

# DigitalAg@Farms

Efforts to put digital technologies and site-specific crop management practices in the hands of farmers (2019 report)

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

Adoption of digital technologies to support site-specific crop management has been, in many cases, slow because of farmers' perception of their effectiveness, usability, comparative advantages, compatibility, and complexity. Easy to use technologies such as GPS auto-steer guidance systems for farm machinery are widely adopted among farms. In contrast, adoption of practices that require collection, processing, and analysis of digital data is still behind. The goal of the **DigitalAg@Farms** program is to work with farmers at their farms on evaluation, demonstration, and training of digital technologies in agriculture.

Although digital agriculture involves the use of communication, sensing, machinery, electronics, computing technologies, and algorithms to support farm operations, "sense-making" of data and derived approaches relies on involvement of multiple disciplines such as agronomy, engineering, computer science, biology, among others. We are currently working with colleagues from various disciplines and colleges within Auburn University, other universities within 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, as well as 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 key part of our technology evaluation and training efforts.

## DigitalAg@Practice

In 2019, eleven sites across Alabama were selected to evaluate, demonstrate, and train various stakeholders on the use of digital technologies in agriculture (figure i). This report includes preliminary results of 11 projects.

### 2019 Demonstration and Training Locations



Several technologies from multiple companies were evaluated for the implementation of practices such as irrigation scheduling, variable rate irrigation, variable rate seeding, seed spacing and depth control, and variable rate fertilization.

The crop response to several management practices and the evaluation of precision agriculture technologies are influenced by several factors including weather, soil, insects, and pests. Monthly rainfall at the demonstration site in Lawrence County was below historic average values in May, June, and August, but ample rain was received in July (corn grain filling period). At the sites in Macon County, rainfall was below historic average values during the period June through August. At the site in Geneva County, rainfall was below historic average values during the period June through July.

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 require at least 2 years of evaluation. It is recommended not to make final conclusions based on a single year of data.

## 2019 DigitalAg Demonstration Topic Areas

Ten digital agriculture topic areas were covered through our demonstration projects (figure ii). Some projects covered more than one topic area. Each topic area is color-coded to help you identify the use of each on every project/location.

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

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



Figure ii. List of digital agriculture areas covered on the 2019 demonstration and training project

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Irrigation Scheduling

Remote Canopy Sensing

Soil Sensing

Telemetry

## 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 on corn growing in the southeastern United States.
- Evaluate the impact of irrigation rate on corn yield.

### Project Justification

Irrigation scheduling based on canopy temperature is advantageous compared to soil sensor-based irrigation due to the potential for capturing early plant water stress deficit and improving irrigation frequency decisions.

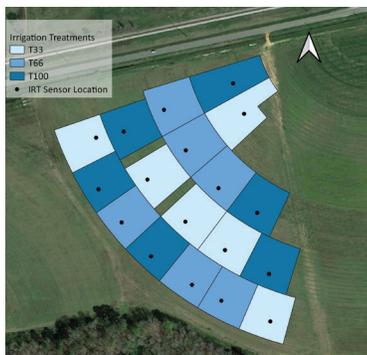
### Planting Details

<b>Location:</b> Shorter, AL	<b>Planting:</b> 05/02/19
<b>Crop:</b> Corn	<b>Hybrid:</b> DKC62-08
<b>Test size:</b> 45 ac	<b>Row width:</b> 36 in
<b>Seeding rate:</b> 36,000/ac	<b>Irrigation system:</b> Valley-7000 Series center pivot
<b>Tillage:</b> Conventional	<b>Predominant soil map unit:</b> Altavista silty loam

### Treatments

<b>T100</b>	Full replenishment to field capacity of water depletion in the top 24 inches of soil
<b>T66</b>	66% of the rate calculated for T100
<b>T33</b>	33% of the rate calculated for T100

### Project Design



**Figure 1.1.** Layout of test plots (0.9 ac/plot) with three irrigation treatments. SapliP-Infrared Thermal (IRT) Dynamax sensors were installed on each plot. The T100 plots were instrumented with Acclima 315LTM sensors installed at 6, 12, and 24 inches soil depth.

## Precision Ag Toolbox

### SapliP-IRT Canopy Temperature Sensor

(Dynamax Inc., Houston, TX, USA)

Infrared temperature sensor used to collect canopy temperature data and calculate CWSI



### Acclima True TDR-315LTM Sensor

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

Acclima TDR 315LTM soil sensors used to collect soil volumetric water content



### Valley-7000 Series Center Pivot Irrigation

(Valley, Lincoln, NE, USA)

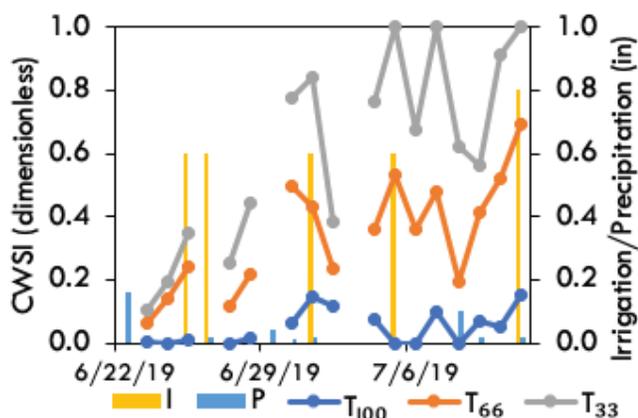
Center pivot irrigation system with a variable rate irrigation system used to apply different irrigation rates throughout the field



## Observations and Preliminary Results

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

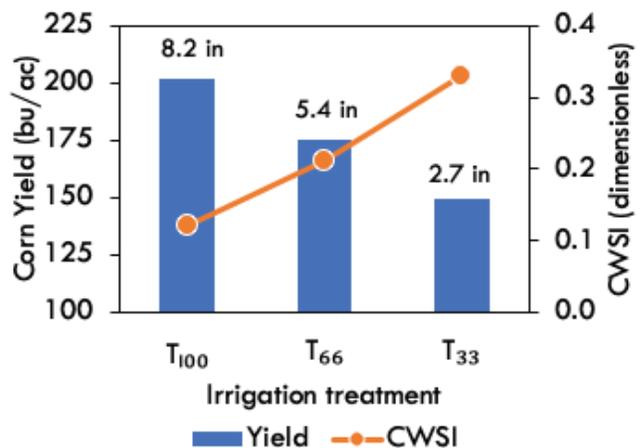
CWSI was sensitive to changes in soil water levels (figure 1.2). CWSI decreased after an irrigation or precipitation event and increased due to plant water uptake or plant water stress increase. The higher irrigation amounts applied in the T100 irrigation treatment resulted in the lowest CWSI values when compared to T66 and T33 treatments (figure 1.3). As total irrigation amount was reduced in the T66 and T33 treatments, plant water stress increased and high CWSI values were found.



**Figure 1.2.** Crop water stress index (CWSI) differences among the full irrigation rate (T100), 66% of full irrigation (T66), and 33% of full irrigation (T33) treatments. Irrigation (I) and precipitation (P) events are also indicated.

In 2019, the corn growing season at the Shorter, Alabama site started wet at planting (3.8 inches of rainfall above historical average in April), but during the months from June to August, the rainfall was below historical average values.

Corn receiving the highest irrigation rate (T100) outyielded the T66 and T33 irrigation treatment by 13.2 percent and 26 percent, respectively. As irrigation levels were reduced, a yield decreasing trend with increasing CWSI values was found (figure 1.3). These results show that CWSI estimated from IRT sensors was sensitive to different plant water stress levels, and therefore could be considered as a potential irrigation scheduling tool for corn growing in the Alabama climate.



**Figure 1.3.** Yield and crop water stress index (CWSI) differences under full irrigation rate (T100), 66% of irrigation (T66), and 33% of irrigation (T33) levels.

## Food for Thought

- Crop water stress index (CWSI) was sensitive to various soil water levels. The greater the soil water deficit, the higher CWSI values and the lower the corn yield.
- The differences in CWSI values among irrigation treatments and the yield results suggest that CWSI could be used as a potential irrigation scheduling tool for subtropical humid environments in the United States.
- Corn yield decreased 13 percent as irrigation rate decreased by 33 percent with respect to the full irrigated treatment.
- Corn yield decreased 26 percent as irrigation rate decreased by 66 percent with respect to the full irrigated treatment.

**Project team:** Bruno P. Lena, Brenda V. Ortiz, Alvaro Sanz-Saez, Greg Pate

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## Comparison of AquaSpy and Acclima Soil Sensors for Determination of Irrigation Timing

### Objective

- Evaluate the performance of two soil sensors as irrigation scheduling (timing) tools.

### Project Justification

Although there are multiple commercially available soil sensors to support farmers' and consultants' irrigation decisions, uncertainty remains about soil sensor performance and irrigation recommendations. The evaluation of two soil sensor types under two different soil types in Alabama was conducted.

### Planting Details

	Site 1	Site 2
<b>Location</b>	Shorter, AL	Samson, AL
<b>Planting date</b>	04/02/19	03/24/19
<b>Crop</b>	Corn	
<b>Hybrid</b>	DKC62-08	D57VP51
<b>Test size</b>	45 ac	40 ac
<b>Row width</b>	36 in	36 in
<b>Seeding rate</b>	36,000/ac	34,000/ac
<b>Tillage</b>	Conventional	
<b>Soil map unit</b>	Altavista silty loam	Alpin sand

### Treatments

<b>Shorter</b>	Clay soil texture
<b>Samson</b>	Fine sand soil texture

### Project Design

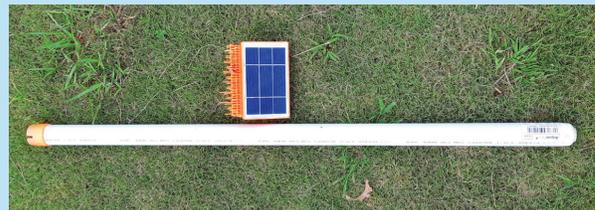
Two soil types were selected for the evaluation of the AquaSpy and Acclima soil sensors. Acclima TDR-315L were installed at the soil depths of 6, 12, and 24 inches. These soil depths were selected because 50 percent of corn root biomass can be found within the first 24 inches of soil. The AquaSpy sensor measures soil moisture every 4 inches up to a depth of 48 inches.

## Precision Ag Toolbox

### AquaSpy Soil Sensor Probe

(AquaSpy Inc., San Diego, CA, USA)

Multi-sensor capacitance probe with solar-powered telemetry that measures and transmits wireless soil moisture data



### Acclima True TDR-315LTM Sensor

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

Time domain reflectometer (TDR) soil sensors used to collect volumetric soil water content



### Aqua Trac Pro Datalogger of Multiple Sensors

(AgSense, Valmont Industries, Inc., Huron, SD, USA)

Aqua Trac Pro solar-powered unit with telemetry reads and uploads to internet data from soil sensors and rain gauges



## Interpreting Acclima and AquaSpy® Data

Acclima provides volumetric soil water content (VWC) data. This data can be converted to soil water storage (SWS) facilitating the determination of irrigation amount and timing. For corn, irrigation has been traditionally initiated when SWS reaches 50 percent depletion from plant available water. Fifty percent of plant available water is represented by the green area in figures 2.1a and 2.2a. Irrigation rate is usually estimated as the amount required to replenish SWS depletion back to field capacity (FC).

AquaSpy provides available moisture (AM) data. AquaSpy users should pay attention to the full point, the refilling point, and the green band of optimum moisture level. The full point is considered the FC, while the refilling point is the AM value at which plants experience water stress that will result in yield losses. When using AquaSpy for irrigation scheduling (figure 2.1b), users should irrigate to maintain AM within the green band. When the AM is approaching the lower boundary of the green band, irrigation should start. The range of AM from 0 to 100 of the AquaSpy sensor is comparable to the green band of SWS for Acclima.

## Observations and Preliminary Results

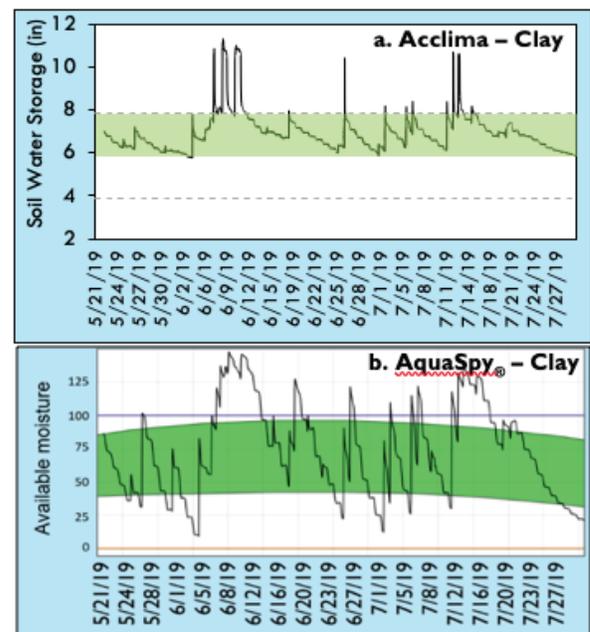
Both sensors captured soil water changes due to irrigation, precipitation, and plant water uptake (figures 2.1 and 2.2). Soil water level dropped because of plant water uptake increased due to irrigation or precipitation. Under a clay soil, changes on AquaSpy AM matched well with SWS values from Acclima (all data within the green band) (figure 2.1). Under sandy soil conditions, differences between AquaSpy and Acclima were found (figure 2.2). While Acclima was suggesting that SWS was above 50 percent depletion during several periods of the season (SWS below the green band), AquaSpy was indicating that AM data was within the green band suggesting less frequent irrigation. If AquaSpy would have been used to determine when to irrigate on sandy soils, under irrigation could have occurred. A yield difference of 149 bushels per acre between the clay and sandy soil areas of the field suggests that the AquaSpy irrigation recommendation (less frequent irrigation) did not reflect the real soil water status of the sandy soil.

**Project team:** Bruno P. Lena, Brenda V. Ortiz, Luca Bondesan, Andres F. Jimenez, Guilherme Morata, Greg Pate

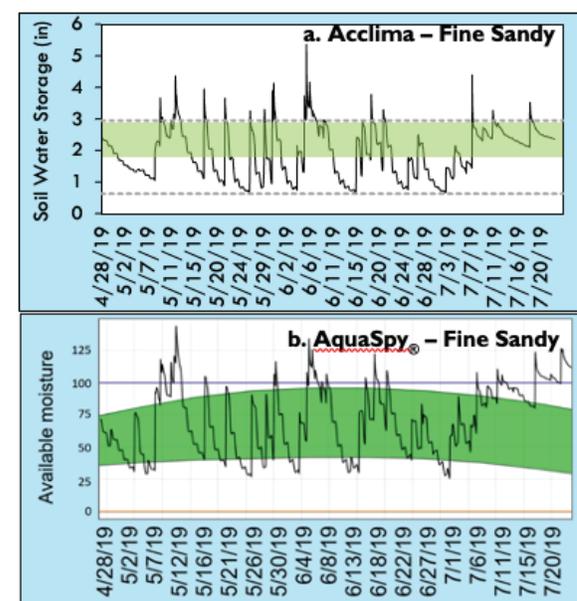
**Project contact:** Bruno P. Lena, Postdoctoral Fellow, Crop, Soil, and Environmental Sciences Department, Auburn University (bzp0043@auburn.edu)

## Food for Thought

- Under a clay soil, AquaSpy irrigation recommendations matched crop water demand.
- Under sandy soil conditions, AquaSpy underestimated irrigation needs (timing).
- Consultants and farmers should carefully track the soil sensor behavior during the growth season to avoid possible misleading data from the sensors that could result in yield losses due to over or under irrigation.



**Figure 2.1.** Soil water storage from Acclima (a) and soil available moisture from AquaSpy sensors (b) on a clay soil



**Figure 2.2.** Soil water storage from Acclima (a) and soil available moisture from AquaSpy sensors (b) on a fine sand soil

## Use of Artificial Neural Networks for Irrigation Management

### Objective

- Evaluate the use of large volumes of data for the development of artificial neural network models for irrigation scheduling.

### Project Justification

Factors such as soil moisture, soil water holding capacity, soil physical properties, crop water demand, and weather conditions influence irrigation decisions. Artificial intelligence–based models (long short-term memory or LSTM) can learn from large volumes of data (e.g., soil sensors, weather data) and then support irrigation scheduling and variable rate irrigation.

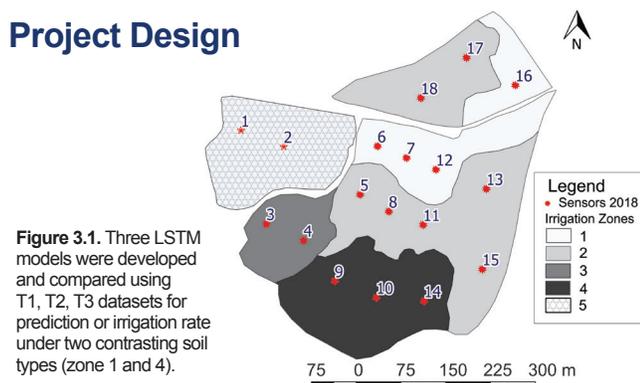
### Planting Details

<b>Location:</b> Samson, AL	<b>Planting:</b> 03/15/17 and 03/24/18
<b>Crop:</b> Corn	<b>Hybrid:</b> D57VP51
<b>Test size:</b> 40 ac	<b>Row width:</b> 36 in
<b>Seeding rate:</b> 34,000/ac	<b>Tillage:</b> Conventional
<b>Predominant soil map unit:</b> Eunola sandy loam	<b>Irrigation System:</b> Zimmatic center pivot

### Treatments

<b>T1</b>	Soil matric potential, management zone, irrigation, and rainfall
<b>T2</b>	Soil matric potential and management zone
<b>T3</b>	Soil matric potential

### Project Design



## Precision Ag Toolbox

### Soil Water Tension Sensor

(Trellis, Atlanta, GA, USA)

Soil water tension used to determine irrigation rate and irrigation scheduling



### Keras Deep Learning Library

(MIT, Massachusetts, USA)

Open-source neural-network library written in Python used to run the model



### Python Programming Language

(Python Software Foundation, Delaware, USA)

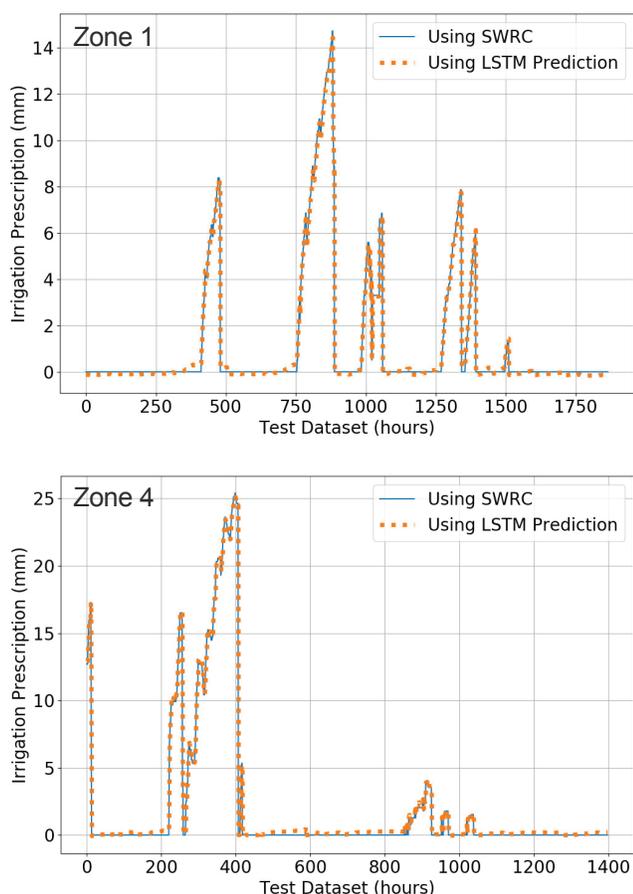
Python programming language used to write script for the artificial intelligence–based model



## Observations and Preliminary Results

Models were trained using data collected in 2017 and tested with data collected in 2018. The training phase of the LSTM neural network showed the T3 model, which used only soil matric potential (SMP) data as the model variable to predict irrigation rate, had similar results to the T1 and T2 models, which used two or more variables. The benefit of using only SMP data as the variable to predict irrigation prescription is the ability to reduce the amount of inputs and the complexity of the model predictions.

The testing phase of the model using data from the 2018 season is presented in figure 3.2. Irrigation prescriptions over the season using only SMP data were well estimated by the model under the conditions of management zones 1 and 4. It shows that the use of a LSTM neural network is a promising method for irrigation requirement predictions.



**Figure 3.2.** Irrigation prescription comparison between observed and predicted data for irrigation on zone 1 (top, sandy clay loam soil) and zone 4 (bottom, sandy soil)

## Food for Thought

- The long short-term memory neural network model showed promising results for prediction of irrigation prescription.
- Long short-term memory neural network models show good prediction performance using only soil matric potential data for predicting irrigation rates as compared to complex models using multiple variables.
- Artificial intelligence could provide significant benefits to agriculture, represented by the use and transformation of large volumes of data collected from digital technologies into information to support farmers and consultants.
- Farmers and consultants could benefit from artificial neural network models to increase promptness and precision in irrigation decisions.

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**Project team:** Andres F. Jimenez, Brenda V. Ortiz, Luca Bondesan, Guilherme Morata

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## Demonstration of Soil Sensor–Based Irrigation Scheduling and Variable Rate Irrigation

### Objective

- Evaluation of soil sensors to determine irrigation timing in support of variable rate irrigation.

### Project Justification

Irrigation scheduling is a science-based tool to determine irrigation timing and amount. An effective strategy to meet crop water demand is the use of soil sensors to keep track of soil water content. They provide key information about soil water levels, helping to answer questions related to irrigation rate and time. Soil sensors can also provide an assessment of in-field soil moisture variability so that, along with the use of a variable rate irrigation system, water can be better allocated over different parts of the field.

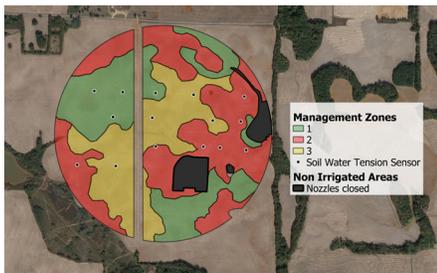
### Planting Details

<b>Location:</b> Town Creek, AL	<b>Planting:</b> 03/26/19
<b>Crop:</b> Corn	<b>Hybrid:</b> DKB 66-97
<b>Test size:</b> 300 ac	<b>Row width:</b> 30 in
<b>Seeding rate:</b> 34,000/ac	<b>Center pivot:</b> Reinke (2043 ft length)
<b>Predominant soil map unit:</b> Decatur silty clay loam	<b>Tillage:</b> No till

### Treatments

<b>MZ1</b>	Zone 1: high yielding zone
<b>MZ2</b>	Zone 2: low yielding zone
<b>MZ3</b>	Zone 3: medium yielding zone

### Project Design



**Figure 4.1.** Study area displayed as three irrigation management zones (MZ) delineated using a combination of multi-year yield maps, soil electrical conductivity, soil properties, and topography

## Precision Ag Toolbox

### Soil Water Tension Sensor Probe

(Trellis, Atlanta, GA, USA)

Soil water tension to determine irrigation rate and irrigation scheduling



### Variable Rate Irrigation System

(Advanced Ag Systems, Dothan, AL, USA)

Center pivot irrigation system retrofitted with variable rate irrigation components to control irrigation by group of nozzles



### Weather Station Vantage Pro2 Plus

(Davis Instruments, Hayward, California, USA)

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



## Observations and Preliminary Results

The high yielding zone of this field, MZ1, showed lower soil water tension values compared to the low yielding zone, MZ2 (figure 4.1). Meanwhile, MZ3 was classified as intermediate yield zone compared to MZ1 and MZ2. Both, soil textural properties and topography, influenced differences in soil water among the MZs. Several soil water tension sensors were installed in each MZ to determine soil water level change and prescribe irrigation during the growing season.

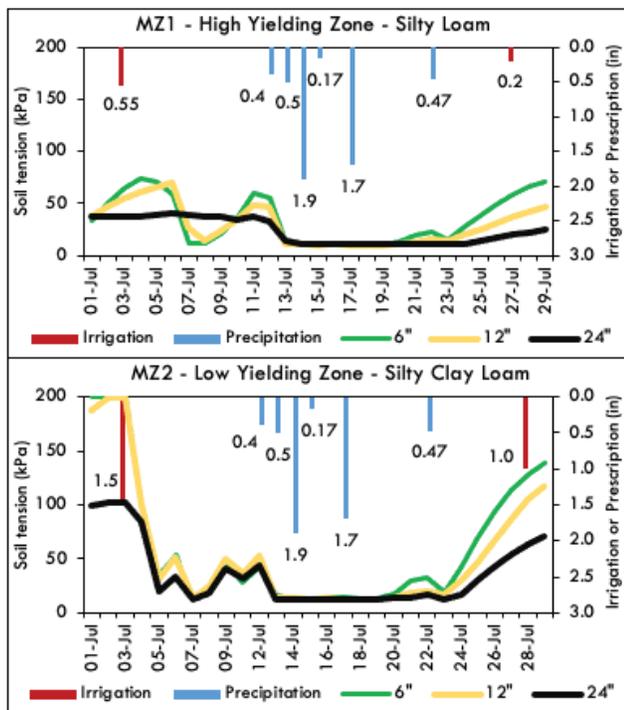


Figure 4.2. Soil matric potential (SMP) and irrigation and precipitation values for corn during grain filling period at management zones 1 (MZ1) and 2 (MZ2)

Watermark-based soil sensor probes were used to monitor soil matric potential (SMP) changes at several locations within each MZ at 2-hour intervals. Figure 4.2 shows the SMP change at 6-, 12-, and 24-inch soil depth at one location on MZ1 and MZ2 during the corn grain filling period. On July 3, greater SMP values were found at MZ2 than on MZ1, resulting in a higher irrigation rate prescription on MZ2 (1.5 inches) when compared to MZ1 (0.55 inches). From July 12 to 22, a series of rainfall events occurred that kept the soil at saturation

levels. After the excess water drained to deeper soil layers, an increase of SMP was observed after July 24, which was a result of plant water uptake from the soil profile. Greater SMP levels were observed again on MZ2, almost double compared to MZ1. On July 28, the irrigation requirement on MZ2 was 1 inch and 0.2 inches on MZ1. Soil sensors made possible the estimation of different irrigation rates. MZ2 covers one-third of the cropped area under the irrigation pivot. The use of a flat rate could have resulted in under-irrigation over this part of the field. The use of soil sensors supported the use of variable rate irrigation, and also helped determine which area should be irrigated first. The use of variable rate irrigation on this 300-acre area, along with soil sensors, could definitely help address issues of over- or under-irrigation.

## Food for Thought

- Different irrigation requirements within the study field were only assessed using soil water sensors installed at several locations with different soil and topographic characteristics.
- Under- or over-irrigation could be minimized if soil sensors and variable rate irrigation are used.
- The use of variable rate irrigation system allowed a better allocation of water within the field that exhibited the different irrigation requirement.

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## Evaluation of Soil Sensor-Based Variable Irrigation Scheduling

### Objective

- Evaluate soil sensor-based irrigation scheduling and to compare variable rate irrigation (VRI), aided by soil sensors, with uniform irrigation.

### Project Justification

Irrigation scheduling assisted by soil water sensors helps address issues related to the field variability. Knowledge of differences in soil water depletion across a field supports variable rate irrigation and helps increase irrigation water use efficiency.

### Planting Details

<b>Location:</b> Samson, AL	<b>Planting:</b> 03/24/19
<b>Crop:</b> Corn	<b>Hybrid:</b> D57VP51
<b>Test size:</b> 40 ac	<b>Row width:</b> 36 in
<b>Seeding:</b> 34,000/ac	<b>Irrigation system:</b> Zimmatic center pivot
<b>Zone 1 Predominant soil map unit:</b> Eunola sandy loam	<b>Variable rate irrigation system:</b> Lindsay Growsmart
<b>Zone 2 Predominant soil map unit:</b> Alpin	<b>Tillage:</b> Conventional

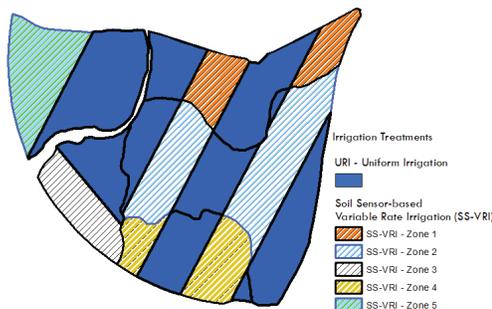
### Treatments

<b>SS-VRI</b>	Soil sensor-based variable rate irrigation
<b>URI</b>	Uniform rate irrigation

**Note:** Irrigation rate and yield were compared between irrigation scheduling methods and between irrigation management zones.

### Project Design

Figure 5.1. Layout of pair-comparison of URI and SS-VRI irrigation treatments. Yield and irrigation differences were evaluated between irrigation treatments across five management zones.



## Precision Ag Toolbox

### Soil Water Tension Sensor Probe

(Trellis, Atlanta, GA, USA)

Watermark sensors integrated into a sensor probe with telemetry measured soil water tension. Data was used for irrigation scheduling.



### Lindsay Growsmart Precision VRI System

(Lindsay Corporation, Omaha, NE, USA)

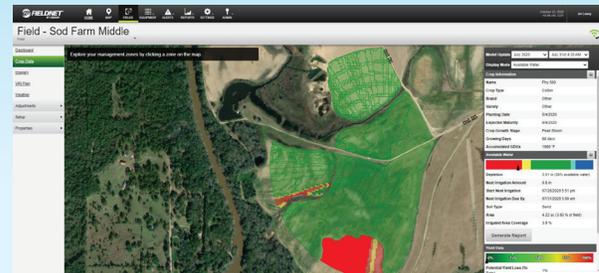
This individual nozzle control VRI system applies different irrigation rates based on the GPS position of the pivot with respect to a FieldMap irrigation prescription map.



### FieldNET Advisor

(Lindsay Corporation, Omaha, NE, USA)

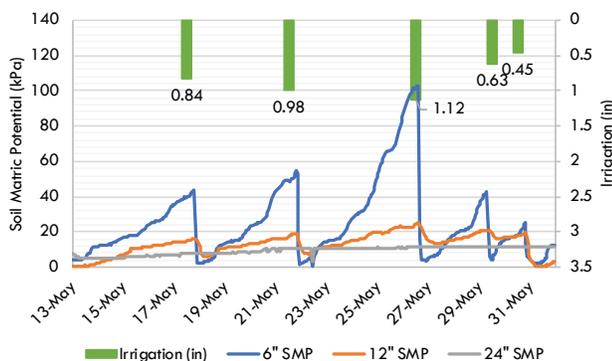
A cloud-based irrigation scheduling system that uses crop growth modeling, soil water balance concepts, and weather data to support irrigation decisions. It automatically generates VRI prescriptions that farmers can upload directly to the VRI control panel.



## Observations and Preliminary Results

Watermark-based soil sensor probes were installed in the middle of each irrigation-zone treatment. Five irrigation zones were delineated based on apparent soil electrical conductivity, terrain elevation, and yield maps. Soil textural differences were observed among the zones at 12 inches: zone 1: sandy clay loam, zone 2: sandy loam, zone 3: loamy sand, Zone 4 and 5: sand.

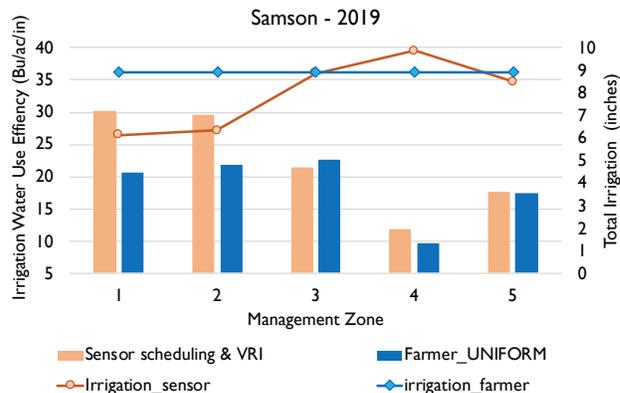
Figure 5.2 shows an example soil matric potential (SMP) changes recorded at 6, 12, and 24 in soil depth on zone 4. As SMP increased, the available water for the plants decreases, and irrigation requirement increases. The sharp drop of SMP values at 6 and 12 in soil depths are the result of irrigation events. SMP data at three soil depths was used to determine irrigation frequency and rate on the SS-VRI treatment. The irrigation events on the URI treatment were triggered based on the FieldNET Advisor™ recommendations.



**Figure 5.2.** Irrigation rates applied and soil matric potential (SMP) values recorded by Watermark® soil sensors at 6, 12, and 24 inches of soil depth. The greater the SMP values, the less water in the soil porous space.

Irrigation water use efficiency (IWUE) and cumulative irrigation during the season are presented in Figure 5.3. Yield produced by total water applied corresponds to IWUE. Efficiency increases when greater yield is achieved with less total irrigation applied. Cumulative irrigation for URI treatment was the same among all zones (9 in) compared to the SS-VRI treatment with total irrigation ranging from 6.1 (zone 1) to 9.9 in (zone 4). Differences in IWUE were observed between irrigation treatments and between treatments within some zones. Greater efficiency was observed with the use of soil sensor-based irrigation scheduling and VRI (SS-VRI) on zones 1 and 2 compared to uniform rate treatment (FieldNET Advisor™ irrigation prescriptions).

These results indicated that uniform irrigation rate resulted in overapplication of water on zones 1 and 2 and underapplication on zone 4. By implementing the use of soil sensors and VRI for application of water at the right time and right place, farmers could prevent plant water stress, increase yield, and reduce overall water use.



**Figure 5.3.** 2019 Irrigation water use efficiency (IWUE) and cumulative irrigation differences among uniform irrigation (URI) and SS-VRI treatments.

Field soil variability represented by changes in soil type and terrain elevation are most times the main factors affecting water movement and availability in the soil. The response of the crop to these variabilities is often related to different water requirements across various areas of a field. A VRI system is a tool that allows better allocation of water within a field according to the within field variability and crop water demand.

## Food for Thought

- Greater irrigation water use efficiency could result from the use of soil sensors for irrigation scheduling and VRI compared to uniform irrigation application.
- Soil water sensors are effective tools to determine different soil water levels within a field which can be used to improve irrigation scheduling (right rate and the right time).

**Project team:** Luca Bondesan, Brenda V. Ortiz, Guilherme T. Morata, Bruno Lena

**Project contact:** Luca Bondesan (luca.bondesan@gmail.com), Research Associate, and Brenda V. Ortiz (bortiz@auburn.edu), Extension Specialist and Professor, both from the Crop, Soil, and Environmental Sciences Department, Auburn University

## Evaluation of Terrain Attributes to Support Precision Irrigation

### Objective

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

### Project Justification

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

### Planting Details

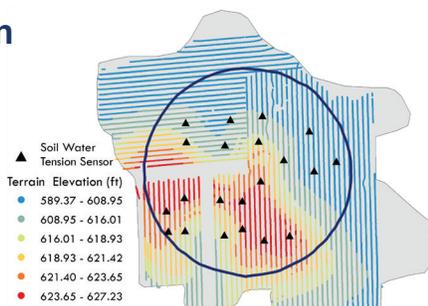
<b>Location:</b> Tanner, AL	<b>Planting:</b> 05/05/19
<b>Crop:</b> Cotton	<b>Row width:</b> 38 in
<b>Test size:</b> 65 ac	<b>Center pivot:</b> Valley 7000 (932 ft length)
<b>Seeding rate:</b> 45,000/ac	<b>Tillage:</b> Conventional
<b>Predominant soil map unit:</b> Decatur silty clay loam	

### Treatments

<b>Soil water tension</b>	
<b>TWI</b>	Topographic wetness index
<b>TPI</b>	Topographic position index

### Project Design

**Figure 6.1.** Soil water tension data was used to evaluate topographic position index (TPI) and topographic wetness index (TWI) derived from elevation data as potential data layers on the delineation of irrigation management zones.



## Precision Ag Toolbox

### Soil Water Tension Sensor Probe

(Trellis, Atlanta, GA, USA)

Watermark sensors integrated into a sensor probe with telemetry measured soil water tension



### StarFire 6000 Real-Time Kinematic (RTK) GPS

(John Deere, Moline, IL, USA)

Real-time kinematic (RTK) GPS receiver used to provide sub-inch position of the grain combine



### System for Automated Geoscientific Analysis (SAGA)

(SAGA User Group Association, Hamburg, Germany)

Saga software used to delineate the topographic indexes based on the digital elevation model



## Observations and Preliminary Results

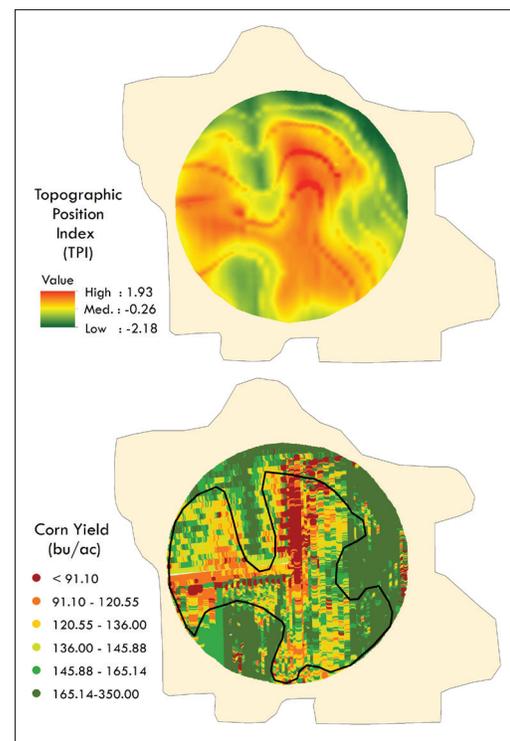
Soil water tension data collected at 12 locations using Watermark sensors installed at 6, 12, and 24 inches soil depth was used for statistical analyses. The soil water tension was converted into soil water content. First, we tried to answer the question whether the soil water content data collected 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 position index (figure 6.2) and the topographic wetness index (TWI) spatial variability was investigated.

Principal component analysis (PCA) is a statistical method that is used to reduce the dimensionality of large datasets by creating new variables out of the original data. In this study, PCA was used to evaluate if the soil water content data could be grouped into clusters. Results indicated that the first principal component (PC1) explained 93 percent of the total variance of the soil water tension spatial variability. When we plot PC1 against PC2, two different groups of soil water tension data could be created.

A correlation analysis between terrain attributes and topographic indices and the PCAs was conducted to identify the terrain data layer that best correlated with the spatial variability of soil water content. The topographic position index (TPI) showed significant correlation with PC1 (table 6.1).

The correlation was negative, indicating that high values of TPI (red areas on top map in figure 6.2) corresponded to areas of low soil water content. The slope of the terrain was another variable with moderate correlation with PC1. Figure 6.1 shows that there is a 38-foot difference between the highest and lowest elevation point on this field, which might explain the correlation between TPI and soil water content.

Table 6.1. Correlation Between Terrain Attributes and Score of the Principal Components			
Terrain attributes	PC1	PC2	PC3
Elevation	0.23	0.5*	-0.005
Slope	-0.46	0.42	-0.03
Topographic position index	-0.57**	0.3	0.13
Topographic wetness index	0.31	-0.42	-0.13



**Figure 6.2.** Spatial variability in topographic position index (top) and corn yield recorded in 2016 (bottom)

A spatial correlation of -0.52 between TPI and a corn yield map (figure 6.2) from 2016 was found. High yielding areas corresponded to areas of low TPI values and high soil water content. These results suggest that TPI could be used as a data layer for the delineation of irrigation management zones.

## Food for Thought

A proper delineation of irrigation management zones is necessary for a better variable rate irrigation implementation, and terrain attributes information can potentially improve the management zone delineation.

- Topographic indices such as TPI or TWI could be used for delineation of irrigation management zones, especially on rolling terrain fields.
- Topographic indices could also be used to explain within-field yield variability. In this case, TPI had a negative correlation with corn yield.

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## Effect of Planter Downforce on Corn Emergence

### Objective

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

### Project Justification

Planting operations could be improved with the use of precision planting technologies that allow 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 for optimal soil-to-seed contact. Hydraulic downforce systems currently available help maintain a target gauge wheel load on individual planter row units using fixed loads (manual mode) and automatically adjusting loads according to soil resistance (automatic mode).

### Planting Details

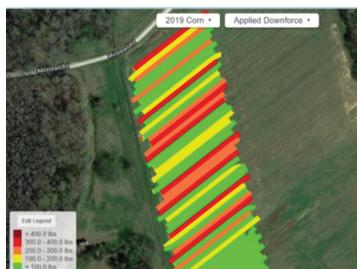
<b>Location:</b> Macon, AL	<b>Planting:</b> 03/29/2019
<b>Crop:</b> Corn	<b>Hybrid:</b> DK64-69 VT3Pro
<b>Test size:</b> 7.2 ac	<b>Seed depth:</b> 1.5 in
<b>Seeding rate:</b> 26,600/ac	<b>Row width:</b> 36 in
<b>Rainfed</b>	<b>Tillage:</b> Conventional
<b>Predominant soil map unit:</b> Cahaba sandy loam	

### Treatments

<b>Manual downforce</b>	0, 125, 250, 375 lb
<b>Automatic downforce</b>	120 lb
<b>Soil type 1</b>	Sandy clay loam
<b>Soil type 2</b>	Sandy loam
<b>Target seed depth</b>	1.5 in

### Project Design

**Figure 7.1.** Five downforce (DF) treatments were replicated four times across two soil types (sandy clay loam and sandy loam). Each downforce treatment covered six planted rows 341 feet in length.



## Precision Ag Toolbox

### DeltaForce Automated Downforce Control

(Precision Planting, Tremont, IL, USA)

DeltaForce is an active downforce system that allows an automatic change of downforce to maintain the same weight on the gauge wheels with respect to different field conditions.



### MaxEmergence Plus Planter

(John Deere, Moline, IL, USA)

A John Deere 7200 Max Emerge 6-row planter can be retrofitted with the Precision Planting DeltaForce system.



### Climate Field View Drive

(Climate Corporation, San Francisco, CA, USA)

Data collected from farm equipment could be readily accessible and easily viewed when Drive is used along with the Climate FieldView Cab app.



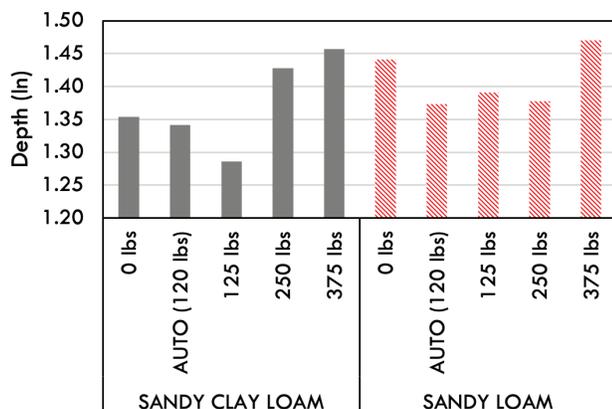
## Observations and Preliminary Results

Seed depth increased as the downforce (DF) (manual mode) increased from 125 to 375 pounds under sandy clay loam soil conditions (figure 7.2). The average seed depth observed for the 125-pound treatment was 1.29 inches, which was far from the target of 1.5 inches. In contrast, the 375-pound DF treatment placed the seed closer to the 1.5-inch depth target.

On a sandy loam soil, the 375-pound DF treatment placed the seed much closer to the 1.5-inch seed depth target compared to other treatments.

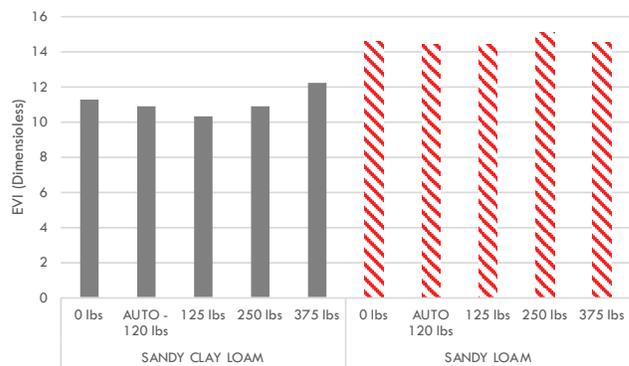
The automatic DF treatment set to 120 pounds placed the seed at much shallower depth than the desired target of 1.5 inches on both soil types (figure 7.2).

Although soil compaction increased as DF increased, on sandy loam soil the overall soil compaction measured on each DF treatment was lower than on the sandy clay loam soil.



**Figure 7.2.** Corn seed depth differences among downforce treatments and soil types

The emergence 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 between the treatments on both soil conditions, faster emergence was observed when 375 pounds of DF was applied under sandy clay loam soil conditions (figure 7.3). This faster emergence could be explained by the greater seeding depth recorded (figure 7.2).



**Figure 7.3.** Corn emergence velocity index (EVI) differences among downforce treatments and soil types

## Food for Thought

- The downforce chosen before planting will impact seeding depth and subsequently emergence velocity.
- The impact of downforce on seeding depth will change by soil type.
- Under the growing conditions of the test location, the manual downforce of 375 pounds placed the corn seed closer to the target soil depth of 1.5 inches than any other treatment evaluated.
- Increasing downforce could result in seed wall compaction.
- The adoption of precision planting technologies has the potential to improve efficiency of planting operations.

**Project team:** Luan Pereira De Oliveira, Brenda V. Ortiz, Greg Pate, Kris Balkcom

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## Effect on Planter Downforce on Cotton Emergence, Growth and Yield

### Objective

- Evaluate the impact of planter downforce settings on seeding depth, emergence, and yield. Yield differences among seeding depths were evaluated.

### Project Justification

At planting, if the planter's opening disks do not properly open the seed furrow because of soil surface resistance or inadequate planter downforce (DF), seeds could be placed too shallow. Delayed emergence and potential yield losses might occur as a result of planting seeds either too shallow or too deep. Active downforce systems now available on planters are designed to place seeds at the right target depth providing better seed-to-soil contact, increasing emergence uniformity and stand.

### Planting Details

<b>Location:</b> Shorter, AL	<b>Planting:</b> 05/22/2019
<b>Crop:</b> Cotton	<b>Hybrid:</b> DP1646B2XF
<b>Test size:</b> 7 ac	<b>Seed depth:</b> 0.75 & 1.5 in
<b>Seeding rate:</b> 35,600/ac	<b>Row width:</b> 36 in
<b>Rainfed</b>	<b>Tillage:</b> Conventional
<b>Predominant soil map unit:</b> Cahaba sandy loam	

### Treatments

<b>Manual downforce</b>	<b>125 and 250 lb</b>
<b>Automatic downforce</b>	<b>120 lb</b>
<b>Seeding depth</b>	<b>0.75 and 1.5 in</b>

### Project Design

Figure 8.1. The performance of three downforce (DF) treatments, replicated three times, was evaluated on 0.75- and 1.5-inch seeding depth targets. Each downforce treatment covered six planted rows 341 feet in length.



### Precision Ag Toolbox

#### DeltaForce Automated Downforce Control

(Precision Planting, Tremont, IL, USA)

DeltaForce is an active downforce system that allows an automatic change of that downforce to maintain the same weight on the gauge wheels with respect to different field conditions



#### SmartFirmer Seed Firmer Sensor

(Precision Planting, Tremont, IL, USA)

Multispectral sensors part of the SmartFirmer measure temperature, moisture, and residue in the v-trench. This data, collected in real time, is used to place the seed down into the bottom of the v-trench. Farmers can adjust the seeding depth using the soil moisture data collected by SmartFirmer



#### 20|20 Display

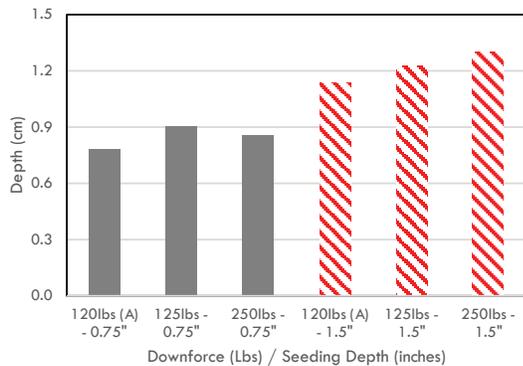
(Precision Planting, Tremont, IL, USA)

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 makes on-the-go changes.



## Observations and Preliminary Results

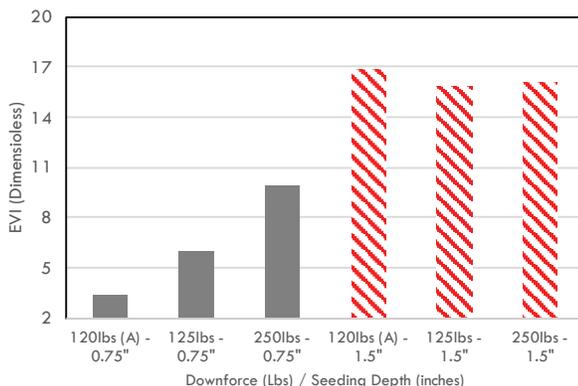
Results from the 0.75-inch seeding depth treatment showed that all three downforce (DF) treatments were able to place the seed at the target seeding depth (figure 8.2). In contrast, none of the DF treatments were able to place the seed at the 1.5-inch target seeding depth. For both target seeding depth treatments, seeding depth increased as downforce increased. Both manual and automatic DF treatments using 120 pounds yielded similar results with respect to seeding depth and neither treatment reached the target depth.



**Figure 8.2.** Cotton seed depth differences among downforce treatments and seeding depths

The emergence rate was assessed through the emergence velocity index (EVI). The greater the EVI value, the faster the emergence. When the target seeding depth was 0.75 inches, EVI increased (faster emergence) as the manual DF increased from 125 to 250 pounds and the automatic DF treatment exhibited the lowest EVI value (slow emergence) (figure 8.3). The greater emergence velocity measured under greater DF treatment might be related to the better seed-to-soil contact.

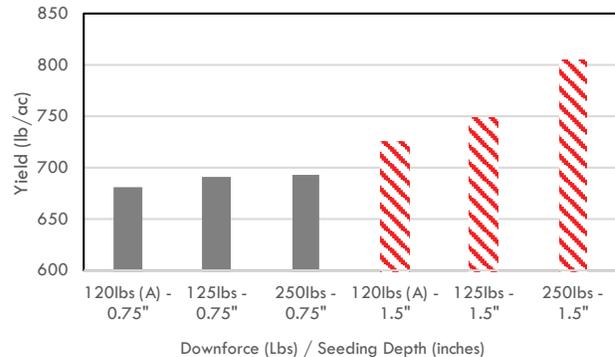
Faster emergence, greater EVI, was observed on the 1.5 in target seeding depth (1.2 in average) treatment compared to the 0.75 in (0.83 in average) treatment.



**Figure 8.3.** Cotton emergence velocity index among downforce treatments and seeding depths

Similar emergence velocity was observed among the three DF treatments when the target seeding depth was 1.5 inches.

Seeding depth and DF impacted cotton yield (figure 8.4). As seed target depth increased, the yield increased. This could be explained by the deeper seed placement that resulted on a higher soil moisture condition, faster emergence, and higher plants stand. When the target seeding depth was set to 1.5 inches and the DF increase from 125 pounds to 250 pounds on the manual mode, yield increased by 7 percent.



**Figure 8.4.** Cotton yield differences among downforce treatments and seeding depths

## Food for Thought

- Seeding depth impact final cotton yield. Preliminary results showed that shallow planted cotton (0.83 in average), yielded less than cotton planted at 1.2 in average.
- Shallow planting of cotton seeds did not require higher downforce. If cotton seeds are required to be planted at 1.5 inches depth on a sandy loam soil, a downforce higher than 125 pounds is required.
- If shallow planting is considered on sandy loam soils, an increase on downforce might favor faster emergence and higher yield.

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## Effect of Planter Downforce on Peanut Emergence, Growth, and Yield

### Objective

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

### Project Justification

Planting depth can impact crop emergence and potentially reduce yield if planter settings are not chosen correctly. An active depth control system available for planters could eliminate the guesswork from the operator making changes on the planter as it traverses the field. The active hydraulic downforce system was designed to keep a target gauge wheel load on an individual planter row unit using fixed loads (manual mode) or adjusting loads according to soil resistance to maintain good soil contact of the gauge wheel (automatic mode).

### Project Details

**Location:** Headland, AL    **Planting:** 05/19/2019

**Crop:** Peanuts    **Hybrid:** Georgia-06

**Test size:** 9 ac    **Seed depth:** 0.75 and 1.5 in

**Seeding:** 86,000/ac    **Row width:** 36 in

**Rainfed**    **Tillage:** Conventional

**Predominant soil map unit:**  
Orangeburg sandy loam

### Treatments

**Manual downforce**    125 and 250 lb

**Automatic downforce**    120 lb

**Depth**    2, 2.5, and 3 in

### Project Design

**Figure 9.1.** The performance of three downforce (DF) treatments, replicated three times, was evaluated on 2, 2.5, and 3.0 inches seeding depths. Each downforce treatment covered six planted rows 1,100 feet in length.



## Precision Ag Toolbox

### vDrive

(Precision Planting®, Tremont, IL, USA)

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



### VERIS 3100 Soil Electrical Conductivity Sensor

(Veris Technologies, Salina, KS, USA)

Mapping within-field variability of soil texture and salinity is possible through the VERIS 3100 sensor. The sensor measures apparent soil electrical conductivity (Soil ECa) at the soil depths of 0 to 1 foot (shallow) and 0 to 3 feet (deep).



### FmX Integrated Display

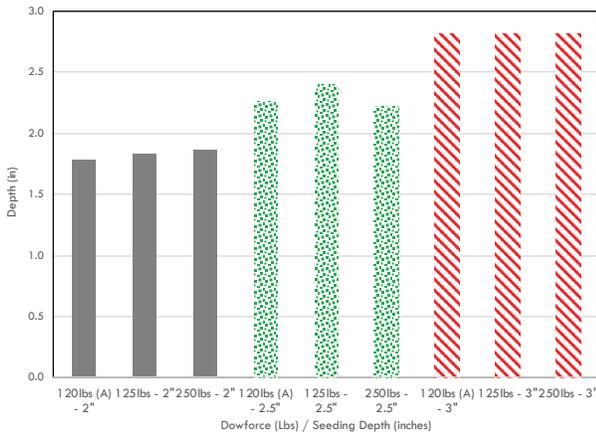
(Trimble Inc., Sunnyvale, CA, USA)

A display that provides guidance, mapping, Field-IQTM for control of inputs, yield monitoring capability, and data management



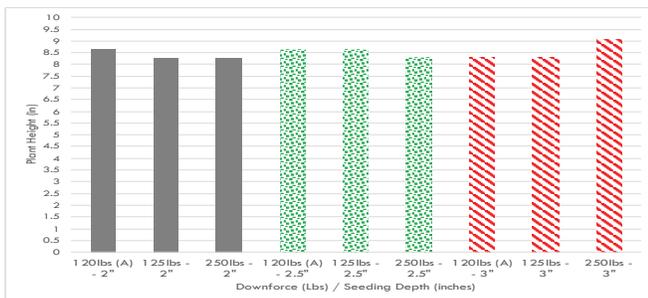
## Observations and Preliminary Results

The three downforce (DF) treatments tested in relation to three seeding depths reached the target depth within +/-0.2 inches of error (figure 9.3). This difference between the target depth and final measured depth could be explained by high soil resistance to penetration and some field topography changes.



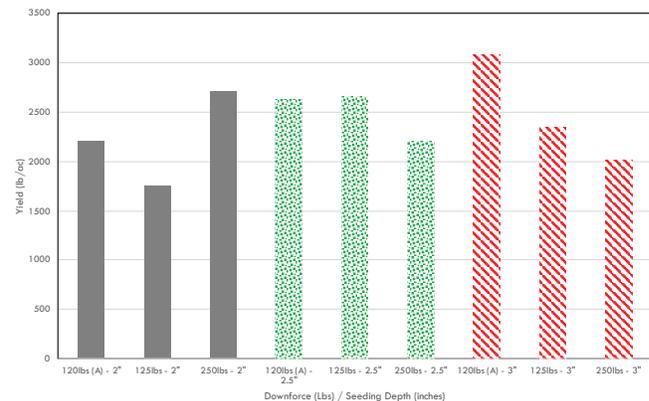
**Figure 9.2.** Peanut seed depth differences for three downforce (DF) treatments (125 and 250 lb manual and 120 lb automatic) with three preset target seeding depths (2, 2.5, and 3 inches).

Peanut plant height for the three target seed depths and three loads is given in figure 8.3. No contrasting differences among all treatments was found suggesting that neither downforce nor seed depth placement influenced plant height at 30 days after planting.



**Figure 9.3.** Peanut plant height 30 days after planting among three downforce (DF) treatments (125 and 250 lb manual and 120 lb automatic) with three preset target seeding depths (2, 2.5, and 3 inches).

Figure 9.4 shows peanut yield results for all combinations of target seed depths and downforce used. A yield reduction was observed as the downforce increased for treatments at 2.5 and 3 inches seed depth. At the 2-inch seed depth, the higher value was found at 250 pounds downforce treatment. The decrease of yield values at 250 pounds downforce treatment as seeds are placed at a deeper soil depth can be associated with obstruction caused by the gauge/closing wheel systems to the seedling emergence. While creating the furrow, the vertical loads increase as seeds are targeted to deeper soil depths, which increases soil density and makes it more difficult for the seedlings to emerge.



**Figure 9.4.** Peanut yield differences for the downforce and seeding depth treatment tested

## Food for Thought

- High soil resistance to penetration may have prevented the active hydraulic downforce system to reach the desired seed depth on both treatments.
- Higher downforces within higher seed depths decreased peanut yield.

**Project team:** Luan Pereira De Oliveira, Kris Balkcom, Brenda V. Ortiz.

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Precision  
Planting—  
Downforce

Soil Sensing

Variable  
Rate  
Seeding

## Evaluation of Precision Planting Technologies for Variable Rate Corn Seeding

### Objective

- Evaluate the agronomic and economic benefits of variable rate seeding and advantages of precision planting technology.

### Project Justification

Seeding is one of the most important and expensive practices. Seed cost increases every year and variability on field conditions do not always allow farmers to receive returns on investment. Precision planting technologies allow farmers to change the seeding rate on the go, plant two varieties at the same time, and control seed depth and seed spacing.

### Planting Details

**Location:** Shorter, AL      **Planting:** 04/15/19

**Crop:** Corn      **Test size:** 20 ac

**Row width:** 36 in      **Seed depth:** 1.5 in

**Hybrid (dryland):** DKC 64-69 VT3P

**Hybrid (irrigated):** DKC 62-08 RIB

### Treatments

**Seeding rate: Dryland**      **Seeding rate: Irrigated**

20,000/ac      32,000/ac

24,000/ac      36,000/ac

28,000/ac      40,000/ac

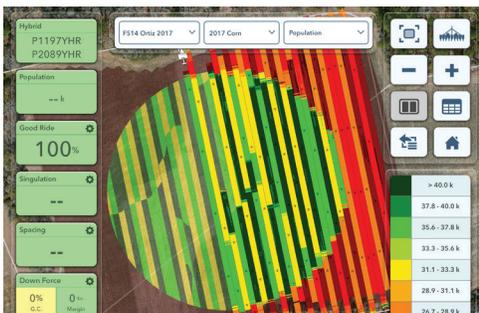
**Management Zones**      **Soil ECa: Shallow**

1: Altavista silt loam      8.1 mS/m

3: Altavista silt loam      6.0 mS/m

4: Compass loamy sand      2.9 mS/m

### Project Design



**Figure 10.1.** Different seeding rates planted across the field. Dryland and irrigated areas were planted with two different hybrids. Irrigated areas had higher seeding rates than dryland areas. Soil electrical conductivity (ECa) was used to delineate the seeding rate.

## Precision Ag Toolbox

### MaxEmergence Plus Planter

(John Deere, Moline, IL, USA)

A John Deere 7200 MaxEmergence 6-row planter can be retrofitted with Precision Planting technologies: DeltaForce system, vSet Select, vDrive, and mSet.



### vSet Select

(Precision Planting, Tremont, IL, USA)

vSet is an accurate seed meter that increases singulation accuracy. Two separate vSet meters (vSet Select) allow on-the-go planting of two hybrids at one time without changing seeds.



### vDrive

(Precision Planting, Tremont, IL, USA)

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

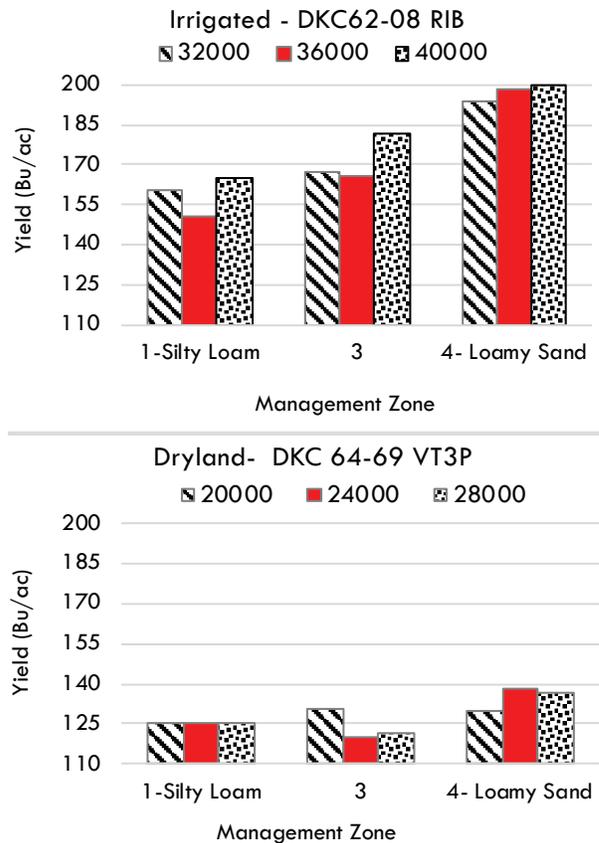


## Observations and Preliminary Results

The 2019 corn growing season at the site started wet at planting (3.8 inches of rainfall above historical average in April), but during the months from June to August, the rainfall was below historical average values.

The irrigated DKC62-08 RIB hybrid outyielded (175 bu/ac) the dryland DKC 64-69 VT3P hybrid (127 bu/ac) irrigated area, resulting in a difference of 46 bu/ac. There were also yield differences between the seeding management zones compared to dryland area. Zone 4 with a loamy sand soil texture had the greatest yield (197 bu/ac) compared to other two zones, specially zone 1 characterized by a silt loam soil texture (158 bu/ac). Although there were not significant yield differences among seeding rates within a zone, results clearly show that areas within a field with different yield potentials should be planted with different seeding rates. In 2017, the same study was conducted on this field and the yield differences between the zone 4 and zone 1 was 71 bu/ac. Based on the results presented for 2019, the 36,000 seed/ac could be a good choice under irrigation and light soil with good soil drainage (zone 4). Under the soil conditions at zone 1, that may present low drainage capabilities, 32,000 seed/ac could be a better option.

Very small to no yield differences were observed between the zones and seeding rates within a zone for the dryland treatment. Greater seeding rates did not result in yield increase. Rainfall below historic average values during the period May to August might have influenced the results. Multi-year seeding rate studies are always recommended.



**Figure 10.2.** Yield results for irrigated (top) and dryland areas (bottom) at seeding rates management zones 1, 3, and 4.

## Food for Thought

- Dryland conditions limited corn yield response and the increment of seeding rate did not promote yield increase.
- Corn yield increased with seeding rate only under high-yield potential environmental conditions (soil with good drainage and irrigation).
- Precision planting technologies could allow farmers to gain agronomic and economic benefits from variable rate seeding and multi-hybrid planting.

**Project team:** Brenda V. Ortiz, Greg Pate, Kris Balkcom

**Project contact:** Brenda V. Ortiz, Extension Specialist and Professor, Crop, Soil, and Environmental Sciences Department, Auburn University (bortiz@auburn.edu)

## Evaluation of Ancillary Data to Support Soil Fertility Sampling Strategies

### Objective

- Evaluate the spatial correlation between soil pH, phosphorus (P), and potassium (K) with apparent soil electrical conductivity (ECa) and satellite multispectral imagery.
- Identification of spatial variables can be used to guide soil fertility sampling.

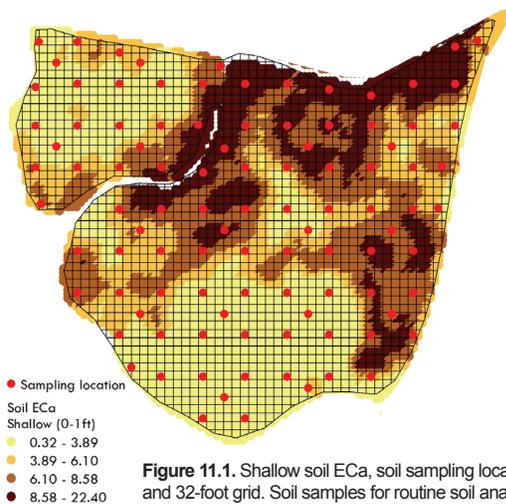
### Project Justification

Grid or zone soil sampling is commonly used to evaluate soil fertility levels before the start of a new crop growing season. However, this practice is expensive, time consuming, and tedious. Soil fertility assessment could be improved if easily or readily available spatial data can be used to identify soil sampling locations.

### Project Details

<b>Location:</b> Samson, AL	<b>Cover crop:</b> Oats
<b>Field size:</b> 40 ac	<b>Previous crop:</b> Corn
<b>Tillage:</b> Conventional	<b>Seeding:</b> 34,000/ac
<b>Predominant soil map unit:</b> Eunola sandy loam	

### Project Design



**Figure 11.1.** Shallow soil ECa, soil sampling locations, and 32-foot grid. Soil samples for routine soil analysis were collected on an 0.6 ac grid. Ordinary kriging interpolation of soil pH, P, and K was conducted at the center of a 32-foot grid to match Landsat 7 and Sentinel-2 satellite imagery. The VERIS 3100 sensor was used to collect shallow (0 to 1 foot) and deep (0 to 3 feet) soil ECa. This data was also interpolated to a 32-foot grid.

## Precision Ag Toolbox

### VERIS 3100 Soil Electrical Conductivity Sensor

(Veris Technologies, Salina, KS, USA)

Mapping within-field variability of soil texture and salinity is possible through the VERIS 3100 sensor. The sensor measures apparent soil electrical conductivity (soil ECa) at the soil depths of 0 to 1 foot (shallow) and 0 to 3 feet (deep).



### Sentinel 2 Satellite

(European Space Agency, Paris, FR)

Satellite that collects optical imagery at high spatial resolution of up to 32-foot pixel size. It provides a revisiting time of 10 days at the equator and 2 to 3 days at mid-latitudes. Its multi-spectral instruments record spectral reflectance on 12 different bands.



### SpaceStats

(BioMedware, Ann Arbor, MI, USA)

Spatial and temporal statistic software used to conduct spatial statistical, geostatistics, analyses. It includes multiple spatial data analyses algorithms.



## Observations and Preliminary Results

This field exhibits a high degree of spatial variability in soil physical properties. The areas with soil ECa above 8.58 mS/m values were characterized by a sandy clay loam soil texture and those with soil ECa values below 3.89 mS/m were mainly composed of a sandy soil texture (figure 11.1).

This field exhibited low temporal variability of K levels among the years evaluated (figure 11.2a and 11.2b). The south portion of the field (sandy soil texture) showed the lowest levels of soil K over 4 years of routine soil fertility analyses (2014, 2017, 2018, and 2019). The opposite occurred with the northern portion of the field, where highest levels of K were observed. This temporal stability supports the idea of potentially using other data layers for possible mapping of soil nutrients or guided soil sampling.

Spatial correlation analyses indicated a strong correlation of soil ECa with soil K and moderate correlation with soil P and pH. Areas with soil ECa below 3.89 mS/m (i.e., sandy soil) had the lowest soil K and highest soil P. From all the spectral bands of Landsat 7, Landsat 8, and Sentinel 2 evaluated, the Shortwave Infrared 2 band of Sentinel 2 and Landsat satellites had the strongest correlation with soil K and P.

**Table 11.1. Pearson Correlation of 2019 Soil Potassium (K), Phosphorus (P), pH, and Ancillary Variables.**

Variable	K	P	pH
ECa (shallow)	0.72	-0.57	0.45
ECa (deep)	0.75	-0.51	0.48
Sentinel 2-B12	-0.68	0.59	-0.23
Landsat 8-B6	-0.68	0.63	-0.10

## Food for Thought

- Data layers such as soil ECa and the Shortwave Infrared 2 band of satellites Sentinel and Landsat could potentially be used to guide soil sampling strategies and soil fertility mapping.
- Prediction of areas with insufficient and sufficient soil K levels was possible by using past soil sampling data and satellite imagery (Shortwave Infrared 2 band) collected in the spring prior to sampling.

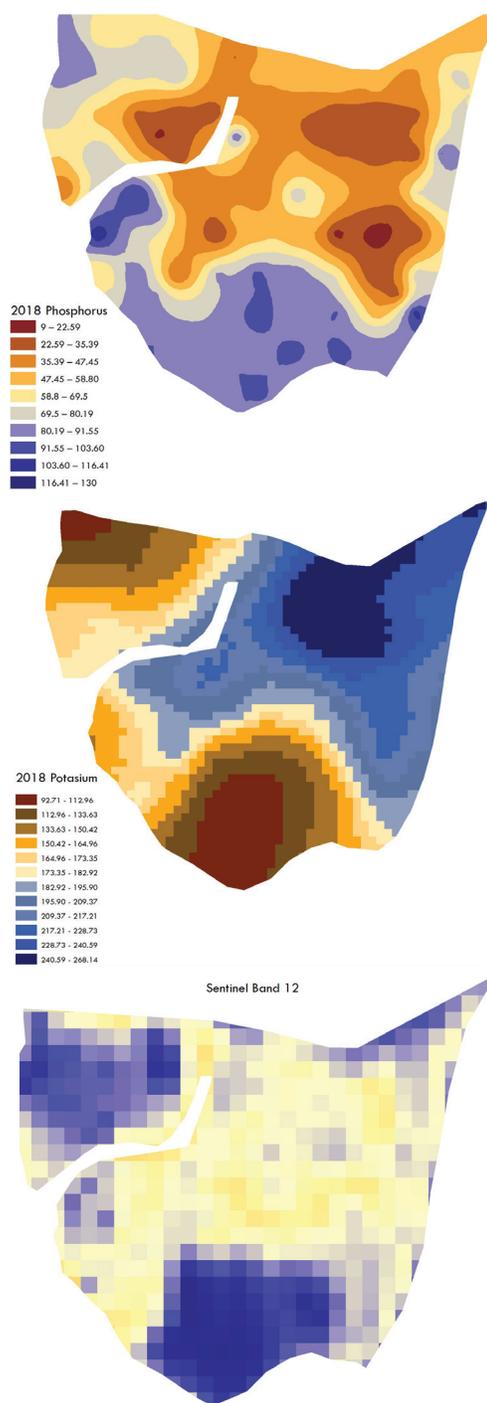


Figure 11.2. Spatial and temporal variability of potassium at 2018 (a) and 2019 (b), and the Shortwave Infrared 2 band of Sentinel 2 satellite

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## Cooperating Farmers and Alabama Agricultural Experiment Station Sites Included



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