daily rainfall distribution and irrigation events during the 2021 corn growing season. Growth stages: E = emergence, V = vegetative, T = tasseling, R = reproductive, PM = physiological maturity.

The SmartIrrigation Corn app uses the soil water balance approach to recommend irrigation depth based on daily crop evapotranspiration, soil characteristics, and soil allowable water depletion (SWD). Irrigation and rainfall are soil water balance inputs, and output is the crop water demand or crop evapotranspiration (ETc). The amount of water the crop uses (ETc) changes dynamically during the growing season, mainly between the corn vegetative and reproductive growth stages. For example, in the early and late corn growth stages, ETc is typically lower than 0.1 inch/day and may reach values of up to 0.30 inches/day during the reproductive growth stage on a hot, dry day.

Figure 6.3 shows the SWD estimated by the SmartIrrigation Corn app during the 2021 corn growing season. The irrigation thresholds selected for this field were 40 percent SWD from early growth stages until V12 and 35 percent SWD from V12 to silking (peak of water demand). Figure 6.3 shows that rainfall was scarce at the peak of corn water demand, and therefore, the SmartIrrigation Corn app recommended irrigation during this period to avoid crop water stress.

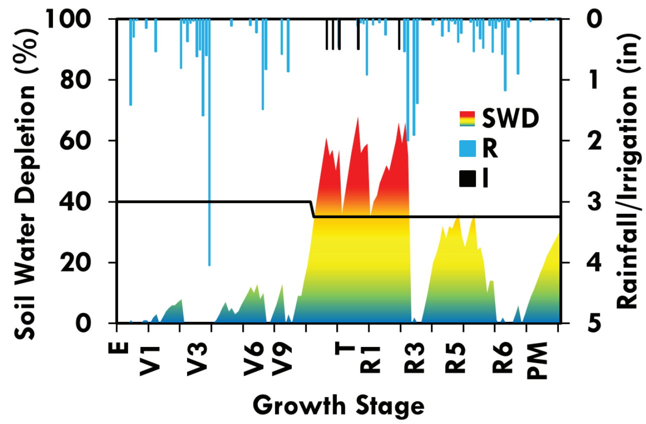

Figure 6.3. Soil water depletion (SWD) used to trigger irrigation (I) throughout the growing season.

When frequent and heavy rainfall events occur, the users of the app should be aware that this tool was not designed to account for water ponding conditions and how long they last. Due to this issue, the corn app might suggest a higher SWD than the actual field conditions. Users could manually account for this by adding one or two rainfall events. For example, the first irrigation on the studied field occurred right before tasseling, coinciding with the twelfth day after the last recorded rainfall event. However, the corn app was recommending irrigation one week after the rainfall (SWD was approaching the 35 percent SWD threshold) even though the field was still under soil saturation conditions after the heavy rainfall. Growers should always look at the actual field condition while using an irrigation scheduling tool to avoid either over- or under-application of irrigation water. Overall, this app showed to be a good tool to support irrigation scheduling decisions. For this specific evaluation, the app's irrigation recommendations agreed with the days the farmer, based on his experience, decided to apply irrigation, which was five times.

Food for Thought

- The SmartIrrigation Corn app is a free mobile app that provides valuable information such as daily crop water demand and soil water depletion to help growers create and manage their irrigation scheduling.
- Growers should not rely solely on digital tools when deciding when and how much to irrigate. It is recommended that they consider the field conditions before making decisions about triggering irrigation.

Project Team: Guilherme Morata, Brenda V. Ortiz, Jarrod Jones, Malcomb Pegues.

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Planting Technologies | Soil Sensing

Effect of Planter Downforce & Speed on Peanut Emergence, Growth & Yield

Objective

- Evaluate the impact of different planter downforce loads and planting speeds on peanut seeding depth, growth, and yield.

Project Justification

Planting depth can affect crop emergence and potentially reduce yield if planter settings are not chosen correctly. The impact of downforce load could be exacerbated by planting speed. The dynamic downforce control system was designed to adjust downforce load according to soil resistance in order to maintain good soil contact of the gauge wheel (dynamic mode).

Planting Details

Location: Fairhope, Alabama	**Planting:** 05/26/21
Crop: Peanuts	**Variety:** Georgia 06G
Test size: 5 acres	**Seed depth:** 2.5 inches
Seeding rate: 82,500/ acres	**Row width:** 38 inches
Rainfed	**Tillage:** Strip Tillage
Predominant soil map unit: Marlboro very fine sandy loam soil	

Treatments

Static downforce	100 & 200 pounds
Dynamic downforce	100, 150, 170, 195 pounds
Travel Speed	3, 4, 5 mph

Project Design

Figure 7.1. Performance of downforce (DF) loads (static and dynamic) replicated three times was evaluated using 3, 4, and 5 miles per hour (mph) planting speeds. Each downforce treatment covered four planter rows by 200-foot lengths.

Precision Ag Toolbox

vDrive
(Precision Planting, Tremont, Illinois, USA)

Figure 7.1TB. This electric motor provides control of the seed meter system on each row. It replaces the hydraulic motors, chains, or cables on old planters.

DeltaForce Automated DownForce Control
(Precision Planting, Tremont, Illinois, USA)

Figure 7.2TB. DeltaForce is a dynamic downforce system that allows a dynamic change of downforce (lift force of downward force) in order to maintain the same weight on the gauge wheels for different field conditions.

20|20 Display
(Precision Planting, Tremont, Illinois, USA)

Figure 7.3TB. 20|20 on board monitor that together with DGPS data records and displays real-time detailed information from the planter allowing the operator to inspect planter performance and make on-the-go changes.

Observations & Preliminary Results

Using the static DF mode resulted in under- application of DF loads, and the difference between target and final applied DF increased as the travel speed increased (clear bars, figure 7.2). In contrast, when the dynamic DF system was used, the loads were very close to the target load and were less affected by travel speed (solid bars, figure 7.2) compared to static DF mode. The variability on the applied DF load increased as the downforce increased.

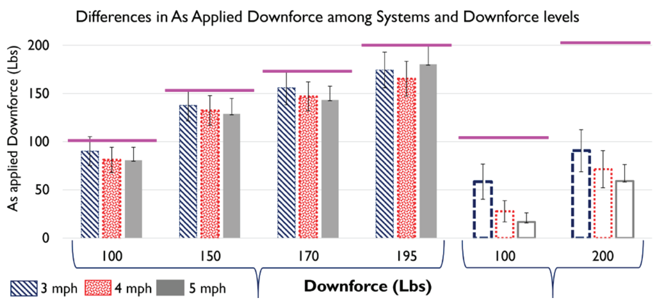

Figure 7.2. Final downforce applied among downforce modes (static = empty color bars; dynamic = filled color bars) and the differences among downforce level and travel speed.

When seeding depth changes were evaluated as a result of the dynamic downforce levels applied, seeding depth variability was the highest when 100- and 170-pound loads were used. This variability might affect peanut emergence. Seeding depth was off target (below 2.5 inches), especially at planting speeds of 3 and 5 miles per hour (figure 7.3). Crop emergence is affected by seeding depth, and in this study, seeding depth was close to the target depth (2.5 inches), and less seed depth variability was observed when the 150- and 195-pound DF treatments were used. Results also showed that as the dynamic downforce level increased, the seeding depth was closer to the target depth. Less seeding depth variability was observed when the crop was planted at a speed of 4 miles per hour.

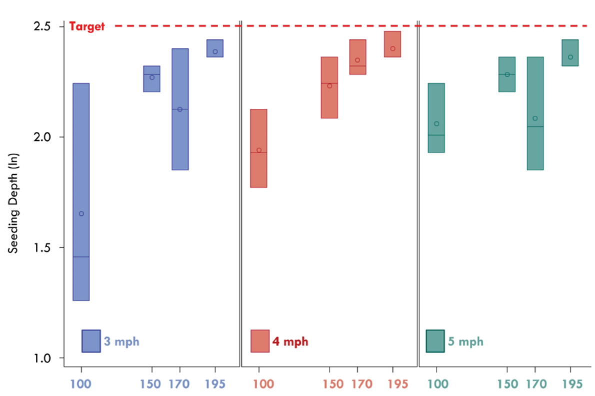

Figure 7.3. Peanut seeding depth differences among dynamic downforce treatments and travel speeds.

Figure 7.4 shows the impact of downforce levels and planting speed on final peanut yield. As downforce load increased, peanut yield and yield variability decreased. The treatment with less yield variability was 150 pounds and was also less affected by planting speed. The combination of travel speed and downforce loads influenced the final peanut yield. The treatment of a 170-pound downforce load was severely affected by changes in travel speed. In contrast, the impact of travel speed on yield was lower than when 150 pounds of downforce was used. Although the DF treatment of 195 pounds placed the peanut seed closer to the seeding depth target, that treatment did not result in the greatest peanut yield.

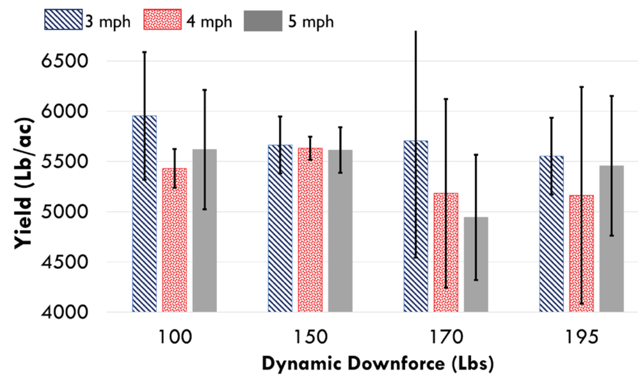

Figure 7.4. Peanut yield for different treatments tested under dynamic downforce conditions.

Food for Thought

- Increasing planting speed might result in yield losses, especially if the downforce load is increased.
- Farmers should consider upgrading their planters with a dynamic downforce system that adjusts downforce on the go and accounts for field variability on soil type and moisture.
- Manual downforce systems (e.g., downforce springs) tend to under- or over-apply loads to the row unit compared to the dynamic downforce systems resulting in greater variability in seeding depth and seed emergence.

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Planting Technologies | Soil Sensing

Evaluation of New Technologies on Planters to Control Downforce & Seeding Depth

Objective

- Evaluate the impact of dynamic planter downforce (DF) loads on cotton seeding depth, emergence, and yield.
- Compare two planting modes, precision planting Smart-Depth system (smart) and the traditional fixed (manual) planting depth mode under various downforce levels.

Project Justification

Seeding depth could affect plant emergence and, subsequently, crop growth and final yield. Although seeding depth recommendations are available for various crop types, these are sometimes linked to optimum soil moisture conditions for seed germination. Soil moisture could change across crop fields due to soil type and terrain elevation, so having sensors installed on the planter's row unit that can read the resistance of soil to penetration and soil moisture levels and adjust seeding depth and downforce on the go could have positive impacts on crop emergence, growth, and final yield.

Planting Details

Location: Fairhope, Alabama	**Planting:** 06/01/21
Crop: Cotton	**Variety:** DP2055B3XF
Test size: 8 acres	**Row width:** 38 inches
Tillage: Strip Tillage	**Soil Type:** Sandy loam

Treatments

Fixed Seeding Depth: 1.25 inch (selected due to dry conductions at planting)	
SmartDepth Seeding Depth:	0.5 to 1.75 inches
Dynamic Downforce:	100, 150, 195 pounds
Seeding Rates: 27,000/acres and 34,500/acres	

Project Design

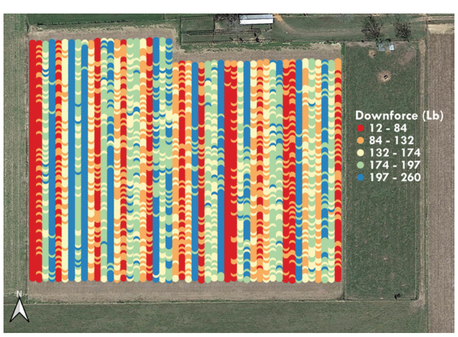

Figure 8.1. Three dynamic downforce (DF) treatments (4 rows of 500-foot length passes) replicated three times were evaluated under two planting modes, Fix and SmartDepth.

Precision Ag Toolbox

DeltaForce Automated DownForce Control
(Precision Planting, Tremont, Illinois, USA)

Figure 8.1TB.. DeltaForce is a hydraulic downforce system that allows a dynamic change of downforce (lift force of downward force) in order to maintain the same weight on the gauge wheels with respect to different field conditions.

SmartDepth
(Precision Planting, Tremont, Illinois, USA)

Figure 8.2TB. SmartDepth allows the planter operator to make seeding depth adjustments from inside the cab. The smart option allows the operator to set a moisture range, which will be measured by the SmartFirmer, and the SmartDepth system will keep the planting depth within the moisture range previously set.

SmartFirmer Seed Firmer Sensor
(Precision Planting, Tremont, Illinois, USA)

Figure 8.3TB. Multispectral sensors, part of SmartFirmer, measure temperature, moisture, organic matter, and residue in the v-trench. Farmers can adjust the seeding depth using the soil moisture data collected by the SmartFirmer.

Observations & Preliminary Results

Preliminary results show that DF level affected the final seeding depth. When the fixed seeding depth planting mode was used (1.25 inches target depth), seeds were planted at much shallower depths at the 100 pounds DF level compared to the 195 pounds DF level (figure 8.2). When the 150-pound DF was used, seeds reached the target seeding depth suggesting that the DF level influences the final seeding depth.

The SmartDepth system and the SmartFirmer sensor work together to place the seed within the predefined seeding depth range considering soil moisture conditions to adjust seeding depth on the go. When the SmartDepth system was used with a seeding depth range of 0.5 to 1.75 inches, the average seeding depth on the 100-pound and 150-pound DF treatments was similar and reached, on average, the target of 1.25 inches (figure 8.2). The 195-pound DF treatment placed seed deeper than the other DF treatments.

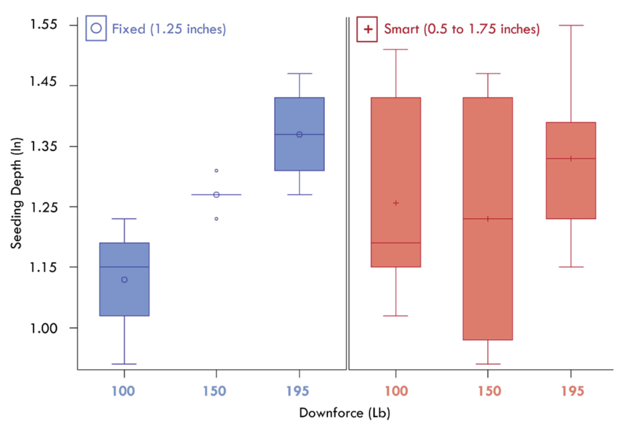

Figure 8.2. Cotton seeding depth differences among planting modes (Fixed and SmartDepth) and downforce levels.

The crop emergence rate was assessed through the Emergence Velocity Index (EVI). The greater the EVI value, the faster the emergence. Figure 8.3 shows that although there was seeding depth variability when the SmartDepth system (moisture sensor data influencing seeding depth) was used compared to the fixed depth mode, less EVI variability was observed on the Smart Depth treatment.

Under the conditions of the SmartDepth treatment, the 150-pound DF level exhibited greater values of EVI and less variability compared to the same DF level but using the fixed depth planting mode (figure 8.3). This might suggest that this DF treatment provided better emergence conditions than the 100-pound DF level.

Higher yield was observed on the SmartDepth treatment compared to the fixed depth and was less affected by the DF level (figure 8.4). Preliminary results suggest that dynamically varying seeding depth according to soil moisture variability (data provided by the SmartFirmer sensor) could favor crop emergence, plant stand, and uniform growth.

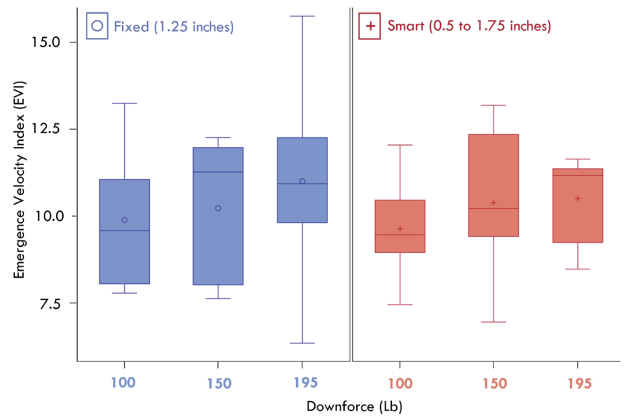

Figure 8.3. Cotton emergence velocity index differences among planting modes (Fixed and SmartDepth) and downforce treatments.

The frequent and heavy rainfall events registered during the 2021 growing season could have affected cotton yield (44 inches of rainfall during the growing season).

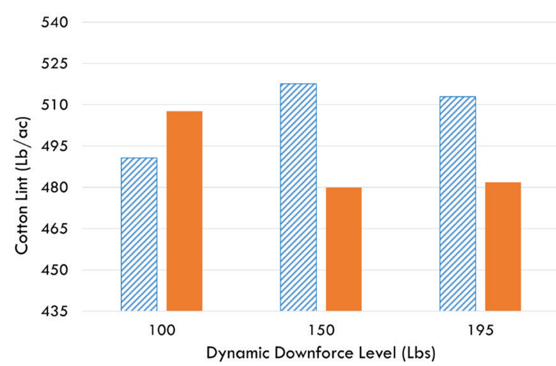

Figure 8.4. Cotton yield changes among downforce treatments and planting modes (SmartDepth and Fixed Depth) at the 27,000 seeds/acre rate.

Food for Thought

- The use of a SmartDepth system might favor better crop emergence, decreasing emergence variability, and impact reduction of high downforce loads.
- Seeding depth and cotton yield might be affected as downforce load increases; however, controlling downforce and seeding depth with the use of dynamic downforce systems like DeltaForce and sensors like SmartDepth and SmartFirmer might favor emergence, growth, and final yield.

Project Team: Luan Pereira De Oliveira, Guilherme Morata, Brenda V. Ortiz, Jarrod Jones, Timothy Squires, Chip Bryars.

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Effect of Planter Downforce on Corn Seeding Depth & Emergence

Objective

- Evaluate the impact of different planter downforce levels and system types on corn seeding depth and emergence.

Project Justification

Planting operations could be improved by using precision technologies on planters to allow better control of seeding depth and plant spacing. The goal of a downforce system is to place the seed into the furrow at the desired depth, ensuring good soil-to-seed contact. Hydraulic downforce systems currently available on the market help maintain a target gauge wheel load on individual planter row units using either fixed loads (static mode) or automatically adjusting loads according to soil resistance (dynamic mode).

Planting Details

Location: Macon, Alabama	**Planting:** 04/02/20
Crop: Corn	**Variety:** DKC62-08
Test Size: 8.2 acres	**Seed depth:** 1.5 inches
Seeding: 36,300 seeds/acres	**Row width:** 36 inches
Irrigated	**Tillage:** Conventional
Predominant Soil Map Unit: Clay loam	

Treatments

Static Downforce:	**0, 100, 125, 150, 200 & 250 pounds**
Dynamic Downforce:	**100, 125, 150, 170 & 195 pounds**
Target Seed Depth:	**1.5 inches**

Project Design

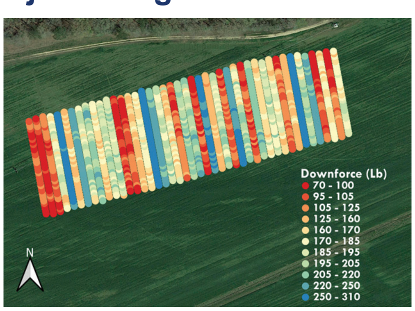

Figure 9.1. Eleven downforce (DF) treatments were replicated four times on a clay loam soil. Each downforce treatment covered six planted rows 350 feet in length.

Precision Ag Toolbox

DeltaForce Automated DownForce Control
(Precision Planting, Tremont, Illinois, USA)

Figure 9.1TB. DeltaForce is an active downforce system that allows an automatic change of downforce to maintain the same weight on the gauge wheels for different field conditions.

MaxEmerge Plus Row-Unit
(John Deere, Moline, Illinois, USA)

Figure 9.2TB. A John Deere 7200 Max Emerge 6-row planter can be retrofitted with the Precision Planting Delta Force system.

Climate Field View Drive
(Climate Corporation, San Francisco, California, USA)

Figure 9.3TB. Data collected from farm equipment could be readily accessible and easily visible when drive is used along with the Climate Field View Cab app.

Observations & Preliminary Results

Figure 9.2 shows the relationship between the target DF load (X-axis) and final applied load (Y-axis). Loads were applied very close to the target when the DF system was used on dynamic mode (light gray color boxes on figure 9.2). When the DF system used a static mode (like a spring DF system), the final loads exceeded the target load, increasing as the DF load increased (dark gray boxes).

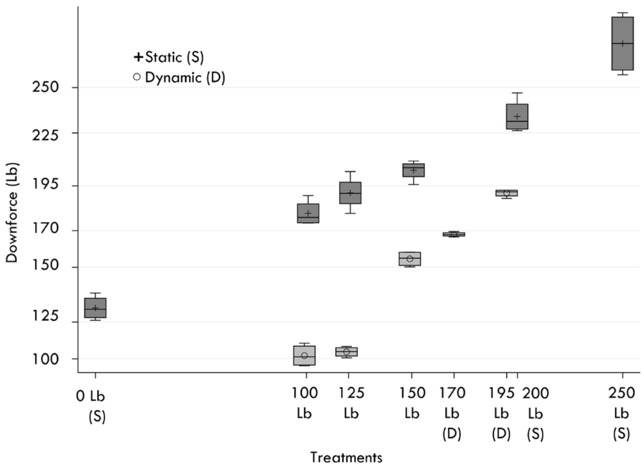

Figure 9.2. Downforce load differences among the two downforce operational modes (static or dynamic).

Seeding depth increased as the downforce level increased (Figure 9.3). The target seeding depth of 1.5 inches was reached when the dynamic DF system used 170 pounds. Shallow planting was observed when DF levels of 100, 120, and 150 pounds were used in either the static or dynamic system mode. When using the static DF system mode, seeding depth was close to the target of 1.5 inches at loads of 200 and 250 pounds. When a DF load of 195 pounds was used on the dynamic mode, seeds were planted deeper than the target.

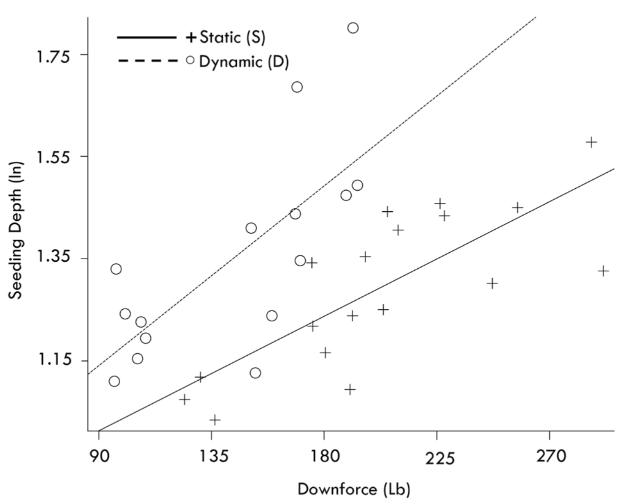

Figure 9.3. Corn seeding depth differences among downforce operational mode (static or dynamic) and level.

The emergence speed rate was assessed through the emergence velocity index (EVI). The greater the EVI value, the faster the emergence. Although very small EVI differences were observed among some DF levels, faster emergence was observed when higher loads were applied using both operational modes (dynamic and static). This could be explained by seeding depth, which was closer to the target as the DF level increased. Overall, EVI values were higher (faster emergence) in the static DF mode than the dynamic mode.

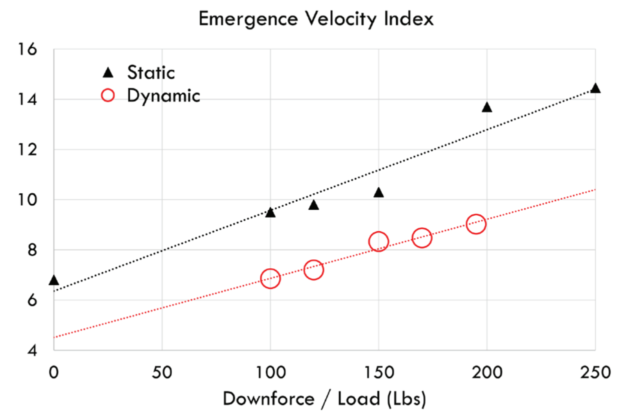

Figure 9.4. Corn emergence velocity index differences among different downforce loads.

Food for Thought

- The study showed the influence of downforce on seeding depth and emergence. Farmers should pay attention to the selection of downforce load before planting a crop.
- The dynamic downforce system has the ability to account for soil moisture and soil resistance, allowing a better control of the load applied to the row-unit (final applied load close to prescribed and less variability), compared to the static downforce system.
- Seeding depth is influenced not only by the downforce load used but also the planter's downforce system. In this study, the dynamic downforce method placed corn seed at the target depth (1.5 inches) using a lower downforce load and less downforce variability than the static downforce method.
- Plant emergence is affected by seeding depth, which is influenced by the downforce system used and the load applied.

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Artificial Intelligence | Remote Sensing | Digital Mapping | Geographic Information System

Prediction of Peanut Maturity Date Using Machine Learning Algorithms & Remote Sensing

Objective

- Evaluate the feasibility of peanut maturity prediction using machine learning algorithms with canopy remote sensing imagery as predictor variables.

Project Justification

Current methods of peanut maturity assessment are subjective, time-consuming, and don't capture within-field variability. Prediction of peanut maturity using a combination of machine learning algorithms and remote sensing imagery has the potential to not only improve the assessment of peanut maturity (PM) timing but also within-field maturity variability.

Planting Details

Location: Society Hill, Alabama	**Planting:** 05/26/22
Crop: Peanut	**Variety:** ACI 3321
Test Size: 45 acres	**Row Width:** 36 inches
Seeding rate: 150 pounds/acre (94,000 seeds per acre)	**Irrigation System:** Valley
Tillage: Conservation	**Predominant soil map unit:** Cowarts loamy sand

Methods Tested

Maturity assessed using the peanut profile board method
Multitarget regression and satellite images used to predict peanut biomass and maturity
Random forest machine learning algorithm

Project Design

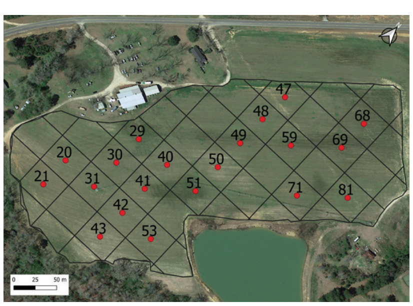

Figure 10.1. Study field with 20 locations where sampling for peanut maturity was conducted.

Precision Ag Toolbox

Planet Lab Imagery
(Planet Labs, San Francisco, California)

Figure 10.1TB. Satellite used to extract spectral bands and vegetation indices.

Scikit Learn
(Google summer code project)

Figure 10.2TB. Open-source machine leaning library used to run the models.

Phyton
(Python Software Foundation, Wilmington, Delaware, USA)

Figure 10.3TB. Python programming language used to write script for the artificial intelligence-based model.

Observations & Preliminary Results

A soil electrical conductivity (Soil ECa) survey using the VERIS 3011 (Veris Technologies) was conducted to assess possible differences in soil texture within the study field. Twenty sampling locations for peanut biomass and maturity were identified based on the survey. These locations showed contrasting conditions not only observed through the Soil ECa survey but also through satellite images from previous peanut-growing seasons. Sampling for peanut aboveground biomass and maturity started 92 days after planting and ran weekly until harvest. Every week, peanut maturity at each sampling location was rated using the peanut profile board, and the peanut maturity indices (PMI) of brown to black and orange to black were determined. The same day of each peanut sampling, crop physiology data and multispectral and hyperspectral remote sensing images were also collected.

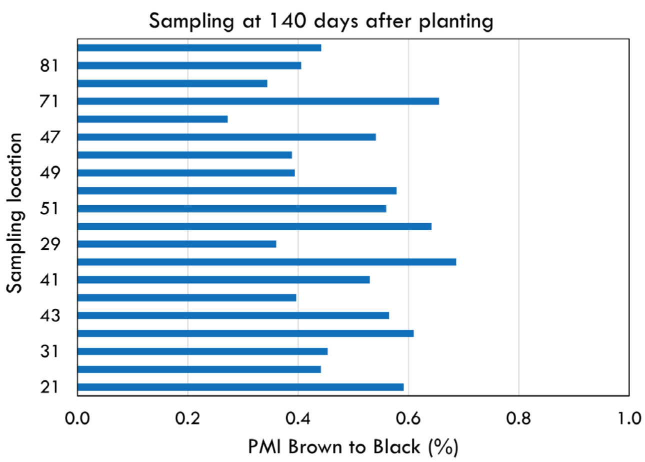

Figure 10.2. Differences in peanut maturity index (PMI) Brown to Black among sampling locations. Sampling at 140 days after planting.

Differences in peanut maturity using the peanut profile board method among locations were observed on the peanut field sampled 140 days after planting (figure 10.2). Over a period of seven weeks, data collected of PMI, peanut above ground biomass, and spectral images were analyzed using a random forests machine learning algorithm. We tested the hypothesis that multi-output regression (MTR) can be used to predict peanut maturity and biomass simultaneously as captured within field variability. Figure 10.3 shows preliminary results of the peanut maturity index prediction using the multi-output regression algorithms. The model predicted peanut maturity with a mean absolute error of 7 percent.

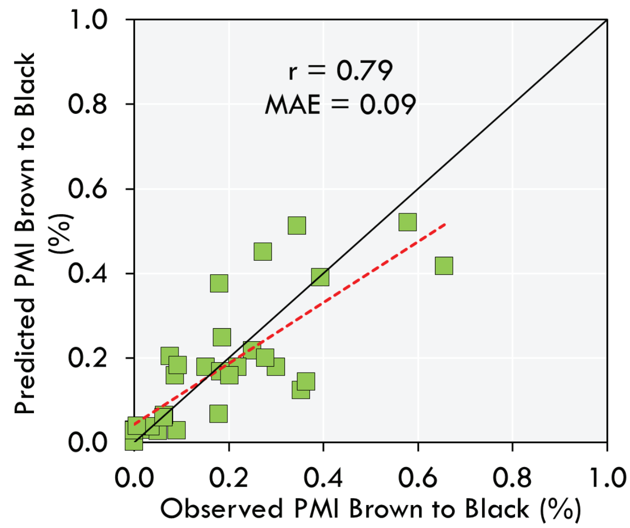

Figure 10.3. Performance of random forest machine learning regression model to predict peanut maturity index using brown to black pods (r = correlation; MAE = mean absolute error).

Our findings demonstrated a promising alternative to predict multiple PMI at the field scale using remote sensing imagery that may reduce the subjectivity of the current peanut maturity determination method. Another promising outcome of this project was the prediction of the aboveground peanut biomass that gives farmers and consultants a quantitative assessment of peanut growth through space and time. Future research should focus on integrating synthetic aperture radar on drones to improve data quality and use of hyperspectral data to develop better prediction models for aboveground peanut biomass and maturity.

Food for Thought

- Multitarget regression model showed promising results for predicting peanut maturity and biomass.
- Satellite or drone images can be used to indirectly predict peanut maturity and biomass at the field level, allowing farmers to segregate harvest to increase peanut quality and reduce yield losses.

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Coupling Machine Learning Algorithms & GIS for Crop Yield Predictions Based on Remote Sensing Imagery & Topographic Indices

Objective

- Predict corn yield at the management zone level.
- Integrate topographic features and remote sensing to increase corn yield predictability accuracy of machine learning (ML) algorithms.

Project Justification

Develop a method capable of integrating topographic indices and remote sensing data to predict corn yield at the management zone level. This method could help farmers understand the yield spatial variability before harvesting and improve crop management.

Planting Details

Location: Town Creek, Alabama	**Planting:** 04/10/19 & 03/27/20
Crop: Corn	**Hybrid:** DKC66-97
Test Size: 300 acres	**Irrigation System:** Reinke – center pivot
Seeding rate: 84,000/ha	**Predominant soil map unit:** Decatur silty clay loam

Treatments

Satellite data (spectral bands)
Topographic indices (topographic wetness index and topographic position index)
Yield data

Project Design

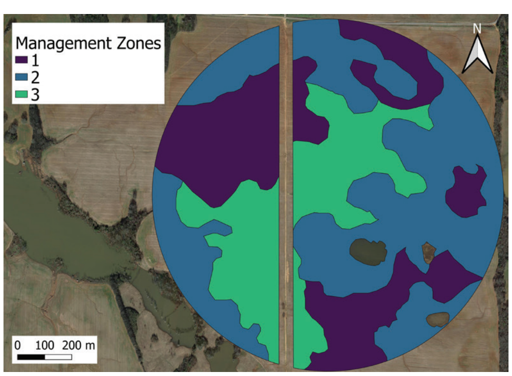

Figure 11.1. Study area showing the management zones (MZ) delineated: MZ1(high yield), MZ2 (low yield), and MZ3 (intermedium yield).

Precision Ag Toolbox

Planet Lab Imagery
(Planet Labs, San Francisco, California)

Figure 11.1TB. Satellite used to extract spectral bands and vegetation indices.

Google Colaboratory
(Google, Mountain View, California, USA)

Figure 11.2TB. Google services that allow users access to interactive working environments called Colab notebooks (e.g., Hosted Jupyter notebook) where they can run code (e.g., Phyton) needed to execute models.

Phyton Programming Language
(Python Software Foundation, Wilmington, Delaware, USA)

Figure 11.3TB. Python programming language used to write scripts for the artificial intelligence-based model development.

Observations & Preliminary Results

Machine learning algorithms, such as extremely randomized trees and extreme gradient boosting (XGboost), deep learning algorithms, and a model ensemble were used for within-field corn yield prediction using two approaches: building yield prediction models by management zone and building a whole field prediction model. For this model development, four different data layer combinations were used: (1) only spectral bands (B) from the planet satellite, (2) spectral bands along with the topographic wetness index (TWI), (3) spectral bands along with the topographic position index (TPI), and (4) all data layers combined (B+TWI+TPI).

Preliminary results showed that corn yield prediction before harvest is possible using a model ensemble algorithm combining B + TWI + TPI variables. Model prediction accuracy increased when the feature selection strategy was used and the prediction was done by zone (isolated model) instead of the whole field. (highlighted circle, figure 11.2). Adding topographic features into the model increased corn yield prediction accuracy by 32 percent.

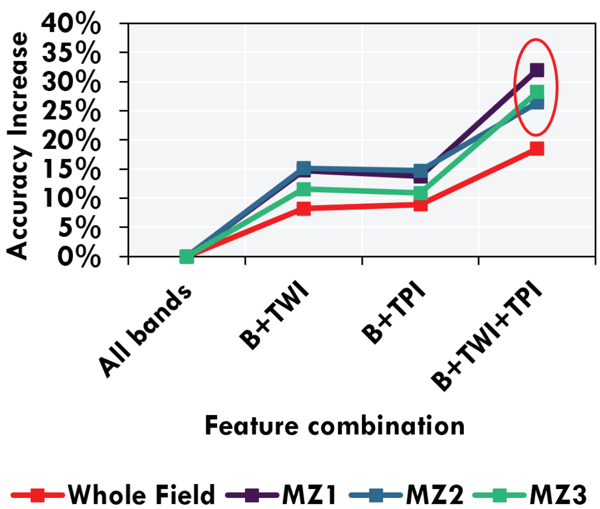

Figure 11.2. Relative increase accuracy for models developed for individual management zones and for the whole field, using multiple variables (spectral bands and topographic indexes). Note: B, spectral bands (blue, green, red, and near-infrared bands together); TWI, topographic wetness index; TPI, topographic position index; MZ1, MZ2, and MZ3, management zones 1 (high yield), 2 (low yield) and 3 (intermediate yield), respectively.

The prediction accuracy among the models developed—whole field and isolated—was compared to the corn yield prediction by zone (high, low, and intermediate; figure 11.3). For example, the whole field model was used for yield prediction of each zone individually and compared with predictions done by the model developed by that specific zone. For all scenarios analyzed, the zone-specific models showed higher accuracy and lower mean absolute error (MAE) than the whole-field model. Additional analyses will be conducted to understand better the factors driving within field yield variability.

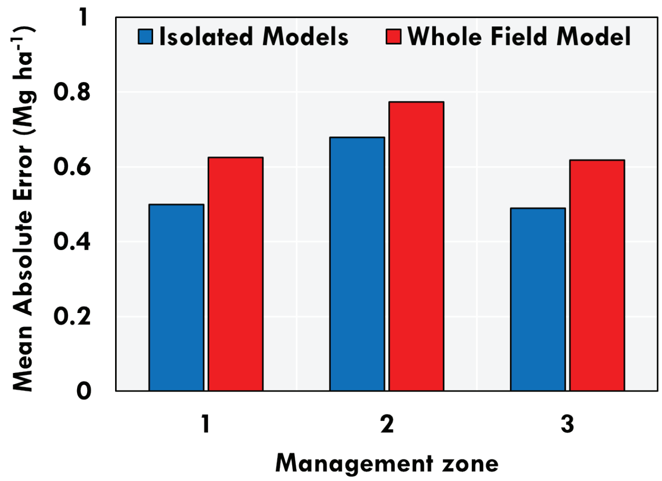

Figure 11.3. Comparison between the accuracy of the whole field model and zone-specific models. Note: MZ1, MZ2, and MZ3 correspond to management zones representing high, low, and intermediate yield, respectively.

Food for Thought

- Topographical indices increase the accuracy of corn yield forecasting when associated with spectral bands as features of ML models.
- Improvements in within-field crop yield prediction might allow farmers and consultants to implement the right in-season management practices and also better select a market price for their crop.
- The methodologies proposed here could be implemented on decision support systems currently being developed by private companies.

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Variable Rate Irrigation | Digital Mapping | Geographic Information System

Evaluation of Terrain Attributes to Support Precision Irrigation

Objective

- Evaluation of terrain attributes and terrain data for delineation of irrigation management zones.

Project Justification

Variable rate irrigation (VRI) is an irrigation strategy that applies different irrigation rates across the field. VRI is better implemented when the field is delineated into different management zones (MZ) that accurately represent the field variability. An entry-level data set for irrigation MZ delineation uses soil SSURGO maps; however, this data often lacks spatial resolution for precision irrigation. Terrain elevation has been used for many years as a variable to understand water movement and, as a result, has been a driver of yield variability.

Planting Details

Location: Town Creek, Alabama	**Planting:** 04/10/18
Crop: Corn	**Row Width:** 36 inches
Test Size: 300 acres	**Center Pivot:** Reinke (2,043-foot length)
Seeding Rate: 32,000/ acres	**Tillage:** Conventional
Predominant Soil Map Unit: Decatur silty clay loam	

Treatments

Soil Water Tension	
TWI	Topographic wetness index
TPI	Topographic position index

Project Design

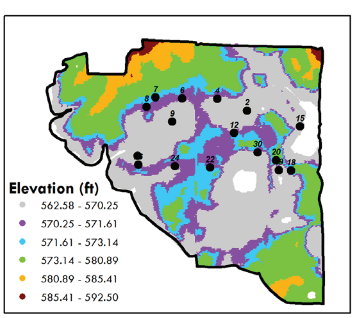

Figure 12.1. Data of soil water tension collected at various locations (black dots on map). Terrain elevation was used to evaluate if topographic indices can describe soil water variability.

Precision Ag Toolbox

Soil Water Tension Sensor Probe
(Trellis, Atlanta, Georgia, USA)

Figure 12.1TB. Watermark sensors integrated into a sensor probe with telemetry measured soil water tension.

StarFire 6000 Real-Time Kinematic (RTK) GPS
(John Deere, Moline, Illinois, USA)

Figure 12.2TB. Real-Time Kinematic (RTK) GPS Receiver used to provide sub-inch position of the grain combine.

System for Automated Geoscientific Analysis
(SAGA User Group Association, Hamburg, Germany)

Figure 12.3TB. Saga software used to delineate the topographic indexes based on the digital elevation model.

Observations & Preliminary Results

Soil water tension data collected at 12 locations using Watermark sensors installed at 6-, 12-, and 24-inch soil depths were used for statistical analyses. First, we tried to answer whether the soil water tension data collected throughout the growing season can be grouped in clusters (e.g., wet areas, dry areas). If different clusters of data existed, then the correlation between those clusters and the topographic wetness index (TWI) (figure 12.2, top) and topographic position index the spatial variability was investigated.

The principal component analysis (PCA) is a statistical technique used to reduce the dimensionality of large data sets by creating new variables out of the original data. This study used PCA to evaluate if the soil water tension data could be grouped into clusters. Results indicated that the first principal component (PC1) explained 62 percent of the total variance of the soil water tension spatial variability. When we plot PC1 against PC2, data from soil sensors installed at different topographic positions grouped in clusters with different TWI or TWI index values.

A correlation analysis between terrain attributes and topographic indices and the PCAs was conducted to identify the terrain data layer that collected best with the spatial variability of soil water content. The topographic position index (TPI) significantly correlated with PC1 (table 12.1).

The correlation between PCI and TWI was negative, indicating that low values of TWI (orange and pink areas on the top map of figure 6.2) corresponded to areas with high water tension corresponding to low soil water content. The slope of the terrain was another variable with moderate correlation with PC1. Low values of TWI have been associated with summits and convex steep slope areas that might dry up first compared to depressions with high TWI values.

Table 12.1. Correlation Between Terrain Attributes and Score of Principal Components*

Terrain Attributes	PC1
Slope	0.61
Topographic position index	0.42
Topographic wetness index	-0.59
Silt content (0 to 24 inches)	-0.51

*Soil sensor date from 2018

The moderate correlation (r=0.55) between TWI and the 2018 corn yield map (figures 12.2 and 12.3) supports using topographic indices to explain and predict crop yield. High-yielding areas corresponded to areas with high TWI values and high soil water content. These results suggest that TWI could be used as a data layer to delineate irrigation management zones.

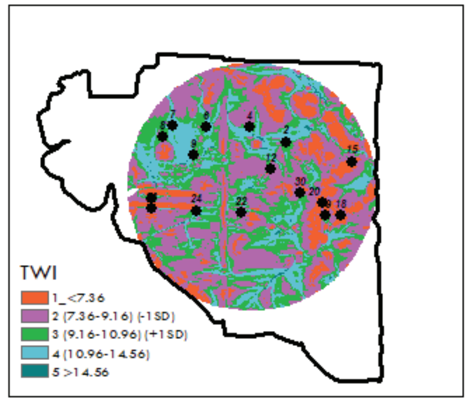

Figure 12.2. Spatial variability in topographic wetness index.

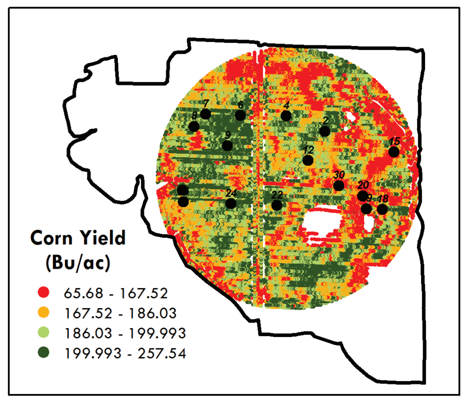

Figure 12.3. Corn yield recorded in 2018.

Food for Thought

- Accurate delineation of irrigation management zones is necessary to implement variable rate irrigation. Information about terrain attributes and indices can improve management zone delineation.
- Topographic indices like TWI or TPI could be used to delineate irrigation management zones, especially on rolling terrain fields.
- Topographic indices could also be used to explain within-field yield variability. In this case, TWI had a positive correlation with corn yield.

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On-Farm Demonstration of Soil Sensor-Based Variable Irrigation Scheduling

Objective

Compare the yield performance between precision irrigation management using soil sensors and variable rate irrigation system with uniform irrigation management.

Project Justification

Most farmers still apply uniform irrigation across crop fields even if field variability exists. This practice may lead to over- or under-application of irrigation water on some parts of the field. The use of soil sensors along with variable rate irrigation can potentially increase yield and water use efficiency, as these technologies allow the application of irrigation at the right time and right rate at the right place.

Planting Details

Location: Town Creek, Alabama	**Planting:** 04/16/20
Crop: Corn	**Hybrid:** DK 70-27
Test Size: 45 acres	**Row Width:** 30 inches
Seeding Rate: 32,000/ acres	**Irrigation System:** Reinke
Tillage: No till	**Soil:** Decatur Silty Clay and Abernathy-Emory Silt Loam

Treatments

HY Zone	High yield zone (HY) / Abernathy-Emory silt loam soil
LY Zone	Low yielding zone (LY)/Decatur Silty Clay Soil (6 to 10 percent slope)
SS/VRI	Soil sensor-based irrigation scheduling and variable rate irrigation (120 acres)
UNIF	Uniform irrigation and scheduling based on farmer's common practice (194 acres)

Project Design

Figure 13.1. Management zones on study field delineated using a combination of multiyear yield maps. SS/VRI treatment outlined in red.

Precision Ag Toolbox

AquaSpy Sensor for Irrigation Scheduling
(AquaSpy, San Diego, California, USA)

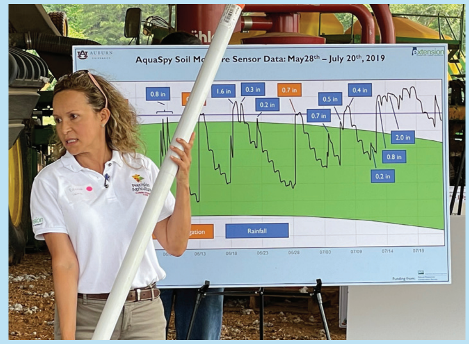

Figure 13.1TB. A soil capacitance sensor probe with sensors every 4 inches covering the first 48-inch soil profile. It not only provides instantaneous soil moisture readings but also has a user-friendly interface with irrigation scheduling recommendations.

Variable Rate Irrigation
(Advanced Ag. Systems, Dothan, Alabama, USA)

Figure 13.2TB. Center pivot irrigation system retrofitted to variable rate irrigation to control irrigation on groups of four nozzles.

Weather Station Vantage Pro2 Plus
(Davis Instruments, Hayward, California, USA)

Figure 13.3TB. Weather station measuring real-time minimum and maximum air temperature and relative humidity, solar radiation, wind speed, and precipitation data.

Observations & Preliminary Results

At this site, the field was divided into two treatment areas: one where soil sensors were installed to support irrigation decisions, soil sensor irrigation scheduling (SS), variable rate irrigation (VRI) (SS/VRI treatment), and another where uniform irrigation was applied and the rate was decided by the farmer (UNIF treatment). The nonirrigated areas (rainfed-R) of the field in close proximity to the SS/VRI were considered for comparison. At two locations in each management zone (MZ), a soil sensor probe with an array of three soil water tension sensors (Watermark) at 6-, 12-, and 24-inch soil depths were installed. Soil water tension (SWT) sensors correlate with plant water stress as they provide measurements analogous to the force needed by plants to extract water from the soil. For this test, the SWT values were converted to soil water content to estimate the irrigation rate needed on each MZ. For each irrigation event, a variable rate irrigation prescription map was prepared that included irrigation rates for the SS/VRI and UNIF treatment areas. The farmer selected the irrigation rates applied to the UNIF treatment area. A total rainfall of 16 inches was recorded at this site during the 2020 corn growing season. Because the SS/VRI test area had differences in soil characteristics, mainly to soil texture and terrain elevation, the HY and LY management zones received different seasonal irrigation amounts (figure 13.2). On the HY zone, there was 9.5 percent water savings (5.6 inches total) compared to the LY zone that received 7.4 inches. Although the UNIF test area also exhibited variability, the farmer applied uniform irrigation and the total irrigation applied was 4.45 inches.

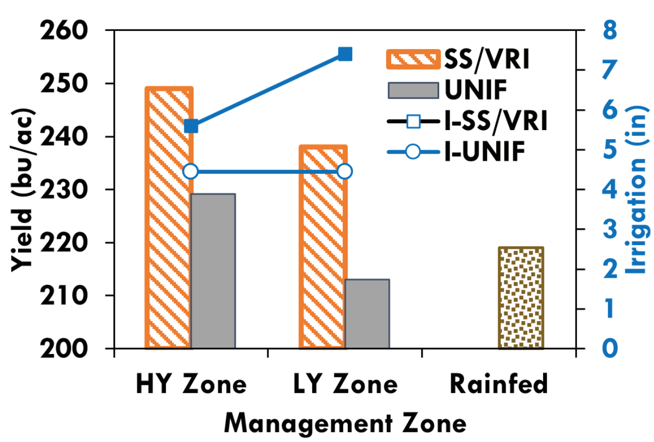

Figure 13.2. 2020 Corn yield and irrigation differences between the SS/VRI, and UNIF irrigation treatments among the high-yielding and low-yielding management zones.

Although the SS/VRI treatment resulted in greater irrigation rates, 25 percent on the HY zone and 67 percent on the LY zone compared to the UNIF treatments, a yield gain was recorded (figure 13.2).

Under the conditions of the HY zone, the SS/VRI irrigation treatment resulted in 20 bushels/acre greater yield than the UNIF treatment and on the LY zone the SS/VRI treatment outyielded the UNIF treatment by 25 bushels/acre average. The greater corn yield observed on the SS/VRI treatment areas could be explained by a better estimation of irrigation timing and rate using soil sensors and also the ability to apply different irrigation rates across the MZ. On the UNIF treatment area, irrigation management could have contributed to the lower yield on the LY zone. Irrigation scheduling supported by the soil sensors not only minimized the risk for yield losses due to low frequency of rainfall June–July but also prevented over-irrigation on areas where soil water was available.

Figure 13.3 shows net returns above variable treatment cost values for the two MZ where the SS/VRI treatment was evaluated. The values correspond to the profit per-acre-inch compared to the rainfed area. Great revenue, 6.2 percent increase, was observed on the HY zone with lower irrigation rate than the LY zone, 4.6 percent revenue increase when compared to the rainfed area.

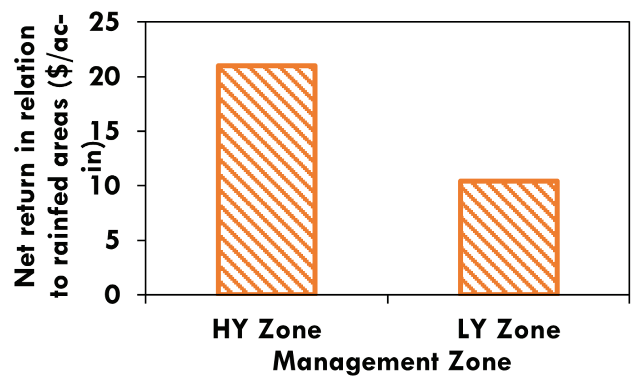

Figure 13.3. 2020 differences in net returns above variable treatment cost with respect to the rainfed area among management zones under the SS/VRI irrigation treatment.

Food for Thought

- Soil sensor and variable rate irrigation contributed to better water allocation and application timing compared to the conventional irrigation methods.
- Precision irrigation strategies increase water, nutrient, and energy use efficiency that could result in higher crop yield or lower yield variability and higher farmer profitability.

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Cooperating Farmers & Alabama Agricultural Experiment Station Sites

Farm 1. Town Creek, Alabama

Farm 2. Courtland, Alabama

Farm 3. Tanner, Alabama

Farm 4. Hacoda, Alabama

Farm 5. Samson, Alabama

Gulf Coast Research and Extension Center, Fairhope, Alabama

E. V. Smith Research Center – Shorter, Alabama

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Alabama Cotton Producers–ALFA
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Alabama Soil and Water Conservation Committee
Alabama Agricultural Experiment Station
Alabama Peanut Producers
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NRCS-CIG–Agreement No: 69-3A75-17-273
NRCS-CIG–Agreement No: 69-3A75-17-317
National Peanut Board

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