Investigating Soil Parameters Effect on Crop Yields and Hydrology at Field Scale in the Southeast US Using the Soil and Water Assessment Tool

by

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Abstract

Over the past forty years, the Apalachicola–Chattahoochee–Flint (ACF) river basin in Alabama, Georgia, and Florida has been the subject of numerous litigation and research regarding water allocation. The state of Georgia's heavy reliance on the ACF's water resources for the city of Atlanta water supply and agricultural production has been a partial cause of this conflict between Alabama, Georgia, and Florida. Regional, watershed, and field-scale models have been employed by researchers to better understand the hydrology of this area; however, few studies exist focusing on proper multi-variable calibration and validation that include plant growth of cotton and peanut, surface runoff, soil moisture, and soil nitrate. Cotton and peanut are primary crops in this region and greatly affect the hydrology. In addition, this area is home to many different types of soils. Soil type and morphology can affect crop yields, but how different soils in Georgia effect crop yields in SWAT has yet to be quantified.

The first objective of this study was to create, calibrate, and validate a field-scale model using the Soil and Water Assessment Tool (SWAT) of fields at a research station in the Lower Flint River Basin. The research station modeled is the Stripling Irrigation Research Park (SIRP) located in Camilla, Georgia and run by the University of Georgia (UGA). UGA provided all management information needed to create the model, including crop type, fertilizer rates, irrigation amounts, planting dates, harvest dates, and crop yields. Three fields were modeled, which grew corn, peanut, and cotton, respectively, after a winter cover crop of Rye and strip-tilling. Each field contained three duplicate plots with 9 different fertilizer/irrigation treatments and had two plots with berms surrounding the plots to isolate overland flow. Plot specific soil nutrients, soil texture, biomass, yields, LAI for cotton, TKN, surface runoff, and composite runoff nutrient samples were obtained for the growing year 2018. Multivariable calibration and

validation for surface runoff, soil moisture, crop biomass, corn and peanut yields, LAI for cotton (yields for cotton were not available), nitrogen uptake by plants, soil nitrate, and nitrate in runoff were conducted in this study. The model performed very good for surface runoff, crop growth, and nitrogen uptake, and fair for soil moisture and nitrate cycling except for soil nitrate in peanuts. Calibration of each variable following runoff gradually improved surface runoff performance. Analysis of nitrogen and water balances over 30 years were also simulated and found nitrate leaching to be very low compared to what is generally expected in this area. However, removing soil moisture and soil nitrate calibration, respectively, resulted in higher leaching values. These results indicate calibrating with fewer variables and higher quality measured data can result in a more properly calibrated model.

The second objective of this study was to use a field scale model to determine the effect of soil types in southwestern Georgia on crop yields and soil moisture. A SWAT model previously calibrated for a cotton-cotton-peanut rotation in Tifton, Georgia was used in this study with 30 years of weather data from NLDAS. 24 different types of soils covering over 98% of Region V Soil-Water Conservation District (SWCD) in the STATSGO map were selected and integrated into the model, with Tifton and Orangeburg covering 46% of the area. Soil properties from SSURGO were matched to the STATSGO soils and used in this study, allowing for the diversity of soils to be accounted for while also using a more detailed soils database. A multiple comparison analysis of the different soils was run with the native SSURGO Tifton soil used as the control. When under UGA Checkbook Irrigation, crop yields had little response to the different Georgia soil types tested in this study excepting for one very sandy soil. Overall yields were lower for all Georgia soils investigated without irrigation, but top 305mm of soil will have a larger response to soil parameterization. Soil moisture for the top layer showed much more variation and all soils were statistically significant compared to the control soil. Soil moisture tended to decrease as available water content decreased, clay content decreased, and hydraulic conductivity increased. Future research into individual soil parameters effect on yields and soil moisture is needed to better understand the relationship between crop yields and soil properties in SWAT.

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ACF	Apalachicola-Chattahoochee-Flint
SWAT	Soil and Water Assessment Tool
FACETS	Floridian Aquifer Collaborative Engagement for Sustainability
UGA	University of Georgia
U.S.	United States
USDA	United States Department of Agriculture
NASS	National Agricultural Statistics Service
UFA	Upper Floridian Aquifer
LRFB	Lower Flint River Basin
NRCS	National Resource Conservation Service
PRMS	Precipitation-runoff Modeling System
FORE-SCE	Forecasting Scenarios of Future Land Cover Model
GCM	Generalized Climate Models
MODFE	MODular Finit-Element model
HRU	Hydraulic Response Units
SSURGO	Soil Survey Geographic Database
SIRP	Stripling Irrigation Research Park
GWN	Georgia Weather Network
CDL	Cropland Data Layer
NLCD	National Land Cover Database

CHAPTER 1: Literature Review

INTRODUCTION

Global warming has thus far had many terrible consequences, including but not limited to more variable weather patterns and severe droughts. As the frequency of droughts increase, high crop production areas are at risk for severe crop losses, which in turn not only causes the farmer to take a serious economic hit, but global agricultural food production would suffer as well. To help compensate for these dry years, agricultural producers often rely on irrigation from local groundwater sources. More than 70% of total water withdrawals globally are used for irrigation and 90% of consumptive water uses (Siebert et al., 2010). In addition, about 40% of groundwater withdrawal in the United States is used for agriculture (Wehr, 2014). Such high levels of pumping have been shown to cause reduction in hydraulic conductivity, aquifer depletion, and land subsidence (Chen et al., 2003; Llamas et al., 2003; Zhu et al., 2015). Thus, it is highly beneficial to investigate the consequences of these weather events as they relate to agriculturally dominated watersheds.

One such area, which has already suffered from increased drought frequency, is the southeastern United States (U.S.). The Apalachicola-Chattahoochee-Flint (ACF) River Basin is an interesting area with respect to droughts because of both the variety of land uses and long history of legislature surrounding the quality and quantity of water in this area. The ACF basin has been a hot topic with water resources since 1989 due to three states' reliance on its freshwater resources: Georgia, Alabama, and Florida (Stevens and Ruscher, 2014). The top of the basin is located in Northern Georgia, where the Chattahoochee River meanders into East Alabama, joins the Flint River in southwestern corner of Georgia to become the Apalachicola River, and final drains through Florida into the Gulf of Mexico. The ACF is nearly 385 miles

(619km) long, 50 miles (80km) wide, and the total drainage area is approximately 19,573 mi2 (50,800 km2) with the greatest portion of the basin located in Georgia. It is home to approximately 24,362 reservoirs, 81% of which are located in Georgia, followed by 11% in Alabama and 8% in Florida. A main cause for the complicated legislature lies with the city of Atlanta, GA that is located at the top of the Chattahoochee River basin. 78% of the ACF system supplies Atlanta's municipal water, and downstream of the river is twelve hydro-electric dams, recreational rivers, irrigation for crops, many habitats for endangered species, and the Apalachicola Bay, home of many estuarine fisheries and hatcheries (Wehr, 2014). In addition, according to the United States Geological Survey, drought years in Georgia outnumber normal and high precipitation years since 1980, meaning Georgia will rely more on this system to help compensate for so many dry years (USGS, 2010). However, over exploitation of the basin's water resources could have highly negative consequences for the Apalachicola Basin. The Apalachicola River is a highly biodiverse area and houses many threatened and endangered species (Ruhl, 2005). Limited water quantity and quality would be damaging to the aquatic life, but especially endangered mussel species in this area. Overall, after thirty-five years of litigations without conclusive decisions, Florida petitioned the Supreme Court to take the case in 2014, arguing to limit Georgia's water use. In October 2017 the Supreme Court decided to create a cap on Georgia's water use during times of drought and the trial was appointed to a special master to determine details (Florida vs Georgia, 2017). Despite the Supreme Court's decision, no actionable changes have been made and the legal battles have no discernable end in sight.

In addition to being the primary water user in the ACF basin, Georgia is also a highly agriculturally productive area. According to the USDA National Agricultural Statistics Service

(NASS), in 2017 Georgia ranked first nationally for broilers, peanuts, and utilized pecans, second for cotton lint and cotton seed, and seventh for sweet corn. Georgia is also a top national producer of fruits and vegetables, ranking third for watermelon; fourth for Bell Peppers, Cantaloupes, and Cucumbers; fifth for Tobacco; sixth for Blueberries, cabbage, eggs, onions, and squash; and finally, seventh for the state fruit – Peaches – and snap beans. There are many factors contributing to this agricultural productivity. First, Georgia has an interesting variety of aquifers, consisting of a surficial aquifer system termed the Biscayne aquifer, an upper confining unit, the upper Floridian aquifer (UFA), a middle confining unit, the lower Floridian aquifer, and a lower confining unit (Torak and Painter, 2006). These aquifers are karstic aquifers, meaning they consist of highly permeable limestone. The upper confining layer consists primarily of clastic rocks with low permeability, mostly from Hawthorn Formation from the Miocene age. Recharge zones for the UFA are throughout the Lower Flint River Basin (LFRB), meaning access to this aquifer for farmers is easier and more cost effective. Thus, the UFA, due to both its size and water availability, is often the source of irrigation from groundwater in this area (Singh et al., 2016).

The second major factor in Georgia's agricultural productivity is the soil and geomorphology of the area. There are hundreds of different types of soil in Georgia, but the National Resource Conservation Service (NRCS) has six major categories: Limestone Valley Soils, Blue Ridge Soils, Southern Piedmont, Sand Hills, Southern Coastal Plain, and Atlantic Coast Flatwoods (2019). Limestone Valley and Blue Ridge Soils are located in the northernmost portion of the state with more loamy, well-drained, fertile lowlands suitable for forage production. The Southern Piedmont contains massive granite features and clayey soils with iron oxides, and the southernmost portions contain nutrient rich soils more suitable for row crops.

Below the Piedmont is the Sand Hills region which, as the name implies, contains largely sandy soils not suitable for plant growth. The large Southern Coastal Plain Region contains a large variety of sandy, red clayey, and gravelly soils. This area was previously an ancient marine coastline during the Mesozoic era, and although the sandier texture and frequent use of these soils for farmland make nutrients less abundant, nutrient management and easy access to the UFA mean this area is primarily used for row crops.

Hydrologic modelling programs are being employed more and more to investigate the impacts of these dangerous weather patterns in agriculture. In 2011, Viger et al. published an article attempting to forecast and better understand the hydrological processes in the Upper Flint River Basin as affected by urbanization and climate change. They used modeling program called Precipitation-Runoff Modeling System (PRMS), which is a physically based, distributed-parameter watershed model. The model was used to produce an 11-year moving average for precipitation, temperature maximum and minimum, evapotranspiration, streamflow, subsurface flow, and groundwater flow through 2050. The PRMS produced results for three configurations: changes in urbanization using a Forecasting Scenarios of Future Land-Cover Model (FORE-SCE), changes in climate using Generalized Climate Models (GCMs), and combined changes in urbanization and climate. Their results showed a general increase in stream flow and surface runoff, slight decrease in groundwater and subsurface flow, and decrease in evapotranspiration (Viger et al., 2011). These results make sense with a predicted reduction in vegetation cover, increase in temperature, precipitation, and impervious surfaces.

Many studies in the Flint River Basin have been conducted with irrigation use as the primary focus. After Georgia attempted to decrease irrigation pumping in 2002 by auctioning off water usage in the Flint River, 33,000 acres were removed from production, which was predicted to increase water savings by 19-24% (Ban et al., 2007). However, despite this effort actual water savings have been overshadowed by irrigation usage in drought years. One study conducted by Mitra et al (2016) compared stream flow and groundwater flux in drought years with and without irrigation in the Lower Flint River Basin. This study found at the time the Upper Floridian Aquifer supplied 80% of irrigation in the area and the remaining irrigation was supplied by streamflow. Cotton, corn, and peanuts are the primary crop in this area, which are highly water consumptive crops. They used the 2011 and 2012 water data (October 2010-September 2012), which was during a two year La Niña drought and MODular Finite-Element model (MODFE) program. This study found both streamflow and groundwater flow were negatively affected by irrigation withdrawal with the combined river-aquifer flux being the primary component effected. Some areas experienced an overall decrease of as much as 9 feet (2 meters). Given this simulation is only for two years and droughts are predicted to increase, such severe irrigation could have serious consequences in the coming years.

Although increased irrigation results in decreased stream and groundwater flow, especially for streams being fed by aquifers, in some watersheds the actual connectivity of these two hydraulic systems are difficult to clarify within a karst watershed. Rugel et al. (2016) conducted an isotopic study on a smaller watershed within the Flint River Basin to attempt to understand the heterogeneity of the watershed. They found 10% of the fifty streams sampled contributed up to 42% of the groundwater along the 50km sampled stretch of river. In addition, only 24% of the rivers entered groundwater dominated tributaries. Some reaches were affected heavily by the 2011 drought and some showed little change in flow (Rugel et al., 2016). This study shows how variable a karstic aquifer can affect a watershed and it also pointed out this sort of variability is often ignored in larger studies.

One common model, which has been adopted around the world and with nearly 4000 published articles to date due to its versatility, capability to handle a variety of watersheds, and great support, is the Soil and Water Assessment Tool (SWAT). SWAT was originally developed by Dr. Jeff Arnold for the USDA Agricultural Research Service to understand the impact of land management practices on water, sediment and agricultural chemical yields on large complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch et al., 2011). SWAT is a physically based model, meaning instead of parameterizing output results with regression relationships, the results are produced based on a wide variety of input data, such as weather, soil, land, vegetation, and land management practices. In this way, highly complex watersheds can be modeled for water, sediment, crop growth, nutrient cycling, and more. It maps a watershed basin, subbasins, and subbasin outlets based on elevation data and streamflow shape files if available. SWAT also has a very high resolution by creating unique categories called Hydraulic Response Units (HRUs). Each HRU has a unique land cover, soil type, and slope. Outputs for the HRUs are calculated and then scaled up to the sub-basin outlet by the percent area of the HRU within the sub-basin. When compared alongside eleven different hydrological models in 2003 by Borah and Berah, SWAT was determined to have high skill and a great potential for expansion. SWAT is also capable of simulating processes in the soil based on a detailed database of soil properties, such as percolation, fixation, conversion of residues into plant available nitrogen and phosphorus, and nutrient losses (Neitsch et al., 2011). However, a warmup period is usually recommended to let all processes equilibrate (Daggupati et al., 2015). Soil properties can be entered manually or imported from a database (Neitsch et al., 2011).

Although SWAT is used primarily to study the hydrology and nutrient cycling of a given study area, integration of the plant growth model Erosion-Productivity Impact Calculator (EPIC) has allowed researchers to also use this program to study the effect of various practices on crop growth and yields (Neitsch et al., 2011). Modelling agricultural activity, such as the crops being grown and management practices, is very important for proper modelling of hydrological processes in agriculturally dominated watersheds because crops can affect soil, nutrients, and surface runoff. SWAT has been used frequently at catchment, watershed, and regional scales at multiple time steps, from sub-daily to yearly. It has been suggested by researchers that soil moisture data should be used to better capture the differences in a regional scale model and satellite measurements have been used since availability of ground data is slim (Uniyal et al., 2017). Also, another study found SWAT can perform better for soluble nitrogen transport at large scales but better for phosphorus transport at smaller scales (Wallace et al., 2018). Thus, interest in using SWAT at the field scale to understand the hydrology and capture the heterogeneity of a watershed has grown. Every farm has its own unique conditions and it is important to be able to simulate field-scale conditions with some confidence. It will also describe the effects of soil chemical and physical properties on crop yields and describe studies using crop and hydrological models to simulate crop yields.

1.2 Field Scale Studies

Depending on the background of a user, the term “field” can mean different things to different people. A study compiling information of many hydrological models at various scales defined a field as a “spatial unit with homogenous characteristics, including soil, topography, cropping system, and management practices” or which is also sometimes referred to as point scale simulations (Arnold et al., 2015). This paper points out that some models have been developed specifically for the purpose of creating field-scale models to understand various environmental and physical processes, such as CREAMS/GLEAMS, DRAINMOD, ADAPT, RZWQM, WEPP Hillslope, and DAISY. Arnold et al. (2015) also mentioned most of these models are point scale models, except for DAISY, and do not consider the area of a watershed or field. As a result, some of these programs are used in conjunction with other models to more appropriately take into account the cycling of a field or watershed. For example, to study the effectiveness of BMP's with controlling surface runoff and pollutant transport, one study compared both ADAPT and SWAT on three fields (Anand et al., 2007). Both models performed similarly by simulating monthly totals well and individual events moderately (Anand et al., 2007).

Since SWAT delineates watersheds based on elevation and then further subdivides by soil and land use, individual fields are sometimes difficult to isolate in the model. A literature review conducted by Karki et al. (2019) identified four methods to properly simulate agricultural fields: individual field SWAT models, modification of input files to create unique HRUs but keeping all properties, post-processing tools, and determining a relationship between model after automatically delineation and the fields in the watershed. All of these methods can be effective depending on the purpose of the model (Karki et al., 2019). For a model to be considered properly calibrated and validated, at least one variable affecting the hydrology must properly fit the observed data then other variables can be calibrated, such as plant growth and nutrient cycling (Daggupati et al., 2015; Moriasi et al., 2015). For watershed or larger scale modeling, usually a stream outlet near a stream gauge can be used for calibration, but smaller areas like individual fields are not always near a stream and thus other variables should be assessed, such as surface runoff, soil moisture, or evapotranspiration (Anand et al., 2007; Chen et al., 2018; Gali et al., 2016; Karki et al., 2019; Maharjan et al., 2018; Wang et al., 2014). Unfortunately, this means observed data can be very difficult to obtain. Many different approaches have been tested to make up for this challenge and one researcher found calibration of multiple variables at the field scale can both increase the confidence of a field-scale model and also improve the prediction of all variables (Karki et al., 2019). In this study, two plots in Tifton, Georgia were calibrated and validated for surface runoff, soil moisture, crop yields, and nitrate leaching. Single HRU method developed by the University of Perdue was used, where during the delineation process each subbasin represents a plot with one slope, soil type, and land use (Karki et al., 2019; Moloney et al., 2015). The scenarios in this study tested different management practices on a cotton-cotton-peanut rotation, and one important conclusion from this study was that proper calibration of crops is a vital aspect of modeling fields well.

Very few other studies exist modeling peanuts. One study conducted by the University of Florida (Dourte et al., 2015) used a SWAT model to estimate irrigation demand for cotton and peanut rotations with the incorporation of sod and conventional rotations over 30 years; however, the model set up, calibration or validation processes used for their study are not clear. The model was assessed for evapotranspiration and crop yields for corn, wheat, and soybeans in a previous study and performed well for both variables in all crops (Dourte et al., 2015; Dourte et al., 2014; Moriasi et al., 2015). Linear regression was used to assess the performance of cotton and peanut yields for this model and the model performed good (R^2 = 0.799) and very good (R^2 = 0.900) for both crops respectively according to the performance measure limits outlined by Moriasi et al. (2015). Two other studies conducted on larger watersheds – 973 hectares – in India tested the effect of fertilizer and tillage practices on corn, peanuts, rice, and soybeans, the predominant crops in the area, on runoff, sediment, nitrate, and phosphate loading (Behera and

Panda, 2006; Tripathi et al., 2005). The model was calibrated for daily surface runoff, sediment yield, nitrate, and phosphate. No plant growth variables were calibrated or validated for this model. Two years of data were available, so the model was calibrated with one year and validated for another year. Even though the models were run at a daily time step they performed very good for all four variables in both calibration and validation. These studies found mould bourd plough and conservation tillage increased yields no matter the fertilizer treatments, and the fertilizer treatments had little effect on yields. In addition, the lowest nitrate loss was found with conservation tillage no matter the fertilization treatment. Phosphorus losses in surface runoff also decreased under conservation tillage but losses increased as fertilizer treatments increased.

On the other hand, apart from the aforementioned studies, more field-scale studies on cotton have been conducted in the Midwestern United States. Over pumping of the Ogallala aquifer has caused investigation into different irrigation strategies with cotton rotations in both Texas and Oklahoma (Chen et al., 2018, 2019; Chen et al., 2017, 2019; Maharjan et al., 2018; Marek et al., 2016, 2017). One study in particular in Bushland, Texas calibrated two fields for LAI and ET for cotton and forage corn (Marek et al., 2016). After calibration, SWAT was able to predict monthly ET very well but only good for LAI, which was attributed to SWAT's faulty plant growth algorithms (Marek et al., 2016). The model in Bushland, Texas was later used in a site comparing crop rotations water-saving capabilities using 90 years of historical weather data (Marek et al., 2017). Three other studies assessing the auto irrigation and later improvement of the auto irrigation function in SWAT, which is triggered when plant or soil water deficit reaches a certain limit similar to soil moisture triggered irrigation (Karki et al., 2019), used evapotranspiration, LAI, and yield to calibrate their model for cotton, soybean, sorghum, forage corn, and sunflower (Chen et al., 2018; Chen et al., 2017, 2018). They found for their model simulated cotton and forage corn LAI and yields very well which was attributed to detailed management inputs (Chen et al., 2018; Chen et al., 2017). When auto-irrigation was used, yields and ET performed much worse except when integrating an external irrigation scheduling program (Chen et al., 2018; Chen et al., 2017). Multiple sites were later integrated into this study with primary concentration on forage corn for the crop of interest (Chen et al., 2019; Chen et al., 2019). SWAT predicted corn biomass and LAI very good for a site in Bushland Texas, Etter Texas, and Greeley, Colorado (Chen et al., 2019).

1.3. Soil Properties effect on Crop Yields

Soil physical and chemical properties can have a major effect on both the hydrology and vegetative growth of an area. The latter has been the subject of much study in the southeast as nitrogen and phosphorus are very important macronutrients for row crops. Nitrogen is available to plants in two forms – ammonium and nitrate. The charged nature of these molecules means there are many ways for nitrogen to be lost to a system. Ammonium can undergo denitrification under aqueous conditions, and both forms of nitrogen can be lost by runoff and leaching, especially in sandier soils with less organic matter to hold the nutrients. Phosphorus can be lost in similar manners; however, the phosphorus cycle does not have an atmospheric component, meaning phosphorus buildup is also a concern in many soils. In addition, in order for nitrogen to become plant available from organic substances, there also needs to be enough active carbon in the system to help promote decomposition. One study using nonlinear parametric modelling technique found for wheat and spring barley Phosphorus and total carbon were some of the greatest contributing factors to crop yields and NDVI in Bedfordshire UK (Whetton et al., 2017). Another study in Denmark found after testing a wide range of soils on winter wheat and spring barley that organic carbon levels above 1% may sustain yields (Oelofse et al., 2015).

Soils' ability to hold water against gravity, or field capacity, is also a consideration in row crops. When so little water is in the soil that the overlying vegetation begins to experience water stress and wilts, a given soil has reached the wilting point. The amount of water available to plants, or field capacity minus the wilting point, is referred to as the available water content. Soil texture can play a large role in soils ability to retain water. Higher silt and clay content, due to the decrease of macropores, results in a higher available water content (Brady and Weil, 2008; Hoegenauer, 2014; van Lanen et al., 1992). However, too high of a clay content can result in water restrictive layers and stunting of root growth. The opposite is true for sandier soils. Fine and sandier soils tend to have much higher hydraulic conductivity, meaning water flows through sandier soils much faster than clayey soils. So although sandy soils have more macropores, can hold more air, and thus provide more underground oxygen exchange, these soils need much more irrigation because water is so quickly lost in the system (van Lanen et al., 1992). Many different management practices have been tested and utilized by growers to increase soil fertility and decrease loss of nutrients and water. Some studies have found when corn is tilled and rotated with a legume, it experienced increased yields and soil fertility (Agber et al., 2018). Other studies have found integration of conservation tillage and cover crops in the southeast can increase soil organic carbon, soil structure, and ultimately yields (Hoegenauer, 2014; Reaves and Delaney, 2002). Cover crops in particular can be beneficial to cash crops by protecting the soil from erosion, sequestering nutrients, reduce fertilizer applications, conserving soil moisture, and increasing soil carbon (Reaves and Delaney, 2002; SARE, 2007, 2019). One study testing a sod-based rotation system and different types of tillage practices found in the Southeastern US found cotton yields were not affected negatively or positively by conservation practices but peanut yields significantly improved with strip tillage (Hoegenauer, 2014).

Because field experiments are time consumptive and costly, researchers have employed modelling programs at regional, watershed, and field scales to better understand the hydrology, soil, and plant growth of a system. Modeling agricultural activity, such as the crops being grown and management practices, is very important for proper modeling of hydrological processes in agriculturally dominated watersheds because crops can affect soil, nutrients, surface runoff, and evapotranspiration (Christopher et al., 2015; Maski et al., 2010; Neitsch et al., 2011). One such study used Aquacrop, a crop water productivity model, to assess maize, wheat, and quinoa at three different sites in three different countries (Van Gaelen et al., 2015). They found after calibration using a semi-quantitative approach, integration of soil fertility and water stress was very important in predicting crop yields (Van Gaelen et al., 2015). Another study conducted in North China Plain using the field-scale model daisy found increasing the detail of soil and weather data improved crop yield prediction, but also greatly improved regional drainage and leaching prediction (Manevski et al., 2019). Similarly, the Environmental Policy Impact Calculator (EPIC) was used by Wang et al. (2018) to investigate phosphorus losses in a corn-soybean rotation. They found EPIC performed well for surface runoff, drainage, and crop yields, but only adequately for Phosphorus due to limitations in simulating soil processes (Z. Wang et al., 2018). Other researchers have found remote sensing, modelling, and machine learning to be effective ways to determine crop yields at various scales (Leroux et al., 2019; Srinivasan, R.; Zhang, X.; Arnold, 2010).

1.4. Statement of Purpose

In a 2016 review of SWAT papers, the number one most outstanding issue with SWAT studies was an improperly built model (Abbaspour et al., 2017). Also, there is a clear lack of studies conducted focusing on proper crop calibration and validation studies in SWAT. There are even fewer studies conducted focusing on proper modeling of cotton and peanuts. Given the importance of these crops in the Southeast and around the world, proper methods for calibrating cotton and peanuts is critical for a successful model. In addition, the soil is very important in both the hydrology and proper simulation of crop yields, and more research into the relationship between soil and crops needs to be investigated. With Georgia being of such agricultural importance, understanding how Georgia soils impact crop yields and soil moisture in SWAT would be very valuable for farmers and researchers to better understand the role soil plays in the ACF river basin.

Thus, the objectives of this research were to:

- Create a field-scale model of a research site in the Lower Flint River Basin, Stripling Irrigation Research Park, GA, which accurately represented the soil, crops grown, and management practices of the area.
- Conduct a multivariable calibration and validation of the model including not just the hydrology but also the crop growth and nutrient cycling of the field with a heavy focus on measures assessing crop growth and cycling, such as biomass, LAI, yield, and nitrogen uptake.
- Run scenarios with the calibrated and validated model and assess the impact of different management practices on recharge and leaching into the shallow aquifer for these plots.
- Use a calibrated and validated field-scale SWAT model to assess the long-term impacts of different soil types in Georgia on crop yields and surface soil moisture.

REFERENCES

Abbaspour, K.C. (2015). SWAT-CUP: SWAT Calibration and Uncertainty Programs- A User Manual,Department of Systems Analysis,Intergrated Assessment and Modelling (SIAM),EAWAG. Swiss Federal Institute of Aqualtic Science and Technology,Duebendorf,Switzerland. *User Manual*, 100p. https://doi.org/10.1007/s00402-009-1032-4

Abbaspour, Karim C., Vaghefi, S. A., Srinivasan, R. (2017). A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 international SWAT conference. *Water (Switzerland)*, *10*(1). https://doi.org/10.3390/w10010006

Agber, P., T., G., S., A. (2018). Soil Properties and Rainfed Maize Yield as Influenced by Tillage Practices Integrated With Soil Conservation Practices in Makurdi , Nigeria. *Sumerianz Journal of Agriculture and Veterinary*, *1*(2), 48–53.

Anand, S., Mankin, K. R., McVay, K. A., Janssen, K. A., Barnes, P. L., Pierzynski, G. M. (2007). Calibration and validation of ADAPT and SWAT for field-scale runoff prediction. *Journal of the American Water Resources Association*, *43*(4), 899–910. https://doi.org/10.1111/j.1752-1688.2007.00061.x

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., Neitsch, S. L. (2012). *Soil and Water Assessment Tool (SWAT) User's Manual, Version 2012*. https://doi.org/10.1007/978-0-387-35973-1_1231

Arnold, J. G., Youssef, M. A., Yen, H., White, M. J., Sheshukov, A. Y., Sadeghi, A. M., … Gowda, P. H. (2015). Hydrological Processes and Model Representation: Impact of Soft

Data on Calibration. *Transactions of the ASABE*, *58*(6), 1637–1660. https://doi.org/10.13031/trans.58.10726

Arundel, S. T., Archuleta, C.-A. M., Phillips, L. A., Roche, B. L., Constance, E. W. (2015). 1-Meter Digital Elevation Model specification. *Techniques and Methods*, 36. https://doi.org/10.3133/tm11B7

Ban, S., Irfan, Y., Lewell, F., Michael, E. (2007). Forecasting Irrigation Water Demand : A Case Study on the Flint River Basin in Georgia.

Behera, S., Panda, R. K. (2006). Evaluation of management alternatives for an agricultural watershed in a sub-humid subtropical region using a physical process based model. *Agriculture, Ecosystems and Environment*, *113*, 62–72. https://doi.org/10.1016/j.agee.2005.08.032

Boryan, C., Yang, Z., Mueller, R., Craig, M. (2011). Monitoring US agriculture: The US department of agriculture, national agricultural statistics service, cropland data layer program. *Geocarto International*, *26*(5), 341–358. https://doi.org/10.1080/10106049.2011.562309

Brady, N., Weil, R. (2008). *The Nature and Properties of Soils*. (V. Anthony & K. Happell, Eds.) (14th ed.). Upper Saddle River: Pearson Prentice Hall.

Chen, C., Pei, S., Jiao, J. J. (2003). Land subsidence caused by groundwater exploitation in Suzhou City, China. *Hydrogeology Journal*, *11*(2), 275–287. https://doi.org/10.1007/s10040-002-0225-5

Chen, Y, Marek, G. W., Marek, T. H., Brauer, D. K., Srinivasan, R. (2018). Improving SWAT auto-irrigation functions for simulating agricultural irrigation management using long-term lysimeter fi eld data. *Environmental Modelling and Software*, *99*(January), 25–38. https://doi.org/10.1016/j.envsoft.2017.09.013

Chen, Y, Marek, G. W., Marek, T. H., Gowda, P. H., Xue, Q., Moorhead, J. E., … He, K. R. (2019). Multisite evaluation of an improved SWAT irrigation scheduling algorithm for corn (Zea mays L .) production in the U . S . Southern Great Plains. *Environmental Modelling & Software*, *118*(April), 23–34. https://doi.org/10.1016/j.envsoft.2019.04.001

Chen, Yong, Marek, G. W., Marek, T. H., Brauer, D. K., Srinivasan, R. (2017). Assessing the efficacy of the SWAT auto-irrigation function to simulate irrigation, evapotranspiration, and crop response to management strategies of the texas high plains. *Water (Switzerland)*, *9*(7). https://doi.org/10.3390/w9070509

Chen, Yong, Marek, G. W., Marek, T. H., Moorhead, J. E., Heflin, K. R., Brauer, D. K., … Srinivasan, R. (2018). Assessment of Alternative Agricultural Land Use Options for Extending the Availability of the Ogallala Aquifer in the Northern High Plains of Texas. *Hydrology*, *53*(5), 2–16. https://doi.org/10.3390/hydrology5040053

Chen, Yong, Marek, G. W., Marek, T. H., Xue, Q., Brauer, D. K., Srinivasan, R. (2019). Assessing Soil and Water Assessment Tool Plant Stress Algorithms Using Full and Deficit Irrigation Treatments. *Agronomy Journal*, *111*(3), 1266–1280. https://doi.org/10.2134/agronj2018.09.0556

Christopher, S. F., Schoenholtz, S. H., Nettles, J. E. (2015). Water quantity implications of regional-scale switchgrass production in the southeastern U.S. *Biomass and Bioenergy*, *83*, 50–59. https://doi.org/10.1016/j.biombioe.2015.08.012

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K. R., Zeckoski, R. W., Jeong, J., … Youssef, M. A. (2015). A recommended calibration and validation strategy for hydrologic and water quality models. *Transactions of the ASABE*, *58*(6), 1705–1719. https://doi.org/10.13031/trans.58.10712

Dourte, D., Bartel, R. L., George, S., Marois, J. J., Wright, D. L. (2015). A sod-based cropping system for irrigation reductions, *31*(6), 14–17. https://doi.org/10.1017/S1742170515000393

Dourte, D. R., Fraisse, C. W., Uryasev, O. (2014). WaterFootprint on AgroClimate: A dynamic, web-based tool for comparing agricultural systems. *Agricultural Systems*, *125*, 33–41. https://doi.org/10.1016/j.agsy.2013.11.006

Gali, R. K., Cryer, S. A., Poletika, N. N., Dande, P. K. (2016). Modeling pesticide runoff from small watersheds through field-scale management practices: Minnesota watershed case study with chlorpyrifos. *Air, Soil and Water Research*, *9*, 113–122. https://doi.org/10.4137/ASWR.S32777

Hoegenauer, K. L. (2014). *Conservation System Impacts on Soil Properties and Water-Use Efficiency in the Southeastern U.S. Coastal Plain*.

Karki, R., Srivastava, P., Kalin, L., Lamba, J., Bosch, D. D. (2019). Multi-variable sensitivity analysis, calibration, and validation of a field-scale SWAT model: Building Stakeholder Trust in Hydrologic/Water Quality Modeling. *ASABE Annual International Meeting*, (Presentation), 1–21.

Leroux, L., Castets, M., Baron, C., Escorihuela, M. J., Bégué, A., Lo Seen, D. (2019). Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. *European Journal of Agronomy*, *108*(July 2018), 11–26.

https://doi.org/10.1016/j.eja.2019.04.007

Llamas, R., Custodio, E., Lopez-Geta, J. A., de la Orden, J. A. (2003). *Intensive use of groundwater: challenges and opportunities*.

Maharjan, G. R., Prescher, A. K., Nendel, C., Ewert, F., Mboh, C. M., Gaiser, T., … Jiao, J. J. (2018). Approaches to model the impact of tillage implements on soil physical and nutrient properties in different agro-ecosystem models. *Soil and Tillage Research*, *180*(August 2017), 210–221. https://doi.org/10.1016/j.still.2018.03.009

Manevski, K., Børgesen, C. D., Li, X., Andersen, M. N., Zhang, X., Shen, Y., Hu, C. (2019). Modelling agro-environmental variables under data availability limitations and scenario managements in an alluvial region of the North China Plain. *Environmental Modelling and Software*, *111*(October 2018), 94–107. https://doi.org/10.1016/j.envsoft.2018.10.001

Marek, G. W., Gowda, P. H., Evett, S. R., Baumhardt, R. L., Brauer, D. K., Howell, T. A., … Point, I. (2016). Calibration and Validation of the SWAT Model for Predicting Daily ET over Irrigated Crops in the Texas High Plains Using Lysimetric Data. *Transactions of the ASABE*, *59*(2), 611–622. https://doi.org/10.13031/trans.59.10926

Marek, G. W., Gowda, P. H., Marek, T. H., Porter, D. O., Baumhardt, R. L., Brauer, D. K. (2017). Modeling long - term water use of irrigated cropping rotations in the Texas High Plains using SWAT. *Irrigation Science*, *35*(2), 111–123. https://doi.org/10.1007/s00271-016-0524-6

Maski, D., Mankin, K. R. D., Janssen, K. A., Tuppad, P., Pierzynski, G. M. (2010). MODELING NUTRIENT RUNOFF YIELDS FROM COMBINED IN-FIELD CROP MANAGEMENT PRACTICES USING SWAT, *53*(5), 1557–1568.

Migliaccio, K. W., Morgan, K. T., Vellidis, G., Zotarelli, L., Fraisse, C., Zurweller, B. A., … Rowland, D. (2015). Smartphone apps for irrigation scheduling. *Joint ASABE/IA Irrigation Symposium 2015: Emerging Technologies for Sustainable Irrigation*, *59*(1), 516–530. https://doi.org/10.13031/trans.59.11158

Moloney, C., Raj, C., Frankenberger, J., Chaubey, I. (2015). Using a Single HRU SWAT Model to Examine and Improve Representation of Field-Scale Processes. In *2015 Purdue SWAT Conference Material* (Vol. Session C3).

Moriasi, D. N., Gitau, M. W., Pai, N., Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R. (2011). Theoretical documentation SWAT.

Oelofse, M., Markussen, B., Knudsen, L., Schelde, K., Olesen, J. E., Stoumann, L., Bruun, S. (2015). Do soil organic carbon levels affect potential yields and nitrogen use efficiency ? An analysis of winter wheat and spring barley field trials. *European Journal of Agronomy*, *66*, 62–73. https://doi.org/10.1016/j.eja.2015.02.009

Reaves, D. W., Delaney, D. P. (2002). CONSERVATION ROTATIONS FOR COTTON PRODUCTION AND CARBON STORAGE. In *25TH SOUTHERN CONSERVATION TILLAGE CONFERENCE* (pp. 344–348).

Rugel, K., Golladay, S. W., Jackson, C. R., Rasmussen, T. C. (2016). Delineating groundwater/surface water interaction in a karst watershed: Lower Flint River Basin, southwestern Georgia, USA. *Journal of Hydrology: Regional Studies*, *5*, 1–19.

https://doi.org/10.1016/j.ejrh.2015.11.011

Ruhl, J. B. (2005). Water Wars, Eastern Style: Divvying Up the Apalachicola-Chattahoochee-Flint River Basin. *Journal of Contemporary Water Research & Education*, *131*(131), 47–54. https://doi.org/10.1111/j.1936-704x.2005.mp131001008.x

SARE. (2007). *Managing Cover Crops Profitably*. (A. Clark, Ed.) (3rd ed.). University of Maryland: Sustainable Agriculture Research and Education (SARE) Program.

SARE. (2019). Crop Rotation with Cover Crops. Retrieved April 4, 2019, from https://www.sare.org/Learning-Center/Books/Managing-Cover-Crops-Profitably-3rd-Edition/Text-Version/Crop-Rotation-with-Cover-Crops

Siebert, S., Burke, J., Faures, J. M., Frenken, K., Hoogeveen, J., Döll, P., Portmann, F. T. (2010). Groundwater use for irrigation - A global inventory. *Hydrology and Earth System Sciences*, *14*(10), 1863–1880. https://doi.org/10.5194/hess-14-1863-2010

Singh, S., Srivastava, P., Mitra, S., Abebe, A. (2016). Journal of Hydrology : Regional Studies Climate variability and irrigation impacts on streamflows in a Karst watershed — A systematic evaluation. *Biochemical Pharmacology*, *8*, 274–286. https://doi.org/10.1016/j.ejrh.2016.07.001

Soil Survey Staff. (2012). SSURGO Data Packaging and Use November 2012, (November).

Srinivasan, R.; Zhang, X.; Arnold, J. (2010). SWAT UNGAUGED: HYDROLOGICAL BUDGET AND CROP YIELD PREDICTIONS IN THE UPPER MISSISSIPPI RIVER BASIN. *Transactions Of The Asabe*, *53*(5), 1533–1546.

Stevens, K. A., Ruscher, P. H. (2014). Large scale climate oscillations and mesoscale surface meteorological variability in the Apalachicola-Chattahoochee-Flint River Basin. *Journal of Hydrology*, *517*, 700–714. https://doi.org/10.1016/j.jhydrol.2014.06.002

Teshager, A. D., Gassman, P. W., Secchi, S., Schoof, J. T., Misgna, G. (2016). Modeling Agricultural Watersheds with the Soil and Water Assessment Tool (SWAT): Calibration and Validation with a Novel Procedure for Spatially Explicit HRUs. *Environmental Management*, *57*(4), 894–911. https://doi.org/10.1007/s00267-015-0636-4

Torak, L. J., Painter, J. A. (2006). Geohydrology of the Lower Apalachicola– Chattahoochee–Flint River Basin, Southwestern Georgia, Northwestern Florida, and Southeastern Alabama Scientific Investigations Report 2006-5070. Retrieved from https://pubs.usgs.gov/sir/2006/5070/pdf/sir06-5070.pdf

Tripathi, M. P., Panda, R. K., Raghuwanshi, N. S. (2005). Development of effective management plan for critical subwatersheds using SWAT model. *Hydrological Processes*, *19*(3), 809–826. https://doi.org/10.1002/hyp.5618

Uniyal, B., Dietrich, J., Vasilakos, C., Tzoraki, O. (2017). Evaluation of SWAT simulated soil moisture at catchment scale by field measurements and Landsat derived indices. *Agricultural Water Management*, *193*, 55–70. https://doi.org/10.1016/j.agwat.2017.08.002

Van Gaelen, H., Tsegay, A., Delbecque, N., Shrestha, N., Garcia, M., Fajardo, H., … Raes, D. (2015). A semi-quantitative approach for modelling crop response to soil fertility: Evaluation of the AquaCrop procedure. *Journal of Agricultural Science*, *153*(7), 1218–1233. https://doi.org/10.1017/S0021859614000872

van Genuchten, M. T. (1980). Closed-Form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. *Soil Science Society of America Journal*.

https://doi.org/10.2136/sssaj1980.03615995004400050002x

van Genuchten, M. T., Leji, F. J., Yates, S. R. (1991). *The RETC Cod for Quantifying the Hydraulic Functions of Unsaturated Soils*. Riverside.

van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., Srinivasan, R. (2006). A global sensitivity analysis tool for the parameters of multi-variable catchment models. *Journal of Hydrology*, *324*(1–4), 10–23. https://doi.org/10.1016/j.jhydrol.2005.09.008

van Lanen, H. A. J., Reinds, G. J., Boersma, O. H., Bouma, J. (1992). Impact of soil management systems on soil structure and physical properties in a clay loam soil, and the simulated effects on water deficits, soil aeration and workability. *Soil and Tillage Research*, *23*(3), 203–220. https://doi.org/10.1016/0167-1987(92)90101-G

Vellidis, G., Liakos, V., Perry, C., Porter, W. M., Tucker, M. A. (2016). Irrigation Scheduling for Cotton Using Soil Moisture Sensors, Smartphone Apps, and Traditional Methods, 772–780. Retrieved from http://vellidis.org/wp-content/uploads/2016/07/Vellidis-Beltwide-Paper-16779-Irrigation-Scheduling.pdf

Vellidis, G., Liakos, V., Porter, W., Tucker, M., Liang, X. (2016). A Dynamic Variable Rate Irrigation Control System. *Proceedings of the 13th International Conference on Precision Agriculture*, 1–9.

Viger, R. J., Hay, L. E., Markstrom, S. L., Jones, J. W., Buell, G. R. (2011). Hydrologic effects of urbanization and climate change on the flint river basin, Georgia. *Earth Interactions*, *15*(20), 1–25. https://doi.org/10.1175/2010EI369.1

Wallace, C. W., Flanagan, D. C., Engel, B. A. (2018). Evaluating the effects ofwatershed size on

SWAT calibration. *Water (Switzerland)*, *10*(7), 1–27. https://doi.org/10.3390/w10070898

Wang, G., Barber, M. E., Chen, S., Wu, J. Q. (2014). SWAT modeling with uncertainty and cluster analyses of tillage impacts on hydrological processes, 225–238. https://doi.org/10.1007/s00477-013-0743-9

Wang, X., Melesse, A. M. (2007). Effects of Statsgo and Ssurgo As Inputs on Swat Model'S Snowmelt Simulation1. *JAWRA Journal of the American Water Resources Association*, *42*(5), 1217–1236. https://doi.org/10.1111/j.1752-1688.2006.tb05296.x

Wang, Z., Zhang, T. Q., Tan, C. S., Taylor, R. A. J., Wang, X., Qi, Z. M., Welacky, T. (2018). Simulating crop yield, surface runoff, tile drainage and phosphorus loss in a clay loam soil of the Lake Erie region using EPIC. *Agricultural Water Management*, *204*(April), 212–221. https://doi.org/10.1016/j.agwat.2018.04.021

Wehr, J. (2014). THE CANARY IN THE COAL MINE: THE APALACHICOLA-CHATTAHOOCHEE-FLINT RIVER BASIN DISPUTE AND THE NEED FOR COMPREHENSIVE INTERSTATE WATER ALLOCATION REFORM. *Alabama Law Review*, *66*(1), 203–219.

Whetton, R., Zhao, Y., Shaddad, S., Mouazen, A. M. (2017). Nonlinear parametric modelling to study how soil properties affect crop yields and NDVI. *Computers and Electronics in Agriculture*, *138*, 127–136. https://doi.org/10.1016/j.compag.2017.04.016

Zhu, L., Gong, H., Li, X., Wang, R., Chen, B., Dai, Z., Teatini, P. (2015). Land subsidence due to groundwater withdrawal in the northern Beijing plain, China. *Engineering Geology*, (193), 243–255.

CHAPTER 2: Challenges with Integration of short-term Soil and Crop Observations in Multi-variable Calibration of SWAT Model at the Field-Scale

ABSTRACT

Over the past forty years, the Apalachicola–Chattahoochee–Flint (ACF) river basin in Alabama, Georgia, and Florida has been the subject of numerous litigation and research regarding water allocation. The state of Georgia's heavy reliance on the ACF's water resources for the city of Atlanta water supply and agricultural production has been a partial cause of this conflict between Alabama, Georgia, and Florida. Regional, watershed, and field-scale models have been employed by researchers to better understand the hydrology of this area; however, few studies exist focusing on proper multi-variable calibration and validation that include plant growth of cotton and peanut, surface runoff, soil moisture, and soil nitrate. Cotton and peanut are primary crops in this region and greatly affect the hydrology. The first objective of this study was to create, calibrate, and validate a field-scale model using the Soil and Water Assessment Tool (SWAT) of fields at a research station in the Lower Flint River Basin. The research station modeled is the Stripling Irrigation Research Park (SIRP) located in Camilla, Georgia and run by the University of Georgia (UGA). UGA provided all management information needed to create the model, including crop type, fertilizer rates, irrigation amounts, planting dates, harvest dates, and crop yields. Three fields were modeled, which grew corn, peanut, and cotton, respectively, after a winter cover crop of Rye and strip-tilling. Each field contained three duplicate plots with 9 different fertilizer/irrigation treatments and had two plots with berms surrounding the plots to isolate overland flow. Plot specific soil nutrients, soil texture, biomass, yields, LAI for cotton, TKN, surface runoff, and composite runoff nutrient samples were obtained for the growing year 2018. Multivariable calibration and validation for surface runoff, soil moisture, crop biomass,

corn and peanut yields, LAI for cotton (yields for cotton were not available), nitrogen uptake by plants, soil nitrate, and nitrate in runoff were conducted in this study. The model performed very good for surface runoff, crop growth, and nitrogen uptake, and fair for soil moisture and nitrate cycling except for soil nitrate in peanuts. Calibration of each variable following runoff gradually improved surface runoff performance. Analysis of nitrogen and water balances over 30 years were also simulated and found nitrate leaching to be very low compared to what is generally expected in this area. However, removing soil moisture and soil nitrate calibration, respectively, resulted in higher leaching values. These results indicate calibrating with fewer variables and higher quality measured data can result in a more properly calibrated model.

INTRODUCTION

Climate resiliency is a growing concern around the world, but especially in agriculture and water resources (Maharjan et al., 2018; Mishra et al., 2017). As the frequency of droughts increase, high crop production areas are at risk for severe crop losses, which in turn not only causes the farmer to take a serious economic hit, but global agricultural food production would suffer as well. To help compensate for these dry years, agricultural producers often rely on irrigation from local groundwater sources. More than 70% of total water withdrawals globally are used for irrigation and 90% of consumptive water uses (Siebert, 2010). In addition, about 40% of groundwater withdrawal in the United States is used for agriculture (Wehr, 2014). Such high levels of pumping have been shown to cause reductions in hydraulic conductivity, aquifer depletion, and land subsidence (Chen et al, 2003; Lopez-Geta & Orden, 2003; Zhu et al, 2015). Thus, it is highly beneficial to investigate the role of agriculture in sustainability with whatever tools at our disposal.

Hydrologic modeling programs are being employed more and more to investigate the impacts of variable weather patterns in agriculture. One common model, which has been adopted around the world and with nearly 4000 published articles to-date due to its versatility, the capability to handle a variety of watersheds, and great support, is the Soil and Water Assessment Tool (SWAT). Although SWAT is used primarily to study the hydrology and nutrient cycling of a given study area, integration of the plant growth model Environmental Policy Impact Calculator (EPIC) has allowed researchers to also use this program to study the effect of various management practices on crop growth and yields (Neitsch et al., 2011). Modeling agricultural activity, such as the crops being grown and management practices, is very important for proper modeling of hydrological processes in agriculturally dominated watersheds because crops can affect soil, nutrients, surface runoff, and evapotranspiration (Christopher et al., 2015; Maski et al., 2010; Neitsch et al., 2011).

SWAT has been used frequently at catchment, watershed, and regional scales, but one study in the Flint River Basin pointed out regional studies frequently neglect to capture the heterogeneity of an area (Rugel et al., 2016). In this study, Rugel et al. (2016) found that, because the LFRB is a karstic system, groundwater and stream water can interact in unpredictable ways in the given watershed and are not captured at larger scales. It has also been suggested by other researchers that soil moisture data should be used to better capture the differences in a regional scale models and satellite measurements have been used since availability of ground data is slim (Uniyal et al., 2017). Another study found SWAT can perform better for soluble nitrogen transport at large scales but better for phosphorus transport at smaller scales (Wallace et al., 2018). Thus, interest in using SWAT at the field scale to understand the hydrology and capture the heterogeneity of a watershed has grown. Every farm has its own unique conditions and it is important to be able to simulate field-scale conditions with some confidence.

Depending on the background of a user, the term "field" can mean different things to different people. A study compiling information of many hydrological models at various scales defined a field as a "spatial unit with homogenous characteristics, including soil, topography, cropping system, and management practices" or which is also sometimes referred to as point scale simulations (Arnold et al., 2015). This paper points out that some models have been developed specifically for the purpose of creating field-scale models to understand various environmental and physical processes, such as CREAMS/GLEAMS, DRAINMOD, ADAPT, RZWQM, WEPP Hillslope, and DAISY. Arnold et al. (2015) also mentioned most of these models are point scale models, except for DAISY, and do not consider the area of a watershed or field. As a result, some of these programs are used in conjunction with other models to more appropriately take into account the cycling of a field or watershed. For example, to study the effectiveness of BMP's with controlling surface runoff and pollutant transport, one study compared both ADAPT and SWAT on three fields (Anand et al., 2007). Both models performed similarly by simulating monthly totals well and individual events moderately (Anand et al., 2007).

Since SWAT delineates watersheds based on elevation and then further subdivides by soil and land use, individual fields are sometimes difficult to isolate in the model. A literature review conducted by Karki et al. (2019) identified four methods to properly simulate agricultural fields: individual field SWAT models, modification of input files to create unique HRUs but keeping all properties, post-processing tools, and determining a relationship between model after automatically delineation and the fields in the watershed. All of these methods can be effective depending on the purpose of the model (Karki et al., 2019). For a model to be considered properly calibrated and validated, at least one variable affecting the hydrology must properly fit the observed data then other variables can be calibrated, such as plant growth and nutrient cycling (Daggupati et al., 2015; Moriasi et al., 2015). For watershed or larger scale modeling, usually a stream outlet near a stream gauge can be used for calibration, but smaller areas like individual fields are not always near a stream and thus other variables should be assessed, such as surface runoff, soil moisture, or evapotranspiration (Anand et al., 2007; Chen et al., 2018; Gali et al., 2016; Karki et al., 2019; Maharjan et al., 2018; Wang et al., 2014). Unfortunately, this means observed data can be very difficult to obtain. Many different approaches have been tested to make up for this challenge and one researcher found calibration of multiple variables at the field scale can both increase the confidence of a field-scale model and also improve the prediction of all variables (Karki et al., 2019). In this study, two plots in Tifton, Georgia were calibrated and validated for surface runoff, soil moisture, crop yields, and nitrate leaching. Single HRU method developed by the University of Perdue was used, where during the delineation process each subbasin represents a plot with one slope, soil type, and land use (Karki et al., 2019; Moloney et al., 2015). The scenarios in this study tested different management practices on a cotton-cotton-peanut rotation, and one important conclusion from this study was that proper calibration of crops is a vital aspect of modeling fields well.

Very few other studies exist modeling peanuts in SWAT. One study conducted by the University of Florida (Dourte et al., 2015) used a SWAT model to estimate irrigation demand for cotton and peanut rotations with the incorporation of sod and conventional rotations over 30 years; however, the model set up, calibration or validation processes used for their study are not clear. The model was assessed for evapotranspiration and crop yields for corn, wheat, and soybeans in a previous study and performed well for both variables in all crops (Dourte et al., 2015; Dourte et al., 2014; Moriasi et al., 2015). Linear regression was used to assess the performance of cotton and peanut yields for this model and the model performed good (R^2 = 0.799) and very good (R^2 = 0.900) for both crops respectively according to the performance measure limits outlined by Moriasi et al. (2015). Two other studies conducted on larger watersheds – 973 hectares – in India tested the effect of fertilizer and tillage practices on corn, peanuts, rice, and soybeans, the predominant crops in the area, on runoff, sediment, nitrate, and phosphate loading (Behera and Panda, 2006; Tripathi et al., 2005). The model was calibrated for daily surface runoff, sediment yield, nitrate, and phosphate. No plant growth variables were calibrated or validated for this model. Two years of data were available, so the model was calibrated with one year and validated for another year. Even though the models were run at a daily time step they performed very good for all four variables in both calibration and validation. These studies found mould bourd plough and conservation tillage increased yields no matter the fertilizer treatments, and the fertilizer treatments had little effect on yields. In addition, the lowest nitrate loss was found with conservation tillage no matter the fertilization treatment. Phosphorus losses in surface runoff also decreased under conservation tillage but losses increased as fertilizer treatments increased.

On the other hand, apart from the aforementioned studies, more field-scale studies on cotton have been conducted in the Midwestern United States. Over pumping of the Ogallala aquifer has caused investigation into different irrigation strategies with cotton rotations in both Texas and Oklahoma (Chen et al., 2018, 2019; Chen et al., 2017, 2019; Maharjan et al., 2018; Marek et al., 2016, 2017). One study in particular in Bushland, Texas calibrated two fields for LAI and ET for cotton and forage corn (Marek et al., 2016). After calibration, SWAT was able to predict monthly ET very well but only good for LAI, which was attributed to SWAT's faulty plant growth algorithms (Marek et al., 2016). The model in Bushland, Texas was later used in a site comparing crop rotations water-saving capabilities using 90 years of historical weather data (Marek et al., 2017). Three other studies assessing the auto irrigation and later improvement of the auto irrigation function in SWAT, which is triggered when plant or soil water deficit reaches a certain limit similar to soil moisture triggered irrigation (Karki et al., 2019), used evapotranspiration, LAI, and yield to calibrate their model for cotton, soybean, sorghum, forage corn, and sunflower (Chen et al., 2018; Chen et al., 2017, 2018). They found for their model simulated cotton and forage corn LAI and yields very well which was attributed to detailed management inputs (Chen et al., 2018; Chen et al., 2017). When auto-irrigation was used, yields and ET performed much worse except when integrating an external irrigation scheduling program (Chen et al., 2018; Chen et al., 2017). Multiple sites were later integrated into this study with primary concentration on forage corn for the crop of interest (Chen et al., 2019; Chen et al., 2019). SWAT predicted corn biomass and LAI very good for a site in Bushland Texas, Etter Texas, and Greeley, Colorado (Chen et al., 2019).

One such area, which has already suffered from increased drought frequency, is the southeastern United States (U.S.). The Apalachicola-Chattahoochee-Flint (ACF) River Basin is an interesting area with respect to droughts because of both the variety of land uses and long history of litigation surrounding the quality and quantity of water in this area. The ACF basin has been a hot topic with water resources since 1989 due to three states' reliance on its freshwater resources: Georgia, Alabama, and Florida (Stevens, 2014). The top of the basin is located in Northern Georgia, where the Chattahoochee River meanders into East Alabama, joins the Flint River in southwestern corner of Georgia to become the Apalachicola River, and final drains through Florida into the Gulf of Mexico. The ACF is nearly 619km long, 80km wide, and the total drainage area is approximately 50,800 km2 with the greatest portion of the basin located in Georgia. It is home to approximately 24,362 reservoirs, 81% of which are located in Georgia, followed by 11% in Alabama and 8% in Florida. A main cause for the complicated legislation lies with the city of Atlanta, GA that is located at the top of the Chattahoochee River basin. The ACF system supplies 78% of Atlanta's municipal water, and downstream of the river is twelve hydro-electric dams, recreational rivers, irrigation for crops, many habitats for endangered species, and the Apalachicola Bay, home of many estuarine fisheries and hatcheries (Wehr, 2014). In addition, according to the United States Geological Survey, drought years in Georgia outnumber normal and high precipitation years since 1980, meaning Georgia will rely more on this system to help compensate for so many dry years (USGS, 2010). However, overexploitation of the basin's water resources could have highly negative consequences for the Apalachicola Basin. The Apalachicola River is a highly biodiverse area and houses many threatened and endangered species (Ruhl, 2005). Limited water quantity and quality would be damaging to the aquatic life, but especially endangered mussel species in this area. Overall, after thirty-five years of litigations without conclusive decisions, Florida petitioned the Supreme Court to take the case in 2014, arguing to limit Georgia's water use. In October 2017, the Supreme Court decided to create a cap on Georgia's water use during times of drought and the trial was appointed to a special master to determine details (Florida vs Georgia, 2017). Despite the Supreme Court's decision, no actionable changes have been made and the legal battles have no discernable end in sight.

In addition to being the primary water user in the ACF basin, Georgia is also a highly agriculturally productive area. According to the USDA National Agricultural Statistics Service (NASS), in 2017, Georgia ranked first nationally for broilers, peanuts, and utilized pecans, second for cotton lint and cotton seed, and seventh for sweet corn. Georgia is also a top national producer of fruits and vegetables, ranking third for watermelon; fourth for Bell Peppers, Cantaloupes, and Cucumbers; fifth for Tobacco; sixth for Blueberries, cabbage, eggs, onions, and squash; and finally, seventh for the state fruit – Peaches – and snap beans. There are many factors contributing to this agricultural productivity. First, Georgia has an interesting variety of aquifers, consisting of a surficial aquifer system termed the Biscayne aquifer, an upper confining unit, the upper Floridian aquifer (UFA), a middle confining unit, the lower Floridian aquifer, and a lower confining unit (Fetter, 2001). These aquifers are karstic aquifers, meaning they consist of highly permeable limestone. The upper confining layer consists primarily of clastic rocks with low permeability, mostly from Hawthorn Formation from the Miocene age. Recharge zones for the UFA are throughout the Lower Flint River Basin (LFRB), meaning access to this aquifer for farmers is easier and more cost-effective. Thus, the UFA, due to both its size and water availability, is often the source of irrigation from groundwater in this area (Mitra et al 2016).

OBJECTIVES

In a 2016 review of SWAT papers, the number one most outstanding issues with SWAT studies was an improperly built model (Abbaspour et al., 2017). Also, there is a clear lack of studies conducted focusing on proper calibration and validation of crop and soil processes in SWAT. There are even fewer studies conducted focusing on proper modeling of cotton and peanuts. Given the importance of these crops in the Southeast and around the world, proper methods for calibrating the growth and nutrient cycling of these crops is critical for a successful model. Also, since calibration of multiple variables has increased the confidence of field-scale models in previous studies, calibration of soil and crop nutrient processes could be beneficial since field data is difficult to obtain. Thus, the objectives of this study were to create a field-scale model of a research site in the Lower Flint River Basin, Stripling Irrigation Research Park, GA, which accurately represented the soil, crops grown, and management practices of the area. Once the model was created, the second objective was to conduct a multivariable calibration and validation of the model including not just the hydrology but also the crop growth and nutrient cycling of the field with a heavy focus on measures assessing crop growth and soil processes, such as biomass, LAI, yield, plant nitrogen uptake, and soil nitrate. Our third objective was to run scenarios comparing the absence and presence of soil moisture and soil nitrate calibration, respectively, to see the long-term impacts on hydrology and nitrogen cycling when calibrating these terms in SWAT.

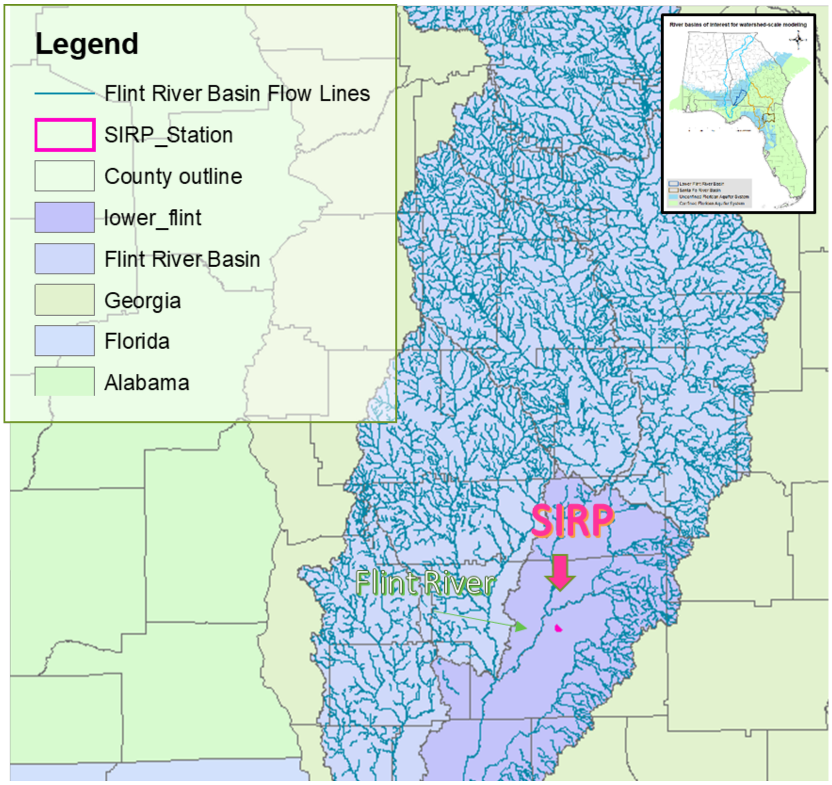


Figure 1.1 Map of the Lower Flint River Basin in southwestern Georgia and location of the Stripling Irrigation Research Park in Mitchell County

METHODS AND MATERIALS

Study Area and Field Experiments

Stripling Irrigation Research Park is a research station, located in Camilla, GA managed by the University of Georgia. The research park lies in a HUC8 watershed that is in the LFRB and is 5 miles from the Flint River in Mitchell County (Figure 1). The primary source for irrigation in this park is the shallow aquifer, the Upper Floridian Aquifer, but wells for the deeper Clairborne aquifer are also in place. A weather station is on site managed by the Georgia Weather Network, which includes but is not limited to daily measurements of precipitation, temperature, solar radiation, wind-speed, and relative humidity (Figure 2). Newton Lateral

Fields containing three fields in a corn-cotton-peanut rotation followed by a rye winter cover crop were the focus of this study. All fields were strip-tilled and all residue from the cover crop was left on the field after termination and prior to planting. The three fields, North, Middle, and South, have a different crop growing in each field such that corn, cotton, and peanuts are all grown at the same time in a given year. This rotation has been in place for many years in order to study variable rate irrigation systems and various fertilizer applications on three crops simultaneously (Migliaccio et al., 2015; Vellidis, et al., 2016a; Vellidiset al., 2016b). Twenty-seven plots are located in each field and in November 2017, berms were installed to isolate surface runoff for two plots each in the three fields. AquaVents were also installed to measure overland flow from the plots; however, the plots were not isolated for subsurface flow. Composite runoff samples were also collected throughout the growing season to be assessed for nutrient content. These water samples were sometimes composed of multiple runoff events depending on the amount of runoff generated by a given event. In each field, nine different

Figure 1.2. Map of Stripling Irrigation Research Park marking the location of the experimental fields and the weather station managed by the Georgia Weather Network

fertilizer and irrigation treatments were tested so each crop would have three duplicates. Soil moisture sensors were installed after planting in each plot for irrigation measurement purposes. These sensors measure soil pressure at 8, 16, and 24 inches and use a cellphone signal to send continuous data to a netbook onsite, which automatically uploads the data to a cloud as it receives it (Vellidis et al., 2016). Soil pressure data was then converted to soil moisture through the Van Genuchten equation and RETC, a program that uses texture and bulk density to generate parameters to be used in the Van Genuchten equation (van Genuchten, 1980; van Genuchten et al., 1991). Each plot contains 8 rows, and tissue samples were collected every 3 feet for one row

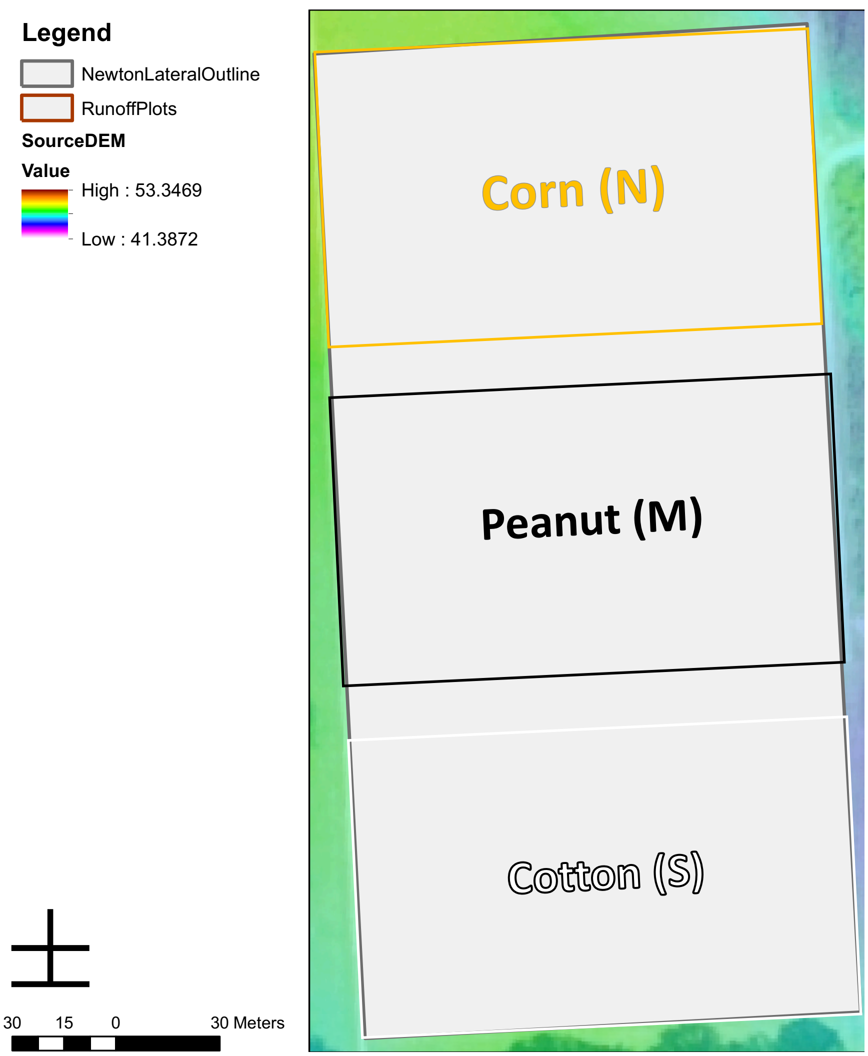


Figure 1.3. Layout of Newton Lateral Fields in 2018 and location of plots isolated for surface runoff

every two weeks, along with backup samples. Biomass and TKN data were collected from these tissue samples. In addition, cotton plots also collected leaf area index throughout the growing season. Composite soil samples in each plot were collected with soils cores prior to planting at depths of 6, 12, 18, 24, 30, and 36 inches, followed by samples at 6, 12, 24, and 36 inches throughout the growing season. These samples were analyzed for texture, organic matter content, and nutrients including but not limited to nitrate concentrations. More soil samples were collected for cotton and corn than for peanuts because nitrogen is not a concern in peanuts due to fixation.

SWAT Model Description

SWAT was originally developed by Dr. Jeff Arnold for the USDA Agricultural Research Service to understand the impact of land management practices on water, sediment and agricultural chemical yields on large complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch et al. 2011). SWAT is a physically based model, meaning instead of parameterizing output results with regression relationships, the results are produced based on a wide variety of input data, such as weather, soil, land, vegetation, and land management practices. In this way, highly complex watersheds can be modeled for water, sediment, crop growth, nutrient cycling, and more. It maps a watershed basin, subbasins, and subbasin outlets based on elevation data and streamflow shapefiles if available. SWAT also has a very high resolution by creating unique categories called Hydraulic Response Units (HRUs). Each HRU has a unique land cover, soil type, and slope. Outputs for the HRUs are calculated and then scaled up to the sub-basin outlet by the percent area of the HRU within the sub-basin. When compared alongside eleven different hydrological models in Borah and Berah

(2003), SWAT was determined to have high skill and a great potential for expansion. SWAT is usually used over long-term studies but is capable of performing well at multiple time steps, including daily, hourly, monthly, and yearly (Abbaspour, 2015; Arnold et al., 2012).

SWAT models plant growth and biomass as a function of leaf area index (LAI) and a species dependent radiation use efficiency (Neitsch et al., 2011). The potential amount of biomass increase for a plant uses LAI to calculate the daily amount of photosynthetically active radiation captured by the plant and then multiplies it by the radiation use efficiency coefficient. The total biomass is a cumulative sum of the daily biomass increase. LAI is simulated following an optimal leaf development curve until it reaches the max LAI, a parameter specified for each plant, after which it steadily declines depending the plant. Nitrogen uptake by the plant from the soil in SWAT is directly related to biomass and is dependent on the growth stage of the plant. Plant nitrogen is taken from the soil nitrate pool, and more is taken from the top layers of the soil depending on the nitrogen uptake distribution parameter and root length. Daily soil nitrate is an output of SWAT and is calculated based on the amount of organic matter, organic carbon, fertilizer applied, nitrification, mineralization, denitrification, volatilization, and decay of plant matter. For legume species, nitrogen fixation is triggered when plant demand exceeds the available nitrate in the soil and goes directly into the plant.

Data Inputs and Model Construction

The Single HRU method developed by Purdue was used, where a mask over the six plots being modeled was added with a low stream threshold, so that each of the six plots would generate an individual outlet on the runoff plots with a unique slope, soil, and land use (Moloney et al., 2015). Digital Elevation Model from the USGS 3-dimensional Elevation Program Initiative, a 1M resolution Lidar elevation dataset, was used for the initial delineation (Arundel et al., 2015). Land use map for 2018 was downloaded from CropScape, projected, and modified so actual land uses were properly represented (Boryan et al., 2011; Teshager et al., 2016). Six outlets located on the experimental plots were selected and thus six subbasins generated – one subbasin for each plot hydrologically separate from the other. To generate a single HRU in each subbasin, 0% land, 60% soil, and single slope was selected for threshold HRU boundaries because one automatically generated subbasin extended into a different soil type. The area of the subbasin in both the text files and access database was modified to the actual plot drainage area.

The primary soil database used was the Soil Survey Geographic Database (SSURGO), first developed by the NRCS in 1990 and updated over time (Soil Survey Staff, 2012). This soil database contains soil properties such as the number of layers and properties of each layer like hydraulic conductivity, bulk density, and texture. The layers were modified such that the bottom of the top three layers matched the depths of the three soil pressure sensors (8, 16, and 24 inches) while keeping all SSURGO properties the same for each layer and the profile as a whole. Observed soil texture and organic carbon – calculated from organic matter content (Brady and Weil, 2008) – was also added to each plots' soil database. All management practices, including dates for planting and harvest, irrigation scheduling and amounts applied, fertilizer application dates and amounts, tillage operations, cover crop, and rotations obtained from UGA and research station personnel were incorporated into the model (See Appendix 1 for details). A new fertilizer needed to be added to fertilizer database – Urea Ammonium Nitrate (UAN 28-0-0) – to properly simulate denitrification. This fertilizer is a liquid based fertilizer applied through the irrigation system composed of 40% Ammonium Nitrate (34-0-0), 30% Urea (46-0-0), and 30% water, which means 71.4% of the nitrogen applied through UAN 28-0-0 goes into the ammonium pool and the remaining nitrogen into the nitrate pool.

Calibration and Validation Strategy

For surface runoff, each calibration plot was automatically calibrated separately using SWAT-CUP and the SUFI-2 algorithm. SWAT-CUP uses a Latin hypercube method to find the best parameters within user-specified ranges for a given performance measure, referred to as objective functions (Abbaspour, 2015). Parameters sensitive to surface runoff were chosen based on previous studies' sensitivity analyses, which included CN2, ALPHA_BF, GW_DELAY, GWQMN, OV_N, and SURLAG (Karki et al., 2019; van Griensven et al., 2006). After surface runoff was sufficiently calibrated, a sensitivity analysis of parameters not sensitive for surface runoff but sensitive for soil moisture followed by layer-by-layer calibration of the top two layers for soil moisture was also conducted. When the top three layers improved for soil moisture prediction in each plot, cumulative soil moisture for the top three layers was then manually calibrated and validated for each field. Parameters used by other researchers were used but parameters affecting crop evapotranspiration were also investigated and used in this study.

After the hydrology was sufficiently calibrated and validated, manual calibration of crop biomass and crop yield were simultaneously conducted for corn and peanuts. Since yield data was not available for cotton due to Hurricane Michael in 2018, biomass and LAI data were calibrated and validated simultaneously instead. Crop nitrogen uptake was then manually calibrated followed by soil nitrate in the top 914mm of the soil profile and nitrate in the surface runoff. Soil nitrate was of particular interest in calibration as leaching data was not available in the field study. All parameters used for calibration and validation are listed in Table 1.

Table 1.1 All parameters used in calibration validation of runoff, soil moisture, biomass, yield, crop nitrogen, and soil nitrate along with the range of their initial perturbation limits as suggested by Moriasi (2015) and Karki (2019).

Runoff Calibration			
Parameter	**Description**	**Database**	**Initial Ranges**
CN2	SCS Curve Number for Moisture Condition 2	.mgt	+/- 0.3
ALPHA_BF	Baseflow alpha factor (days	.gw	0.01-1
GW_DELAY	Groundwater Delay (days)	.gw	1-1000
GWQMN	Threshold depth of water in the shallow aquifer (mm)	.gw	0.01-5000
OV_N	Manning's "n" value for overland flow	.hru	+/- 0.3
SURLAG	Surface runoff lag time (days)	.hru	1-20

Soil Moisture Calibration			
Parameter	**Description**	**Database**	**Initial Ranges**
ESCO	Soil evaporation compensation factor	.hru	0.01-1
GSI	Max stomatal conductance in drought	plant.dat	0.001-0.009
EPCO	Plant uptake compensation factor	.hru	0.01-1
SOL_BD	Bulk Density (g/cm^3; unique for each layer)	.sol	+/- 0.25
SOL_AWC	Available Water Capacity (mm/mm; unique for each layer)	.sol	Texture dependent
SOL_K	Hydraulic Conductivity (mm/hr; unique for each layer)	.sol	Texture dependent
SOL_ALB	Soil Albeto (unique for each layer)	.sol	+/- 0.3

Crop Growth Calibration			
Parameter	**Description**	**Database**	**Initial Ranges**
HVSTI	Harvest Index	plant.dat	+/- 0.3
BLAI	Max Leaf Area Index	plant.dat	+/- 0.3
FRGRW	Fraction of the plant growing season corresponding to the 1st and 2nd point on the optimal leaf area development curve	plant.dat	+/- 0.15
LAIMX	Fraction of the max leaf area index corresponding to the 1st and 2nd point on the optimal leaf area development curve	plant.dat	+/- 0.3
DLAI	Fraction of Growing season when leaf starts declining	plant.dat	+/- 0.3
T_BASE	Min temperature for plant growth (degrees Celsius)	plant.dat	+/- 0.15

Crop and Soil Nitrate Calibration			
Parameter	**Description**	**Database**	**Initial Ranges**
ANION_EXCL	Anion Exclusion Coefficient (fraction)	.sol	+/- 0.3
SOL_K	Hydraulic Conductivity (mm/hr; unique for each layer)	.sol	Texture dependent
RSDCO_PL	Residue Decomposition Coefficient for each plant	plant.dat	+/- 0.3
NPERCO	Nitrate Percolation Coefficient	.bsn	0.01-1
NUPIDS	Nitrogen Uptake Distribution Parameter	.bsn	+/- 0.3
SDNCO	Threshold value for Nutrient cycling water factor for denitrification	.bsn	+/- 0.15
BN	Fraction of N in plant at emergence, 0.5 maturity, and full maturity	plant.dat	+/- 0.15

The performance measures or objective functions in this study were R^2, percent bias (PBIAS), and Nash-Sutcliffe efficiency (NSE). R^2 measures the goodness of fit of the observed and simulated data, percent bias measures the model's tendency to over-simulate or under-simulate with respect to the observed data, and NSE measures the capability of the model to simulate the observed extreme events (Moriasi et al., 2015). R^2 and NSE values close to 1 and PBIAS values of 0 are considered perfect. A negative and positive PBIAS indicates the model's tendency to over-predict and under-predict relative to the observed data, respectively. Appropriate values for each variable calibrated and validated are based on the literature presented in the appropriate table. To account for the limitations and variability of the measured data and the limitations of SWAT to predict well at a daily time step, the simulated soil moisture, crop growth, and nutrient cycling in this study were compared to all three duplicate plots. If the simulated variables followed the trend or fell within the maximum and minimum values of the three plots, then the model was considered to be performing reasonably. This is an especially useful strategy since cotton and peanuts have unique growth patterns and SWAT has had difficulty modeling these patterns in previous studies.

Scenario Analyses

Using 30 years of weather data from the National Land Data Assimilation System (NLDAS), water and nitrogen balances were compared under three different conditions: 1) calibration of runoff, soil moisture, crop growth, crop nitrogen uptake, and soil nitrate; 2) calibration of all aforementioned variables except soil moisture; 3) calibration of all variables except soil nitrate. In this way, the effect of soil processes in SWAT on hydrological and nitrogen cycling can be investigated in greater detail and the benefits of calibration of soil moisture and soil nitrate can be assessed.

RESULTS AND DISCUSSION

Due to complications with the field data, the plot used for corn surface runoff validation was not able to be used in this study. A preliminary sensitivity analysis showed only CN2, GWQMN, and OV_N were sensitive for runoff in this model, thus only these values are presented in Table 1.4. Although SWAT initial surface runoff predictions were good, SWAT-CUP produced better runoff parameter changes and better simulation results relative to the observed (Table 1.3; Figure 1.4**Error! Reference source not found.Error! Reference source not found.**). Some parameters for runoff initially seem high, but they are all not outside of the recommended calibration bounds from previous studies (Karki et al., 2019; Wallace et al., 2018). Not only were the statistics within the acceptable ranges, but the trend was also able to be captured for all calibration and validation plots.

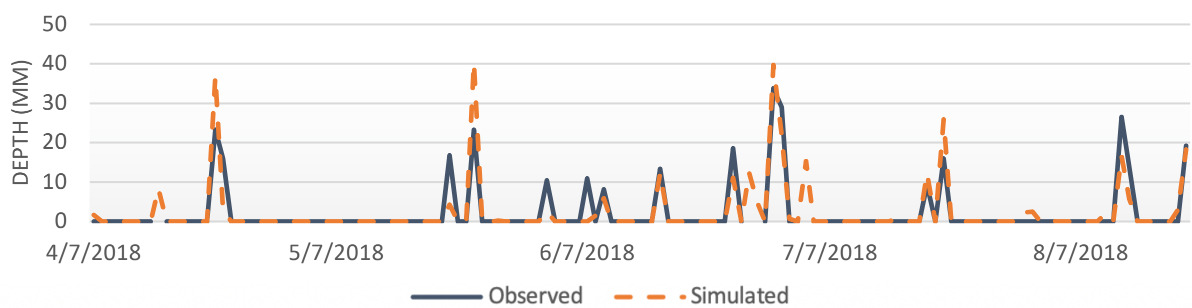


Figure 1.4 Runoff observed versus simulated calibration results for corn calibration plot. Note, observed validation data was not available in this study due to instrument complications.

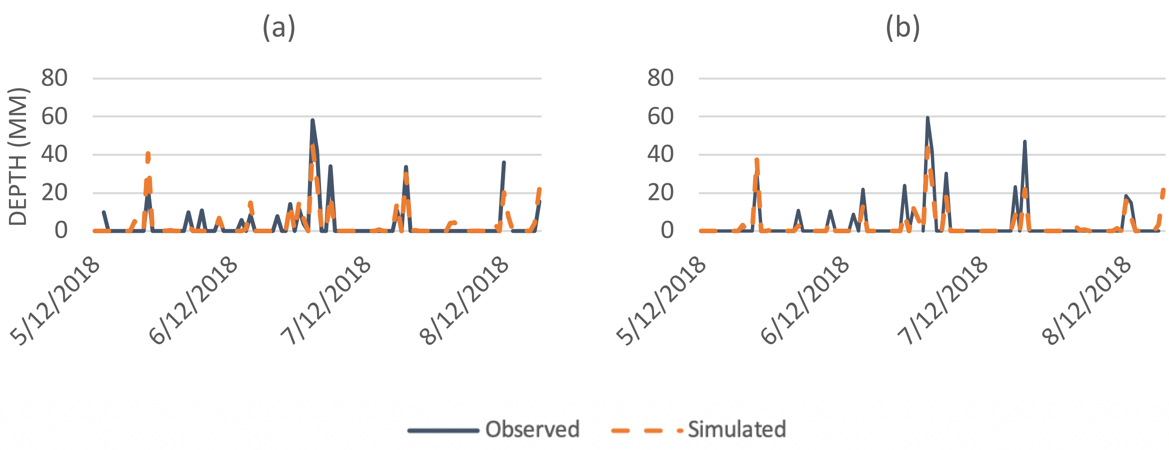


Figure 1.5. Runoff observed versus simulated calibration results for peanut calibration (a) and validation (b) plots

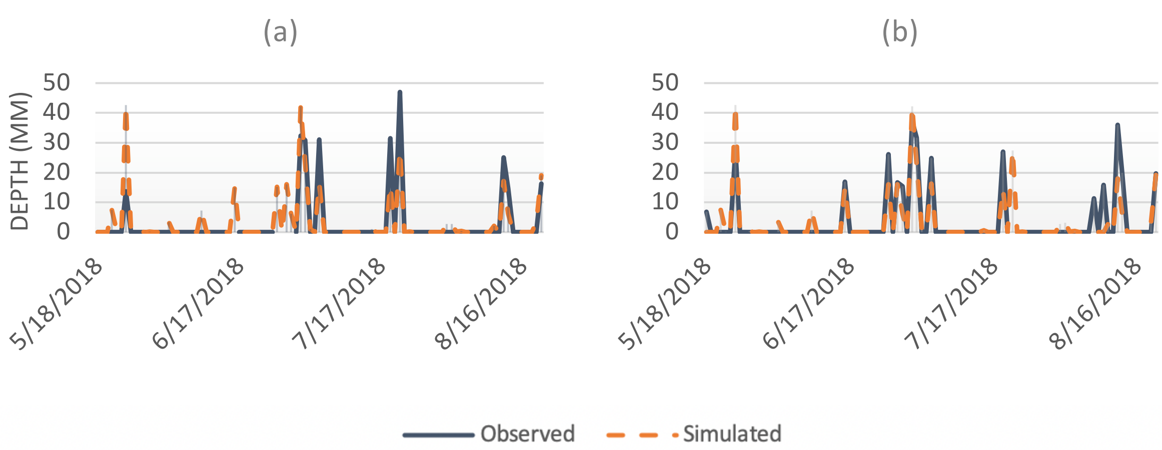


Figure 1.6. Runoff observed versus simulated calibration results for cotton calibration and validation plot

The field measurements for soil moisture were very high and more variable for all plots. These atypically high values provided challenges in calibration of soil moisture. Many variables were changed to the maximum values for the soil texture just to reach the range of the observed. For example, nearly all available water content and albeto values were placed to the maximum textural limits of the soil, which are unrealistic for this area. Also, even though soils are capable of having very high bulk densities with significant compaction, the value needed to assist the

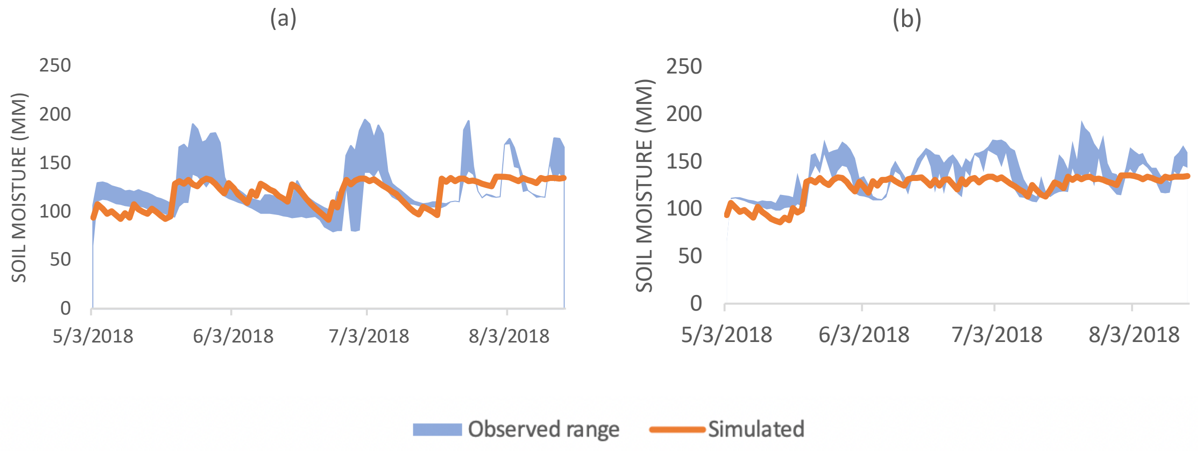


Figure 1.7. Observed versus simulated soil moisture calibration results for corn calibration (a) and validation (b) plots

Table 1.3 Final Calibration and Validation statistics for all variables assessed.

Corn plots						
	Calibration			Validation		
Variable	***R2***	***PBIAS***	***NSE***	***R2***	***PBIAS***	***NSE***
RUNOFF	0.775	-8%	0.736	-	-	-
SOIL MOISURE	0.479	6%	0.307	0.363	-1%	0.366
BOIMASS	0.988	5%	0.984	0.963	-22%	0.884
YIELD	-	8%	-	-	2%	-
CROP NITROGEN	0.933	18%	0.831	0.936	-8%	0.924
SOIL NITRATE	0.345	34%	0.240	0.775	-5%	0.787

Peanut plots						
	Calibration			Validation		
Variable	***R2***	***PBIAS***	***NSE***	***R2***	***PBIAS***	***NSE***
RUNOFF	0.812	6%	0.810	0.876	26%	0.801
SOIL MOISURE	0.271	1%	0.272	0.482	-20%	0.175
BOIMASS	0.966	2%	0.922	0.901	-12%	0.845
YIELD	-	-12%	-	-	4%	-
CROP NITROGEN	-	-2%	0.443	-	-7%	0.383
SOIL NITRATE	0.005	60%	-0.165	0.011	67%	-0.152

Cotton plots						
	Calibration			Validation		
Variable	***R2***	***PBIAS***	***NSE***	***R2***	***PBIAS***	***NSE***
RUNOFF	0.717	-10%	0.719	0.758	18%	0.747
SOIL MOISURE	0.575	0%	0.327	0.512	4%	0.433

BOIMASS	0.673	12%	0.709	0.871	-14%	0.836
LAI	0.742	-10%	0.645	0.980	3%	0.879
CROP NITROGEN	0.671	27%	0.546	0.785	-3%	0.760
SOIL NITRATE	0.681	14%	0.587	0.213	14%	0.337

trend in this study was unrealistically high for this study area. For example, available water content and soil reflectivity were increased for all plots to match amount of water held by the soil but not past the textural limits of the soil (0.25 mm H_2O/mm soil for loamy sand) (**Error! Reference source not found.**).

Bulk density was adjusted in a similar fashion. Parameters affecting evapotranspiration were used to increase soil moisture variability, including a parameter in the crop database called the maximum stomatal conductance at high solar radiation and low vapor pressure deficit (GSI; units

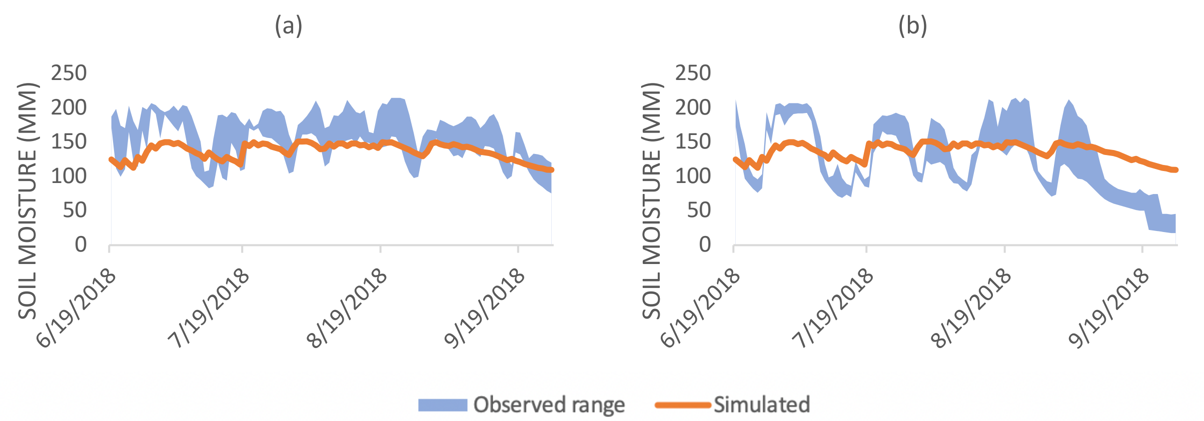


Figure 1.8. Observed versus simulated soil moisture calibration results for Peanut calibration (a) and validation (b) plots

of m/s). Other parameters used were the soil evaporation and plant uptake compensation factors (ESCO; EPCO). Although all of these parameters helped SWAT capture the trend of the observed data, a majority of the variability was not able to be captured by this model. We attribute this lack of ability to match the observed data to the placement of the soil moisture sensors, the method used to convert soil pressure to soil moisture, and the limited amount of data available (3-4 months in each plot). However, even when multiple years of data are available, SWAT has had difficulty predicting extreme values of observed soil moisture levels (Karki et al., 2019). One study found if the SWAT code was modified such that soil moisture was predicted

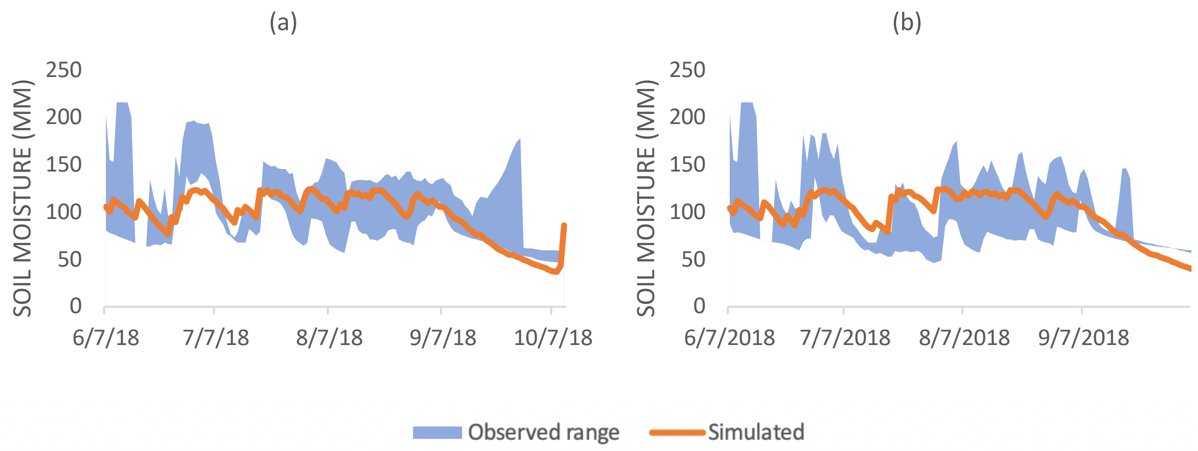


Figure 1.9 Observed versus simulated soil moisture calibration results for cotton calibration and validation plots

based on curve number, prediction improved (Rajib et al., 2016). However, Rajib et al. (2016) note with this method, the effect on nutrients and plant growth is uncertain.

For all plots, after calibration of crop growth, biomass performed very well for all performance measures and matched the trends well by being within the range of the three duplicate plots (**Error! Reference source not found.**1.3; Figure 1.7). Although the performance statistics for cotton biomass were not as great as corn and peanuts, this is not surprising since cotton growth is very different from corn and peanut growth. Cotton is much more sensitive to lack of rainfall or irrigation and,

as of yet, there is not a feature of SWAT to simulate chemical termination of cotton growth for harvest. Yields for corn and peanuts were very good compared to the observed. Similarly,

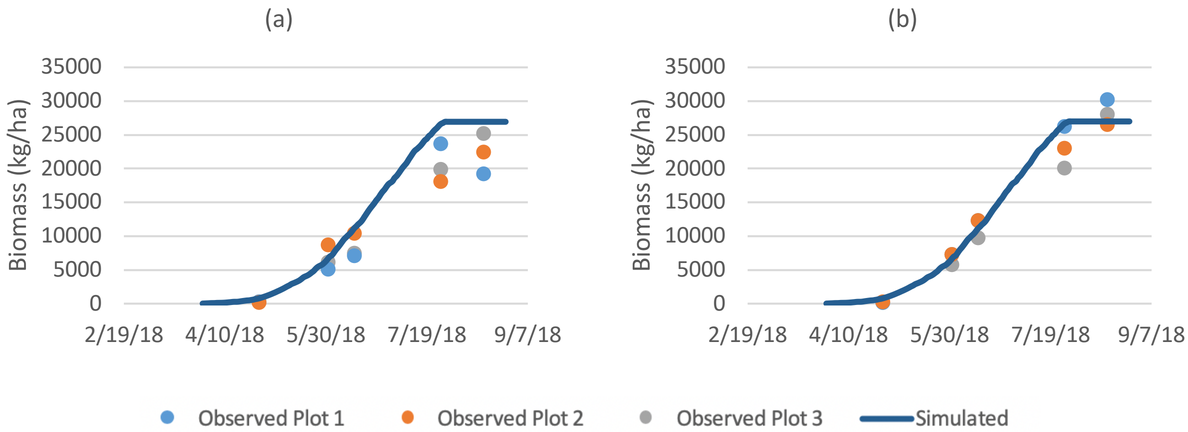


Figure 1.10. Observed versus simulated biomass calibration results for corn calibration (a) and validation (b) plots

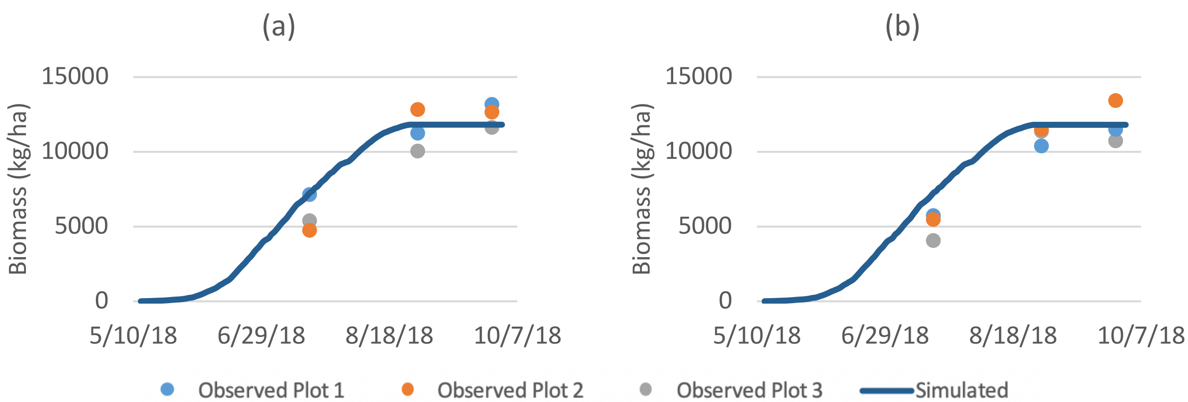


Figure 1.11. Observed versus simulated biomass calibration results for peanut calibration (a) and validation (b) plots

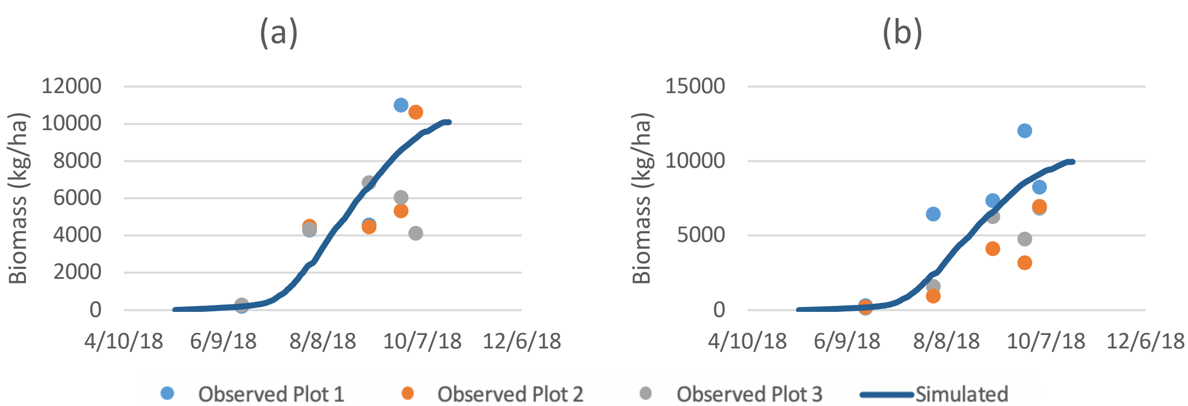


Figure 1.12. Observed versus simulated biomass calibration results for cotton calibration (a) and validation (b) plots

cotton LAI performed well for both calibration and validation plots, with good performance measure statistics and the trend was followed. However, only one year of data was available so it is uncertain if this model accounts years under different weather conditions.

Previous studies on cumulative uptake of nitrogen in crops and daily nitrate levels in the soil have not been conducted, thus a sensitivity analysis of parameters affecting these variables needed to be performed alongside calibration. The most sensitive variables affecting both crop uptake of nitrogen and soil nitrate were the amount of nitrogen in the plant at planting, half-maturity, and maturity (BN1, BN2, and BN3). Another highly sensitive parameter for soil nitrate was the anion exclusion coefficient (ANION_EXCL), which affects the soil's ability to hold

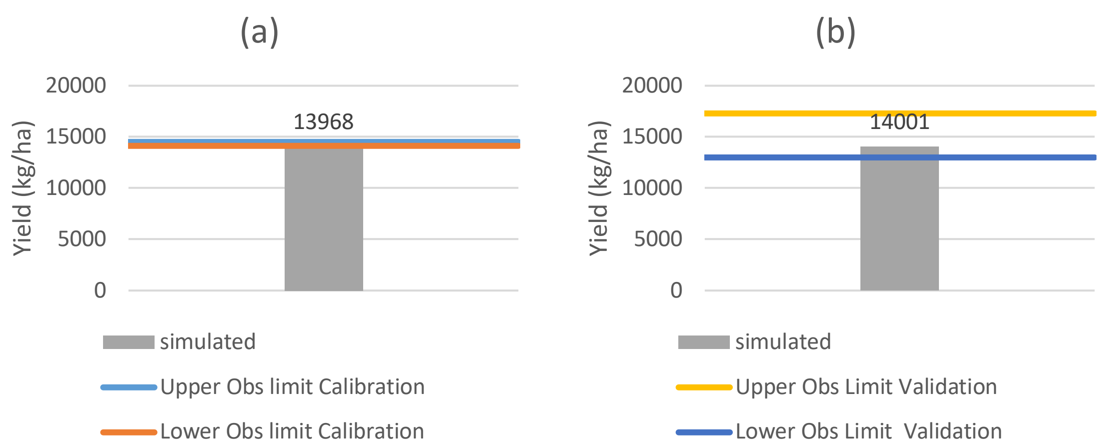


Figure 1.13. Corn yield results after simultaneous biomass and yield calibration (a) and validation (b)

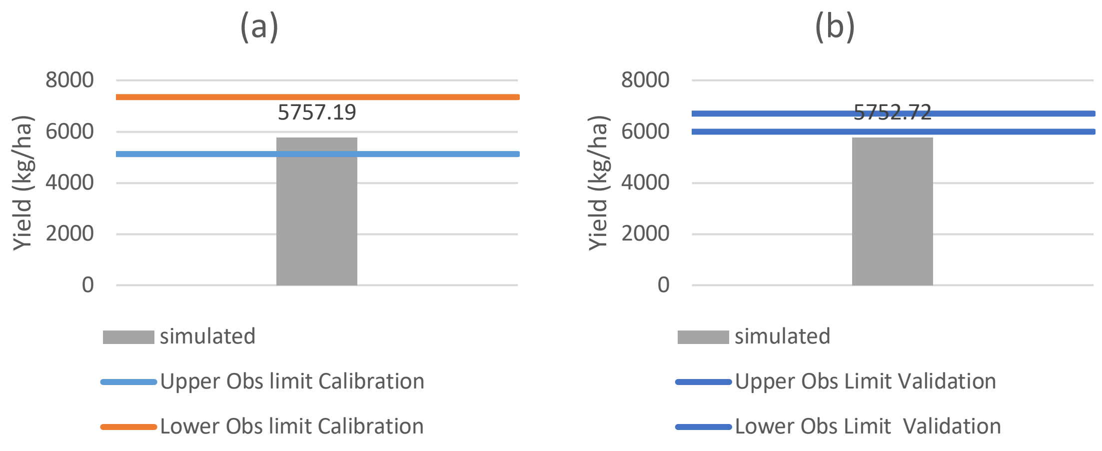


Figure 1.14. Peanut yield results after simultaneous biomass and yield calibration (a) and validation (b)

anions in soil. Increasing this parameter will exclude more anions, thus resulting in less nitrate and the soil but decreasing this parameter will have the opposite effect. This parameter was more sensitive after hydraulic conductivity was lowered. Other sensitive parameters included the rate at which a given crop residue moves to the soil nitrate pool (RSDCO_PL), fresh residue mineralization (CMN), threshold water level for denitrification (SDNCO), and the nitrogen uptake distribution parameter (NUPDIS). It should be noted in this study that RSDCO in the .bsn database did not affect crop nitrogen or soil nitrate. Also, although CMN was sensitive, adjusting this parameter did not improve the trend of soil nitrate, so the default value was

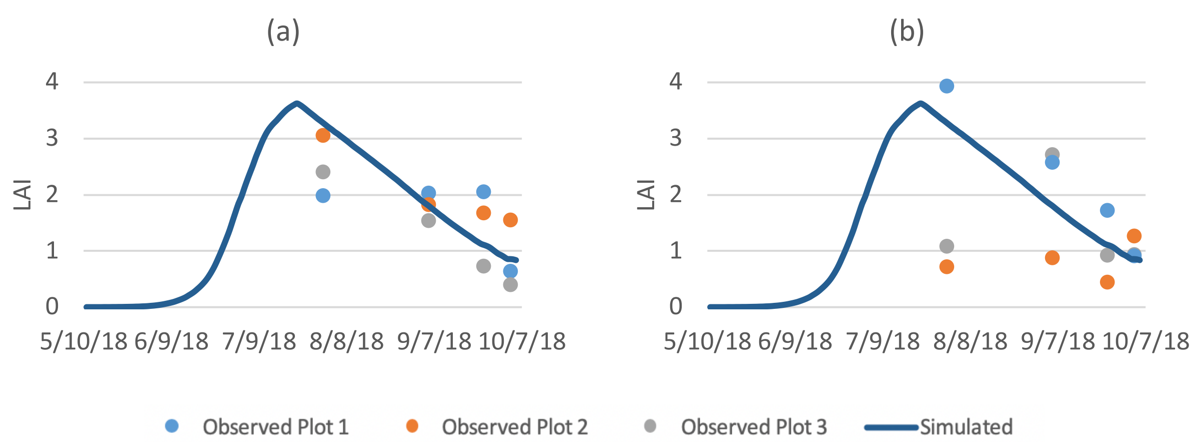


Figure 1.15. Cotton LAI results after simultaneous biomass and LAI calibration (a) and validation (b)

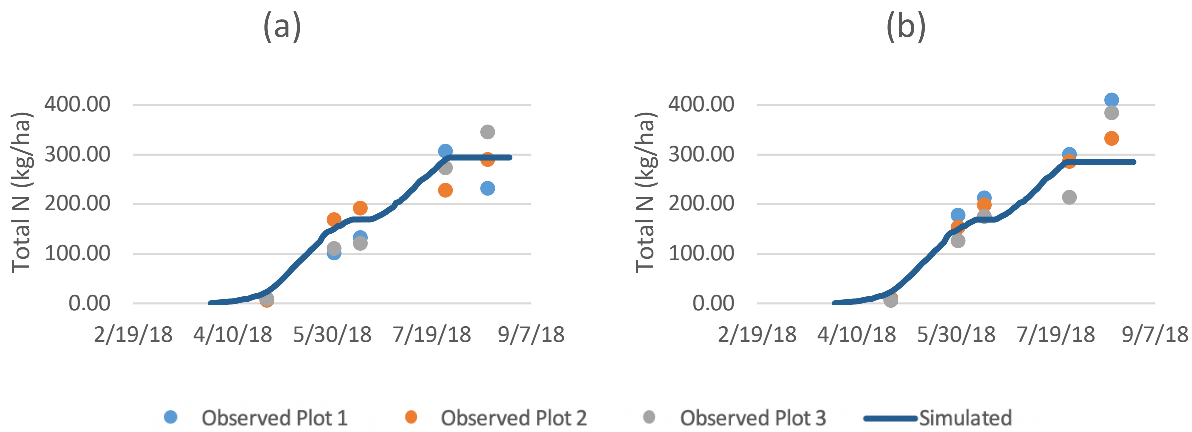


Figure 1.16. Corn crop nitrogen results after simultaneous crop nitrogen and soil nitrate calibration (a) and validation (b)

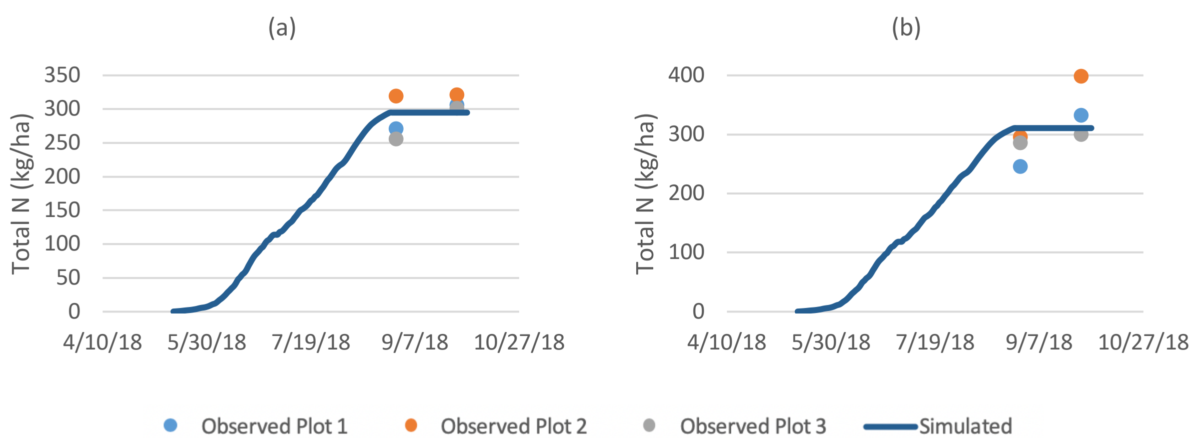


Figure 1.17. Peanut crop nitrogen results after simultaneous crop nitrogen and soil nitrate calibration and validation

retained in this study (0.0003). Crop nitrogen matched the observed values very well and followed the trend, especially for corn and cotton. Soil nitrate levels were simulated more poorly, so other hydrologic parameters not used or sensitive in the surface runoff and soil moisture calibration were explored. Lowering soil hydraulic conductivity helped capture the trend of the observed data; however, SWAT failed to fully capture the trend for the peanut plots. This could be because, although SWAT simulates nitrogen fixation, the model only simulates fixation of symbiotic bacteria living in the plant and not free-living fixating organisms within the soil. Also, nitrogen fixation in the model is only triggered when there is no soil nitrate available

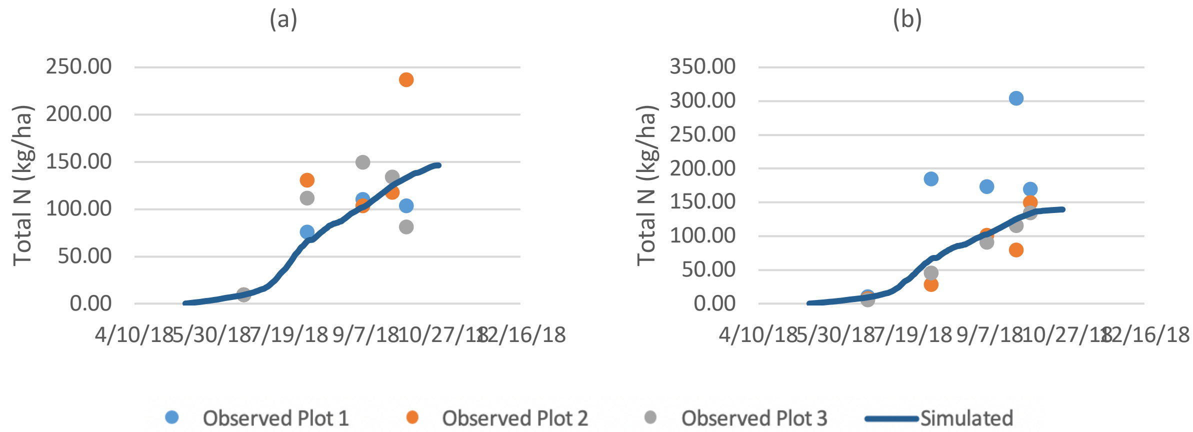


Figure 1.18. Cotton crop nitrogen results after simultaneous crop nitrogen and soil nitrate calibration (a) and validation (b)

in the soil, which is not realistic to real-world conditions. Modifying the code to produce a steadier supply of nitrogen to the plant by fixation might produce more realistic soil nitrogen cycling in the future for legumes.

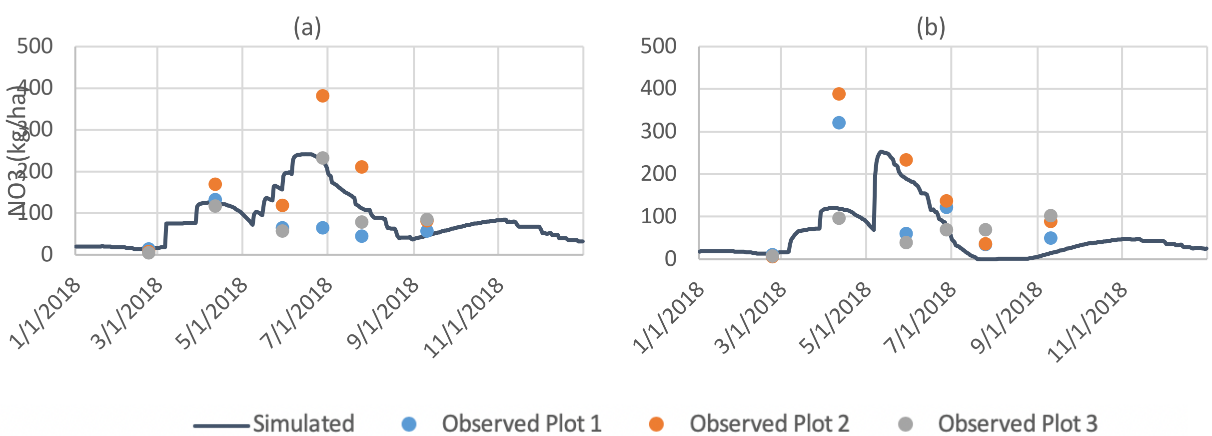


Figure 1.19. Corn soil nitrate results after simultaneous crop nitrogen and soil nitrate calibration (a) and validation (b)

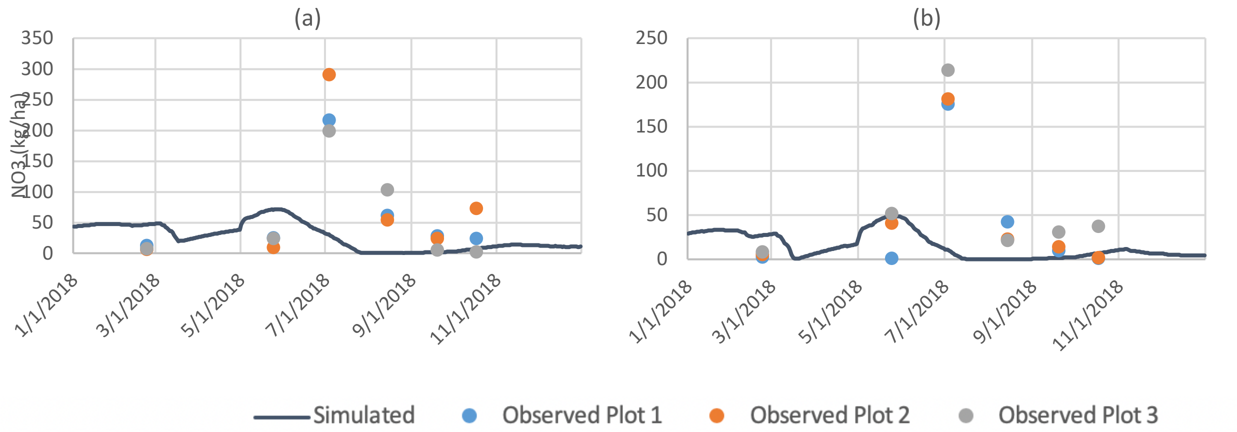


Figure 1.20. Peanut soil nitrate (kg/ha) results after simultaneous crop nitrogen and soil nitrate calibration (a) and validation (b)

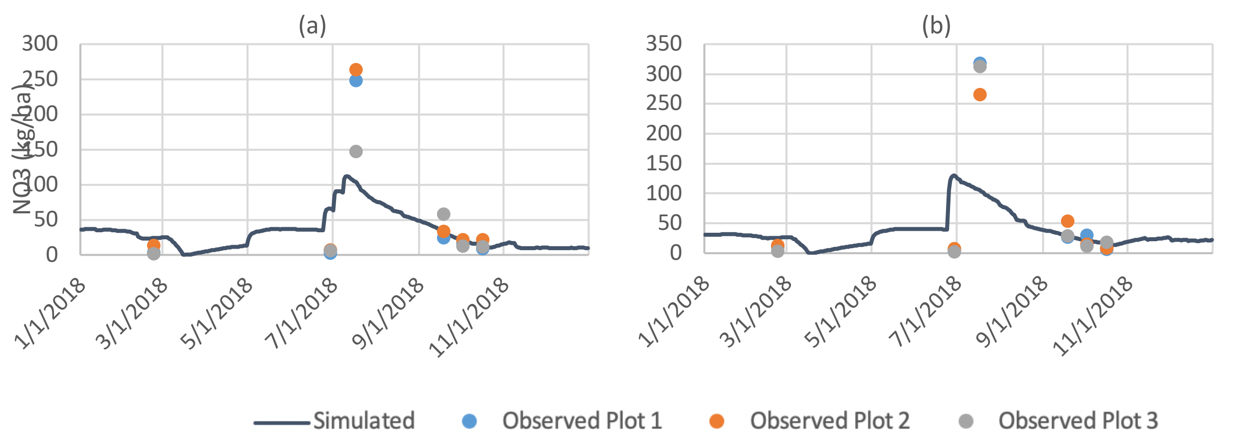


Figure 1.21. cotton soil nitrate results after simultaneous crop nitrogen and soil nitrate calibration (a) and validation (b)

After running the model for 30 years (3 years of warmup), lack of soil moisture calibration and soil nitrogen calibration resulted in less actual evapotranspiration (AET), more surface runoff, and more recharge to both the shallow and deep aquifers. Surface runoff was especially higher when soil moisture was not calibrated, which could be because the default SSURGO database has much lower available water content, which means less water will be held by the soil and instead escape either above the profile in surface runoff or below through shallow aquifer recharge. This could also be why AET is much higher when soil moisture is calibrated – less water leaving the soil profile means more is available for uptake by plants and evaporation.

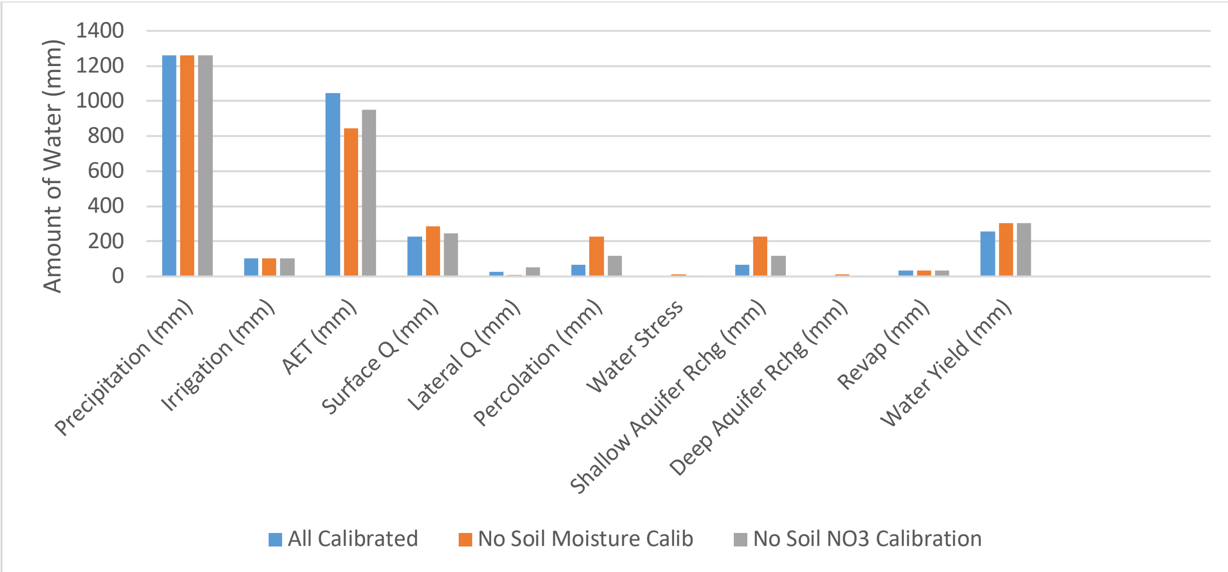


Figure 1.22. Average Annual Hydrological Balance for Simulation (1990-2016)

The scenario results also indicated calibration of nitrate in the soil resulted in more nitrogen uptake from plants, less nitrogen fixation, less denitrification, and less nitrate escaping in lateral flow and leaching. These results also make sense because the observed data used for calibration indicated more nitrate was being held by the soil than what the model was producing,

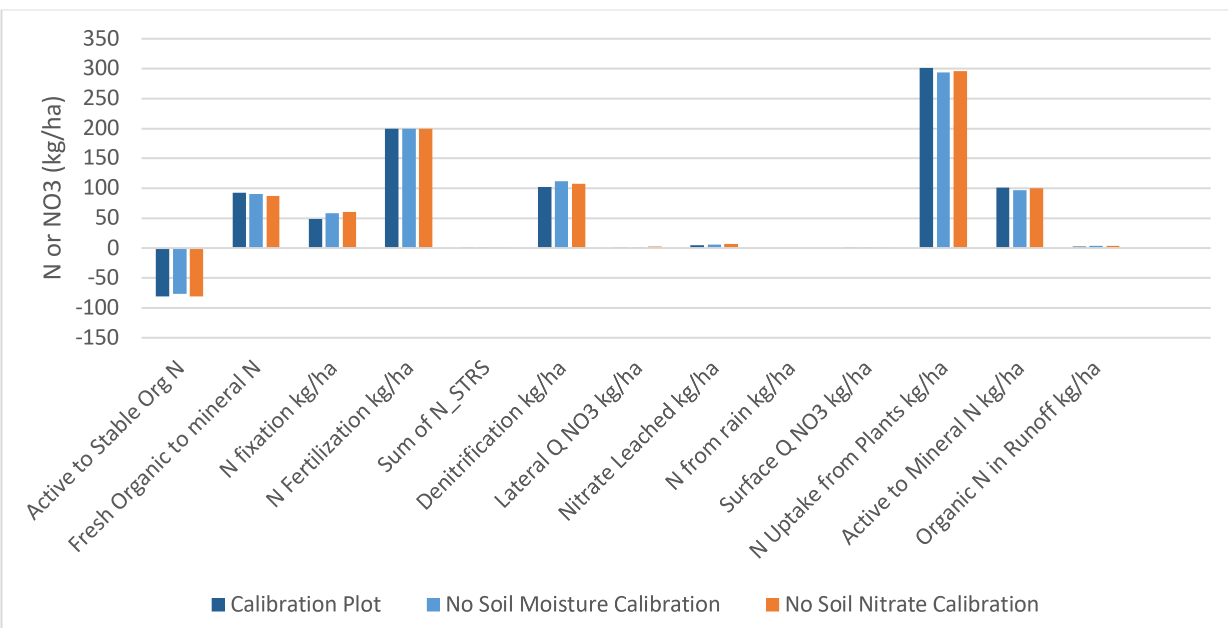


Figure 1.23. Average Annual Nitrogen Balance for Simulation (1990-2016)

Table 1.2 Default and calibrated values of the different sensitive parameters and all three crops assessed

Runoff Calibration						
	Corn		Peanut		Cotton	
Parameters	***Default***	***Calibrated***	***Default***	***Calibrated***	***Default***	***Calibrated***
CN2	77	79.02	77	83.55	77	80.55
GWQMN	1000	758	1000	324	1000	588
OV_N	0.14	0.153	0.14	0.203	0.14	0.179

Soil Moisture Calibration						
	Corn		Peanut		Cotton	
Parameters	***Default***	***Calibrated***	***Default***	***Calibrated***	***Default***	***Calibrated***
ESCO	0.95	0.65	0.95	0.7	0.95	0.6
GSI	0.007	0.001	0.006	0.002	0.009	0.002
EPCO	1	1	1	0.25	1	0.25
SOL_BD1	1.59	2	1.59	1.4	1.59	1.4
SOL_AWC1	0.08	0.17	0.08	0.25	0.08	0.22
SOL_K1	331.2	284.4	331.2	331.2	331.2	331.2
SOL_ALB1	0.16	0.16	0.16	0.26	0.16	0.26
SOL_AWC2	0.08	0.25	0.08	0.25	0.08	0.25
SOL_K2	331.2	152	331.2	152	331.2	152
SOL_ALB2	0.16	0.16	0.16	0.26	0.16	0.26
SOL_AWC3	0.08	0.25	0.08	0.25	0.08	0.15
SOL_K3	331.2	152	331.2	152	331.2	152
SOL_AWC4	0.11	0.11	0.11	0.25	0.11	0.25
SOL_ALB4	0.16	0.16	0.16	0.26	0.16	0.26
SOL_AWC5	0.13	0.13	0.13	0.25	0.13	0.2
SOL_ALB5	0.16	0.16	0.16	0.26	0.16	0.26

Crop Growth Calibration						
	Corn		Peanut		Cotton	
Parameters	***Default***	***Calibrated***	***Default***	***Calibrated***	***Default***	***Calibrated***
HVSTI	0.5	0.67	0.4	0.63	0.5	0.57
BLAI	6	5.5	4	4.3	4	3.9
FRGRW1	0.15	0.13	0.15	0.17	0.15	0.23
FRGRW2	0.5	0.7	0.5	0.5	0.5	0.5
LAIMX1	0.05	0.05	0.01	0.05	0.01	0.01
LAIMX2	0.95	0.9	0.95	0.95	0.95	0.95
DLAI	0.7	0.9	0.75	0.6	0.95	0.5
T_BASE	8	10	14	15.5	15	14.5

Crop and Soil Nitrate Calibration						
	Corn		Peanut		Cotton	
Parameters	***Default***	***Calibrated***	***Default***	***Calibrated***	***Default***	***Calibrated***
ANION_EXCL	0.5	0.2	0.5	0.2	0.5	0.2
SOL_K1	331.2	121.6	331.2	331.2	331.2	331.2
SOL_K2	331.2	121.6	331.2	152	331.2	152
SOL_K3	331.2	121.6	331.2	152	331.2	152
SOL_K4	100.8	80	100.8	32	100.8	100.8
SDNCO	1.1	1	1.1	1	1.1	1
RSDCO_PL	0.05	0.0101	0.05	0.0101	0.05	0.0101
RSDCO_PL	0.05	0.0101	0.05	0.0101	0.05	0.0101
NPERCO	0.2	0.1	0.2	0.1	0.2	0.1
NUPIDS	20	1	20	1	20	1
BN1	0.047	0.032	0.0524	0.0524	0.058	0.058
BN2	0.0177	0.0177	0.0265	0.02	0.0192	0.023
BN3	0.0138	0.11	0.0258	0.022	0.0177	0.0147

so the model was adjusted accordingly. With more nitrate being held by the soil, more will be available by plants and less will be prone to vertical or lateral movement. Similar to the results in the hydrological balances, lack of soil moisture calibration resulted in more nitrate being lost through leaching or surface runoff. When compared to a different study conducted in Tifton, Georgia, leaching is much less in this site with soil moisture and soil nitrate calibration than without (Karki et al., 2019). Plant nitrogen stress was much higher without calibration of soil nitrate but not very different without soil moisture calibration, likely because nitrogen deficiencies were compensated by fixation of peanuts. These results indicate calibration of extra soil variables could result the model behaving differently than what is expected of the system.

Thus, an important implication of this study is that calibration of many variables for field-scale studies is not necessarily a suitable option for a long-term modelling software like SWAT when temporal observed data is lacking because instead of capturing more aspects of a field model, model non-uniqueness or equifinality can occur. This finding is consistent with other studies in watersheds at larger scales. For example, a study conducted with SWAT and MODFLOW in agriculturally dominated watershed in Oklahoma showed a model calibrated very well for streamflow resulted in highly variable recharge patterns across the watershed (Acero Triana et al., 2019). In this study, the authors point out the model produced great performance measure statistics but still resulted in the model behaving differently than what was known of the watershed. Similar results were seen in the western united states for snowmelt dominant watersheds (Ficklin and Barnhart, 2014). Ficklin and Barnhart found after using five different adequate calibration parameters sets for SWAT models of the Clearwater, Gunnison, and Sacramento River watersheds resulted in different future streamflow projections using downscaled Global Climate Models (2014).

CONCLUSIONS

After carefully building the field-scale model and thorough calibration and validation of the hydrology, crop growth, and nutrient cycling, the model performed reasonably well for most variables at this site except for soil moisture and soil nitrate in peanuts. Biomass and nitrogen uptake from the crop were able to be simulated well and could be used to calibrate SWAT models in future studies. Integration of crop database parameters into the calibration and validation of the model resulted in a better simulation of soil moisture; however, SWAT soil moisture and soil nitrate outputs had great difficulty matching the observed data, especially for peanuts. It is not clear whether these difficulties are because of problems with the model or problems with the observed data. Multiple years of data at a given site would result in a better understanding of the trends of the area. More research into modeling fixation in legumes, in particular, is a necessity if soil nitrate is to be properly studied in peanuts with SWAT. The scenario analysis conducted in this study revealed additional calibration of soil processes with low quality data could result in a model behaving differently than what is known of the study area. Thus, calibration of more variables for a fewer number of years at the field scale, instead of providing a more comprehensive understanding of the area, could instead cause model equifinality. The methods and results from this study can help provide more information for modelers in proper simulation of field scale models, especially of corn, peanuts, and cotton, to better capture the uniqueness of a landscape in larger-scale models.

REFERENCES

Abbaspour, K.C. (2015). SWAT-CUP: SWAT Calibration and Uncertainty Programs- A User Manual,Department of Systems Analysis,Intergrated Assessment and Modelling (SIAM),EAWAG. Swiss Federal Institute of Aqualtic Science and Technology,Duebendorf,Switzerland. *User Manual*, 100p. https://doi.org/10.1007/s00402-009-1032-4

Abbaspour, Karim C., Vaghefi, S. A., Srinivasan, R. (2017). A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 international SWAT conference. *Water (Switzerland)*, *10*(1). https://doi.org/10.3390/w10010006

Acero Triana, J. S., Chu, M. L., Guzman, J. A., Moriasi, D. N., Steiner, J. L. (2019). Beyond model metrics: The perils of calibrating hydrologic models. *Journal of Hydrology*, *578*(August), 124032. https://doi.org/10.1016/j.jhydrol.2019.124032

Anand, S., Mankin, K. R., McVay, K. A., Janssen, K. A., Barnes, P. L., Pierzynski, G. M. (2007). Calibration and validation of ADAPT and SWAT for field-scale runoff prediction. *Journal of the American Water Resources Association*, *43*(4), 899–910. https://doi.org/10.1111/j.1752-1688.2007.00061.x

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., Neitsch, S. L. (2012). *Soil and Water Assessment Tool (SWAT) User's Manual, Version 2012*. https://doi.org/10.1007/978-0-387-35973-1_1231

Arundel, S. T., Archuleta, C.-A. M., Phillips, L. A., Roche, B. L., Constance, E. W. (2015). 1-Meter Digital Elevation Model specification. *Techniques and Methods*, 36. https://doi.org/10.3133/tm11B7

Behera, S., Panda, R. K. (2006). Evaluation of management alternatives for an agricultural watershed in a sub-humid subtropical region using a physical process based model. *Agriculture, Ecosystems and Environment*, *113*, 62–72. https://doi.org/10.1016/j.agee.2005.08.032

Boryan, C., Yang, Z., Mueller, R., Craig, M. (2011). Monitoring US agriculture: The US department of agriculture, national agricultural statistics service, cropland data layer program. *Geocarto International*, *26*(5), 341–358. https://doi.org/10.1080/10106049.2011.562309

Brady, N., Weil, R. (2008). *The Nature and Properties of Soils*. (V. Anthony & K. Happell, Eds.) (14th ed.). Upper Saddle River: Pearson Prentice Hall.

Chen, Y, Marek, G. W., Marek, T. H., Brauer, D. K., Srinivasan, R. (2018). Improving SWAT auto-irrigation functions for simulating agricultural irrigation management using long-term lysimeter fi eld data. *Environmental Modelling and Software*, *99*(January), 25–38. https://doi.org/10.1016/j.envsoft.2017.09.013

Chen, Y, Marek, G. W., Marek, T. H., Gowda, P. H., Xue, Q., Moorhead, J. E., … He, K. R. (2019). Multisite evaluation of an improved SWAT irrigation scheduling algorithm for corn (Zea mays L .) production in the U . S . Southern Great Plains. *Environmental Modelling & Software*, *118*(April), 23–34. https://doi.org/10.1016/j.envsoft.2019.04.001

Chen, Yong, Marek, G. W., Marek, T. H., Brauer, D. K., Srinivasan, R. (2017). Assessing the efficacy of the SWAT auto-irrigation function to simulate irrigation, evapotranspiration, and crop response to management strategies of the texas high plains. *Water (Switzerland)*, *9*(7). https://doi.org/10.3390/w9070509

Chen, Yong, Marek, G. W., Marek, T. H., Moorhead, J. E., Heflin, K. R., Brauer, D. K., …

Srinivasan, R. (2018). Assessment of Alternative Agricultural Land Use Options for Extending the Availability of the Ogallala Aquifer in the Northern High Plains of Texas. *Hydrology*, *53*(5), 2–16. https://doi.org/10.3390/hydrology5040053

Chen, Yong, Marek, G. W., Marek, T. H., Xue, Q., Brauer, D. K., Srinivasan, R. (2019). Assessing Soil and Water Assessment Tool Plant Stress Algorithms Using Full and Deficit Irrigation Treatments. *Agronomy Journal*, *111*(3), 1266–1280. https://doi.org/10.2134/agronj2018.09.0556

Christopher, S. F., Schoenholtz, S. H., Nettles, J. E. (2015). Water quantity implications of regional-scale switchgrass production in the southeastern U.S. *Biomass and Bioenergy*, *83*, 50–59. https://doi.org/10.1016/j.biombioe.2015.08.012

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K. R., Zeckoski, R. W., Jeong, J., … Youssef, M. A. (2015). A recommended calibration and validation strategy for hydrologic and water quality models. *Transactions of the ASABE*, *58*(6), 1705–1719. https://doi.org/10.13031/trans.58.10712

Dourte, D., Bartel, R. L., George, S., Marois, J. J., Wright, D. L. (2015). A sod-based cropping system for irrigation reductions, *31*(6), 14–17. https://doi.org/10.1017/S1742170515000393

Dourte, D. R., Fraisse, C. W., Uryasev, O. (2014). WaterFootprint on AgroClimate: A dynamic, web-based tool for comparing agricultural systems. *Agricultural Systems*, *125*, 33–41. https://doi.org/10.1016/j.agsy.2013.11.006

Ficklin, D. L., Barnhart, B. L. (2014). SWAT hydrologic model parameter uncertainty and its implications for hydroclimatic projections in snowmelt-dependent watersheds. *Journal of Hydrology*, *519*(PB), 2081–2090. https://doi.org/10.1016/j.jhydrol.2014.09.082

Gali, R. K., Cryer, S. A., Poletika, N. N., Dande, P. K. (2016). Modeling pesticide runoff from small watersheds through field-scale management practices: Minnesota watershed case study with chlorpyrifos. *Air, Soil and Water Research*, *9*, 113–122. https://doi.org/10.4137/ASWR.S32777

Karki, R., Srivastava, P., Kalin, L., Lamba, J., Bosch, D. D. (2019). Multi-variable sensitivity analysis, calibration, and validation of a field-scale SWAT model: Building Stakeholder Trust in Hydrologic/Water Quality Modeling. *ASABE Annual International Meeting*, (Presentation), 1–21.

Maharjan, G. R., Prescher, A. K., Nendel, C., Ewert, F., Mboh, C. M., Gaiser, T., … Jiao, J. J. (2018). Approaches to model the impact of tillage implements on soil physical and nutrient properties in different agro-ecosystem models. *Soil and Tillage Research*, *180*(August 2017), 210–221. https://doi.org/10.1016/j.still.2018.03.009

Marek, G. W., Gowda, P. H., Evett, S. R., Baumhardt, R. L., Brauer, D. K., Howell, T. A., … Point, I. (2016). Calibration and Validation of the SWAT Model for Predicting Daily ET over Irrigated Crops in the Texas High Plains Using Lysimetric Data. *Transactions of the ASABE*, *59*(2), 611–622. https://doi.org/10.13031/trans.59.10926

Marek, G. W., Gowda, P. H., Marek, T. H., Porter, D. O., Baumhardt, R. L., Brauer, D. K. (2017). Modeling long - term water use of irrigated cropping rotations in the Texas High Plains using SWAT. *Irrigation Science*, *35*(2), 111–123. https://doi.org/10.1007/s00271-016-0524-6

Maski, D., Mankin, K. R. D., Janssen, K. A., Tuppad, P., Pierzynski, G. M. (2010). MODELING NUTRIENT RUNOFF YIELDS FROM COMBINED IN-FIELD CROP MANAGEMENT PRACTICES USING SWAT, *53*(5), 1557–1568.

Migliaccio, K. W., Morgan, K. T., Vellidis, G., Zotarelli, L., Fraisse, C., Zurweller, B. A., …

Rowland, D. (2015). Smartphone apps for irrigation scheduling. *Joint ASABE/IA Irrigation Symposium 2015: Emerging Technologies for Sustainable Irrigation*, *59*(1), 516–530. https://doi.org/10.13031/trans.59.11158

Mishra, N., Srivastava, P., Singh, S. (2017). W HAT D O C LIMATE C HANGE P ROJECTIONS S AY A BOUT, *60*(4), 1139–1151.

Moloney, C., Raj, C., Frankenberger, J., Chaubey, I. (2015). Using a Single HRU SWAT Model to Examine and Improve Representation of Field-Scale Processes. In *2015 Purdue SWAT Conference Material* (Vol. Session C3).

Moriasi, D. N., Gitau, M. W., Pai, N., Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R. (2011). Theoretical documentation SWAT.

Rajib, M. A., Merwade, V., Yu, Z., Adnan, M., Merwade, V., Yu, Z., … Yu, Z. (2016). Multi-objective calibration of a hydrologic model using spatially distributed remotely sensed/in-situ soil moisture. *Journal of Hydrology*, *536*, 192–207. https://doi.org/10.1016/j.jhydrol.2016.02.037

Rugel, K., Golladay, S. W., Jackson, C. R., Rasmussen, T. C. (2016). Delineating groundwater/surface water interaction in a karst watershed: Lower Flint River Basin, southwestern Georgia, USA. *Journal of Hydrology: Regional Studies*, *5*, 1–19. https://doi.org/10.1016/j.ejrh.2015.11.011

Soil Survey Staff. (2012). SSURGO Data Packaging and Use November 2012, (November).

Teshager, A. D., Gassman, P. W., Secchi, S., Schoof, J. T., Misgna, G. (2016). Modeling

Agricultural Watersheds with the Soil and Water Assessment Tool (SWAT): Calibration and Validation with a Novel Procedure for Spatially Explicit HRUs. *Environmental Management*, *57*(4), 894–911. https://doi.org/10.1007/s00267-015-0636-4

Tripathi, M. P., Panda, R. K., Raghuwanshi, N. S. (2005). Development of effective management plan for critical subwatersheds using SWAT model. *Hydrological Processes*, *19*(3), 809–826. https://doi.org/10.1002/hyp.5618

Uniyal, B., Dietrich, J., Vasilakos, C., Tzoraki, O. (2017). Evaluation of SWAT simulated soil moisture at catchment scale by field measurements and Landsat derived indices. *Agricultural Water Management*, *193*, 55–70. https://doi.org/10.1016/j.agwat.2017.08.002

van Genuchten, M. T. (1980). Closed-Form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. *Soil Science Society of America Journal*. https://doi.org/10.2136/sssaj1980.03615995004400050002x

van Genuchten, M. T., Leji, F. J., Yates, S. R. (1991). *The RETC Cod for Quantifying the Hydraulic Functions of Unsaturated Soils*. Riverside.

van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., Srinivasan, R. (2006). A global sensitivity analysis tool for the parameters of multi-variable catchment models. *Journal of Hydrology*, *324*(1–4), 10–23. https://doi.org/10.1016/j.jhydrol.2005.09.008

Vellidis, G., Liakos, V., Perry, C., Porter, W. M., Tucker, M. A. (2016). Irrigation Scheduling for Cotton Using Soil Moisture Sensors, Smartphone Apps, and Traditional Methods, 772–780. Retrieved from http://vellidis.org/wp-content/uploads/2016/07/Vellidis-Beltwide-Paper-16779-Irrigation-Scheduling.pdf

Vellidis, G., Liakos, V., Porter, W., Tucker, M., Liang, X. (2016). A Dynamic Variable Rate Irrigation Control System. *Proceedings of the 13th International Conference on Precision*

Agriculture, 1–9.

Wallace, C. W., Flanagan, D. C., Engel, B. A. (2018). Evaluating the effects ofwatershed size on SWAT calibration. *Water (Switzerland)*, *10*(7), 1–27. https://doi.org/10.3390/w10070898

Wang, G., Barber, M. E., Chen, S., Wu, J. Q. (2014). SWAT modeling with uncertainty and cluster analyses of tillage impacts on hydrological processes, 225–238. https://doi.org/10.1007/s00477-013-0743-9

CHAPTER 3: Comparison of Crop Yields and Soil Moisture with South Georgia Soils at the Field Scale under UGA Checkbook Irrigation

ABSTRACT

Proper water allocation can be a complicated and difficult matter solve, as is evidenced by the past forty years of litigation and conflict between Georgia, Alabama, and Florida over this very matter. The state of Georgia's use of the Apalachicola-Chattahoochee-Flint river basin's water resources for the city of Atlanta and agricultural production is a primary cause for this litigation. To help stakeholders and researchers understand this basin, the Soil and Water Assessment Tool has been employed to model the hydrology and land use practices in this area. Cotton and peanut are primary crops in this region and greatly affect the hydrology. In addition, this area is home to many different types of soils. Soil type and morphology can affect crop yields, but how different soils in Georgia effect crop yields in SWAT has yet to be quantified. Thus, the objective of this study was to use a field scale model to determine the effect of soil types in southwestern Georgia on crop yields, soil moisture, and nitrate leaching. A SWAT model previously calibrated for a cotton-cotton-peanut rotation in Tifton, Georgia was used in this study with 30 years of weather data from NLDAS and the most common management practices in Georgia, including UGA Checkbook method for irrigation. Twenty-four different types of soils covering over 98% of Region V Soil-Water Conservation District (SWCD) in the STATSGO map were selected and integrated into the model, with Tifton and Orangeburg covering 46% of the area. Soil properties from SSURGO were matched to the STATSGO soils and used in this study, allowing for the diversity of soils to be accounted for while also using a more detailed soils database. A multiple comparison analysis of the different soils was run with the native SSURGO Tifton soil used as the control. When under UGA Checkbook Irrigation,

crop yields had little response to the different Georgia soil types tested in this study excepting for one very sandy soil. Overall yields were lower for all Georgia soils investigated without irrigation, but top 305mm of soil will have a larger response to soil parameterization. Soil moisture for the top layer showed much more variation and all soils were statistically significant compared to the control soil. Soil moisture tended to decrease as available water content decreased, clay content decreased, and hydraulic conductivity increased. Future research into individual soil parameters effect on yields and soil moisture is needed to better understand the relationship between crop yields and soil properties in SWAT.

INTRODUCTION

Water is an amazing resource and liquid water is one of the many things that distinguishes earth from billions of planets in the universe. Water is what sustains most life, from humans to plant life, and the availability and quality of water is very important for a community to thrive. As a result, the allocation of water can be a disputed subject as evidenced by the water wars in the southeastern united states. Georgia, Alabama, and Florida in particular have fought over proper practices and allocation of the Apalachicola-Chattahoochee-Flint river basin's water resources since 1989 (Stevens and Ruscher, 2014). The top of the basin is located in Northern Georgia, where the Chattahoochee River meanders into East Alabama, joins the Flint River in southwestern corner of Georgia to become the Apalachicola River, and final drains through Florida into the Gulf of Mexico. The ACF is nearly 385 miles (619km) long, 50 miles (80km) wide, and the total drainage area is approximately 19,573 mi2 (50,800 km2) with the greatest portion of the basin located in Georgia. It is home to approximately 24,362 reservoirs, 81% of which are located in Georgia, followed by 11% in Alabama and 8% in Florida. A main cause for the complicated legislation lies with the city of Atlanta, GA that is located at the top of the Chattahoochee River basin. The ACF system supplies 78% of Atlanta's municipal water, and downstream of the river is twelve hydro-electric dams, recreational rivers, irrigation for crops, many habitats for endangered species, and the Apalachicola Bay, home of many estuarine fisheries and hatcheries (Wehr, 2014). In addition, according to the United States Geological Survey, drought years in Georgia outnumber normal and high precipitation years since 1980, meaning Georgia will rely more on this system to help compensate for so many dry years (USGS, 2010). However, overexploitation of the basin's water resources could have highly negative consequences for the Apalachicola Basin. The Apalachicola River is a highly biodiverse area and houses many threatened and endangered species (Ruhl, 2005). Limited water quantity and quality would be damaging to the aquatic life, but especially endangered mussel species in this area. Overall, after thirty-five years of litigations without conclusive decisions, Florida petitioned the Supreme Court to take the case in 2014, arguing to limit Georgia's water use. In October 2017, the Supreme Court decided to create a cap on Georgia's water use during times of drought and the trial was appointed to a special master to determine details (Florida vs Georgia, 2017). Despite the Supreme Court's decision, no actionable changes have been made and the legal battles have no discernable end in sight.

In addition to being the primary water user in the ACF basin, Georgia is also a highly agriculturally productive area. According to the USDA National Agricultural Statistics Service (NASS), in 2017, Georgia ranked first nationally for broilers, peanuts, and utilized pecans, second for cotton lint and cotton seed, and seventh for sweet corn. Georgia is also a top national producer of fruits and vegetables, ranking third for watermelon; fourth for Bell Peppers, Cantaloupes, and Cucumbers; fifth for Tobacco; sixth for Blueberries, cabbage, eggs, onions, and squash; and finally, seventh for the state fruit – Peaches – and snap beans. There are many factors contributing to this agricultural productivity. First, Georgia has an interesting variety of aquifers, consisting of a surficial aquifer system termed the Biscayne aquifer, an upper confining unit, the upper Floridian aquifer (UFA), a middle confining unit, the lower Floridian aquifer, and a lower confining unit (Torak and Painter, 2006). These aquifers are karstic aquifers, meaning they consist of highly permeable limestone. The upper confining layer consists primarily of clastic rocks with low permeability, mostly from Hawthorn Formation from the Miocene age. Recharge zones for the UFA are throughout the Lower Flint River Basin (LFRB), meaning access to this aquifer for farmers is easier and more cost-effective. Thus, the UFA, due to both its size and water availability, is often the source of irrigation from groundwater in this area (Mitra et al 2016).

The second major factor in Georgia's agricultural productivity is the soil and geomorphology of the area. There are hundreds of different types of soil in Georgia, but the National Resource Conservation Service (NRCS) has six major categories: Limestone Valley Soils, Blue Ridge Soils, Southern Piedmont, Sand Hills, Southern Coastal Plain, and Atlantic Coast Flatwoods (2019). Limestone Valley and Blue Ridge Soils are located in the northernmost portion of the state with more loamy, well-drained, fertile lowlands suitable for forage production. The Southern Piedmont contains massive granite features and clayey soils with iron oxides, and the southernmost portions contain nutrient rich soils more suitable for row crops. Below the Piedmont is the Sand Hills region which, as the name implies, contains largely sandy soils not suitable for plant growth. The large Southern Coastal Plain Region contains a large variety of sandy, red clayey, and gravelly soils. This area was previously an ancient marine coastline during the Mesozoic era, and although the sandier texture and frequent use of these soils for farmland make nutrients less abundant, nutrient management and easy access to the UFA mean this area is primarily used for row crops.

Soil physical and chemical properties can have a major effect on both the hydrology and vegetative growth of an area. The latter has been the subject of much study in the southeast as nitrogen and phosphorus are very important macronutrients for row crops. Nitrogen is available to plants in two forms – ammonium and nitrate. The charged nature of these molecules means there are many ways for nitrogen to be lost to a system. Ammonium can undergo denitrification under aqueous conditions, and both forms of nitrogen can be lost by runoff and leaching, especially in sandier soils with less organic matter to hold the nutrients. Phosphorus can be lost in similar manners; however, the phosphorus cycle does not have an atmospheric component, meaning phosphorus buildup is also a concern in many soils. In addition, in order for nitrogen to become plant available from organic substances, there also needs to be enough active carbon in the system to help promote decomposition. One study using nonlinear parametric modelling technique found for wheat and spring barley Phosphorus and total carbon were some of the greatest contributing factors to crop yields and NDVI in Bedfordshire UK (Whetton et al., 2017). Another study in Denmark found after testing a wide range of soils on winter wheat and spring barley that organic carbon levels above 1% may sustain yields (Oelofse et al., 2015).

Soils' ability to hold water against gravity, or field capacity, is also a consideration in row crops. When so little water is in the soil that the overlying vegetation begins to experience water stress and wilts, a given soil has reached the wilting point. The amount of water available to plants, or field capacity minus the wilting point, is referred to as the available water content. Soil texture can play a large role in soils ability to retain water. Higher silt and clay content, due to the decrease of macropores, results in a higher available water content (Brady and Weil, 2008; Hoegenauer, 2014; van Lanen et al., 1992). However, too high of a clay content can result in water restrictive layers and stunting of root growth. The opposite is true for sandier soils. Fine and sandier soils tend to have much higher hydraulic conductivity, meaning water flows through sandier soils much faster than clayey soils. So although sandy soils have more macropores, can hold more air, and thus provide more underground oxygen exchange, these soils need much more irrigation because water is so quickly lost in the system (van Lanen et al., 1992). Many different management practices have been tested and utilized by growers to increase soil fertility and decrease loss of nutrients and water. Some studies have found when corn is tilled and rotated with a legume, it experienced increased yields and soil fertility (Agber et al., 2018). Other studies have found integration of conservation tillage and cover crops in the southeast can increase soil organic carbon, soil structure, and ultimately yields (Hoegenauer, 2014; Reaves and Delaney, 2002). Cover crops in particular can be beneficial to cash crops by protecting the soil from erosion, sequestering nutrients, reduce fertilizer applications, conserving soil moisture, and increasing soil carbon (Reaves and Delaney, 2002; SARE, 2007, 2019). One study testing a sod-based rotation system and different types of tillage practices found in the Southeastern US found cotton yields were not affected negatively or positively by conservation practices but peanut yields significantly improved with strip tillage (Hoegenauer, 2014).

Because field experiments are time consumptive and costly, researchers have employed modelling programs at regional, watershed, and field scales to better understand the hydrology, soil, and plant growth of a system. Modeling agricultural activity, such as the crops being grown and management practices, is very important for proper modeling of hydrological processes in agriculturally dominated watersheds because crops can affect soil, nutrients, surface runoff, and evapotranspiration (Christopher et al., 2015; Maski et al., 2010; Neitsch et al., 2011). One such study used Aquacrop, a crop water productivity model, to assess maize, wheat, and quinoa at three different sites in three different countries (Van Gaelen et al., 2015). They found after calibration using a semi-quantitative approach, integration of soil fertility and water stress was very important in predicting crop yields (Van Gaelen et al., 2015). Another study conducted in North China Plain using the field-scale model daisy found increasing the detail of soil and weather data improved crop yield prediction, but also greatly improved regional drainage and leaching prediction (Manevski et al., 2019). Similarly, the Environmental Policy Impact Calculator (EPIC) was used by Wang et al. (2018) to investigate phosphorus losses in a corn-soybean rotation. They found EPIC performed well for surface runoff, drainage, and crop yields, but only adequately for Phosphorus due to limitations in simulating soil processes (Z. Wang et al., 2018). Other researchers have found remote sensing, modelling, and machine learning to be effective ways to determine crop yields at various scales (Leroux et al., 2019; Srinivasan, R.; Zhang, X.; Arnold, 2010).

One model used worldwide with nearly 4000 published articles to-date due to its versatility, capability to handle a variety of watersheds, and great support, is the Soil and Water Assessment Tool (SWAT). Although SWAT is used primarily to study the hydrology and nutrient cycling of a given study area, integration of the plant growth model Environmental Policy Impact Calculator (EPIC) has allowed researchers to also use this program to study the effect of various management practices on crop growth and yields (Neitsch et al., 2011). SWAT is also capable of simulating processes in the soil based on a detailed database of soil properties, such as percolation, fixation, conversion of residues into plant available nitrogen and phosphorus, and nutrient losses (Neitsch et al., 2011). However, a warmup period is usually recommended to let all processes equilibrate (Daggupati et al., 2015). Soil properties can be entered manually or imported from a database (Neitsch et al., 2011).

OBJECTIVES

A majority of the research connecting soil and crop yields in SWAT is related to nutrients in the soil and best management practices. Given the importance of soil on both the hydrology and proper simulation of crop yields, more investigation into the relationship between soil and crops needs to be investigated. Also, with Georgia being of such agricultural importance, understanding how Georgia soils impact crop yields and soil moisture in SWAT would be very valuable for farmers and researchers to better understand the role soil plays in the ACF river basin. Thus, the objectives of this study were to use a calibrated and validated field-scale SWAT model to assess the long-term impacts of different soil types in Georgia on crop yields and surface soil moisture.

METHODS AND MATERIALS

Study Area

Soils in Region V of Georgia Soil Water Conservation Districts were used in this study. The Georgia General Assembly established Soil and Water Conservation Districts (SWCDs) in 1937 after the dust bowl as means to protect Georgia's soil and water resources. SWCDs are based on county lines, and Region V in particular contains 6 districts with 47 different counties (Table 2.1; Figure 2.24). This area was chosen for many reasons: 1) it is a massive row crop hot spot in the state of Georgia 2) It is above the UFA 3) it contains both our model study site and counties in the ACF River Basin 4) has a very large variety of soils, from sandy soils to clay loams.

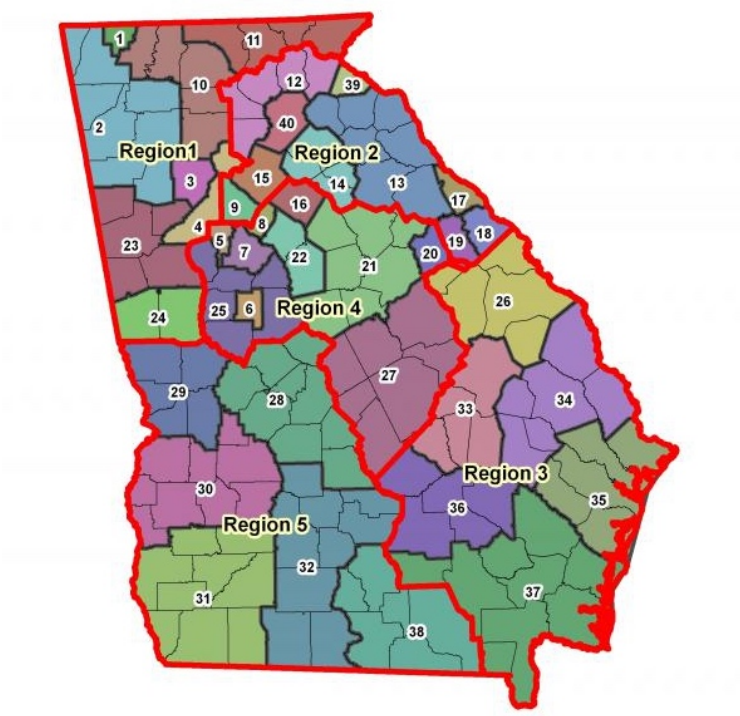


Figure 2.24. Map of Georgia Soil and Water Conservation Districts (SWCDs) grouped by regions. Legend of Region 5 SWCDs can be found in Table 2.1.

Table 2.3. Legend for Georgia Region V Soil and Water Conservation Districts (SWCDs). Numbers are followed by SWCD names and list of counties within each respective district

#	SWCD	Counties
38	Alapaha	Berrien, Clinch, Cook, Echols, Lanier & Lowndes
31	Flint River	Baker, Calhoun, Decatur, Dougherty, Early, Grady, Miller, Mitchell & Seminole
30	Lower Chattahoochee River	Clay, Lee, Quitman, Randolph, Schley, Stewart, Sumter, Terrell & Webster
32	Middle South Georgia	Ben Hill, Brooks, Colquitt, Crisp, Irwin, Thomas, Tift, Turner & Worth
28	Ochmulgee River	Bibb, Crawford, Dooly, Houston, Macon, Peach, Pulaski, Taylor & Wilcox
29	Pine Mountain	Chattahoochee, Harris, Marion, Muscogee & Talbot

SWAT Model Description

SWAT was originally developed by Dr. Jeff Arnold for the USDA Agricultural Research Service to understand the impact of land management practices on water, sediment and agricultural chemical yields on large complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch et al. 2011). SWAT is a physically based model, meaning instead of parameterizing output results with regression relationships, the results are produced based on a wide variety of input data, such as weather, soil, land, vegetation, and land management practices. In this way, highly complex watersheds can be modeled for water, sediment, crop growth, nutrient cycling, and more. It maps a watershed basin, subbasins, and subbasin outlets based on elevation data and streamflow shape files if available. SWAT also has a very high resolution by creating unique categories called Hydraulic Response Units (HRUs). Each HRU has a unique land cover, soil type, and slope. Outputs for the HRUs are calculated and then scaled up to the sub-basin outlet by the percent area of the

HRU within the sub-basin. When compared alongside eleven different hydrological models in 2003 by Borah and Berah, SWAT was determined to have high skill and a great potential for expansion. SWAT is usually used over long-term studies but is capable of performing well at multiple time steps, including daily, hourly, monthly, and yearly (Abbaspour, 2015; Arnold et al., 2012).

The model used in this study is a field-scale model and was originally calibrated and validated in a previous study at a site in Tifton, Georgia (Karki et al., 2019). This model underwent a multi-variable calibration and validation of surface runoff, soil moisture, crop yields, and nitrate with measured data from 1999-2006. Surface runoff was calibrated and validated at a daily time step for four years and three years, respectively. Soil moisture was limited, so it was calibrated from 2001-2003 and validated from 2004-2006 at a daily time step for the top 305 mm. This site was also calibrated and validated with 5 years of cotton data and 3 years of peanut data each. Surface runoff flow and nitrate performed well and crop yields satisfactorily based on coefficient of determination (R^2), Nash Sutcliffe efficiency (NSE), and percent bias (PBIAS) (Moriasi et al., 2015). Recommended performance measure values were not available for soil moisture, but the trend was followed, and the performance measures were determined to be adequate.

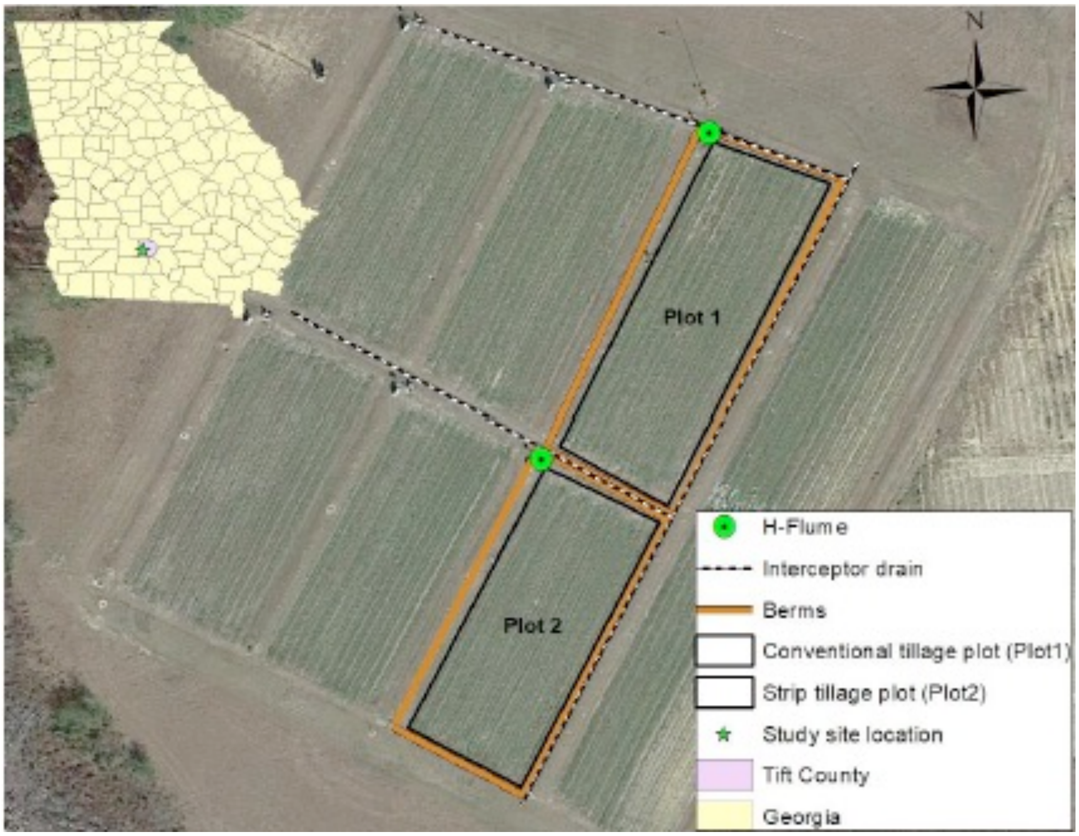


Figure 2.2. Map of calibrated and validated SWAT field-scale model used in this study, which is based on fields in Tifton, Georgia (Karki et al., 2019).

Data Inputs and Isolating Soil Types

30 years of daily weather data from the National Land Data Assimilation network were used for the simulation to allow 3 years of warmup (1987-1989) and 27 years of simulation (1990-2016). Georgia extension agents were consulted regarding specific common management practices from a typical cotton-cotton-peanut rotation and were integrated into the model (Table 2). In order to isolate soils covering Region V Georgia SWCDs, soils from the State Soil Geographic Dataset (STATSGO) were used in this study. STATSGO was developed by the National Cooperative Soils Survey to develop a broad inventory of soils and non-soil areas that occur in a repeatable pattern on the landscape and can be cartographically shown at the map scale of 1:250,000. 25 Different Types of soils were selected covering 98% of the Region V. These soils were then matched to soils from the Soil Survey Geographic Database (SSURGO).

This database was used for the simulation because a preliminary analysis with STATSGO indicated the depth and number of soil layers were not representative of the area. SSURGO is much more detailed than STATSGO with information collected at scales ranging from 1:12,000 to 1:63,360. SSURGO also generally results in better hydrological performance due to the higher resolution (Wang and Melesse, 2007). The soils were matched between the databases on the basis of name, texture, location (within Region V), and depth of the individual soil layers.

Table 2.4. Management schedule for 3-year cotton-cotton-peanut rotation during the 30 simulation years

	Peanut		**Cotton**	
Operation	***Description***	***Date***	***Description***	***Date***
Fertilizer Application	None	-	4483 kg/ha poultry litter	17-Apr
Tillage	Conventional	5-May	Conventional	24-Apr
Planting	-	9-May	-	1-May
Irrigation	UGA Checkbook based	Weather dependent	UGA Checkbook based	Weather dependent
Fertilizer Application	-	-	78.6 kg/ha of N-sidedress	20-Jun
Cover Crop	None	-	None	-
Harvest	-	30-Sep	-	30-Sep

Data Analysis

Annual crop yields and daily soil moisture for the top 305 mm were outputs analyzed in this study over the 30 years simulation. A multiple comparison analysis was conducted using the R multcomp package on each simulation output with the control being the original soil type at the field site and the treatments being the Georgia soil types tested. One-way ANOVA followed by Tukey's post-hoc test was conducted and p-values less than 0.05 were considered significant when compared to the control. For this study, the soil native to the research station – Tifton – with the SSURGO default settings as the control soil. Any data without a normal distribution were transformed with Box-Cox transformation (1964).

RESULTS AND DISCUSSION

Due to non-normalized distributions of the data, Box-Cox transformations had to be applied to non-irrigated yield, irrigated soil moisture, and non-irrigated soil moisture data. Data transformations were ineffective in normalizing the distribution for both nitrate leaching scenarios, thus consultations with statisticians will occur to properly analyze the effect on nitrate leaching.

Although there was some variation between the soil types, only Mandarin soil produced significantly lower yields than the control under checkbook irrigation (Table 2.3; Figure 2.3 and 2.4). This is likely because, despite being under UGA checkbook irrigation, Mandarin had the highest amount of sand content (97%) and lowest available water content of all the soils tested. However, without irrigation, all soils resulted in lower yields and more soil types showed statistically significant difference in yields thank the control (pval<0.05) – specifically, Nankin, Cecil, Chewacla, Valdosta, Osier, Troup, Lakeland, Wilkes, Pelham, Leefield, and Mandarin (Figure 2.4). Lakeland, Leefield, Pelham, and Wilkes all had similar yield results to Mandarin in the absence of irrigation, which is likely due to the high sand content and low available water content of these soils (Figure 2.4; Table 2.4). However, it is unclear at this time the precise variable which caused the differences in yields in the absence of irrigation.

On the other hand, soil moisture was significantly different for all soils compared to the control in both scenarios (Table 2.3; Figure 2.5 and 2.6). Available water content is likely major

Table 2.5. One-way ANOVA results of crop yields and soil moisture for the different Georgia soil types

	Degrees of Freedom	F-value	P-value
Yields – Checkbook	23	1.513	0.0592
Soil Moisture – Checkbook	23	6557	<2e-16
Yields – No irrigation	23	12.81	<2e-16
Soil Moisture – No irrigation	23	4687	<2e-16

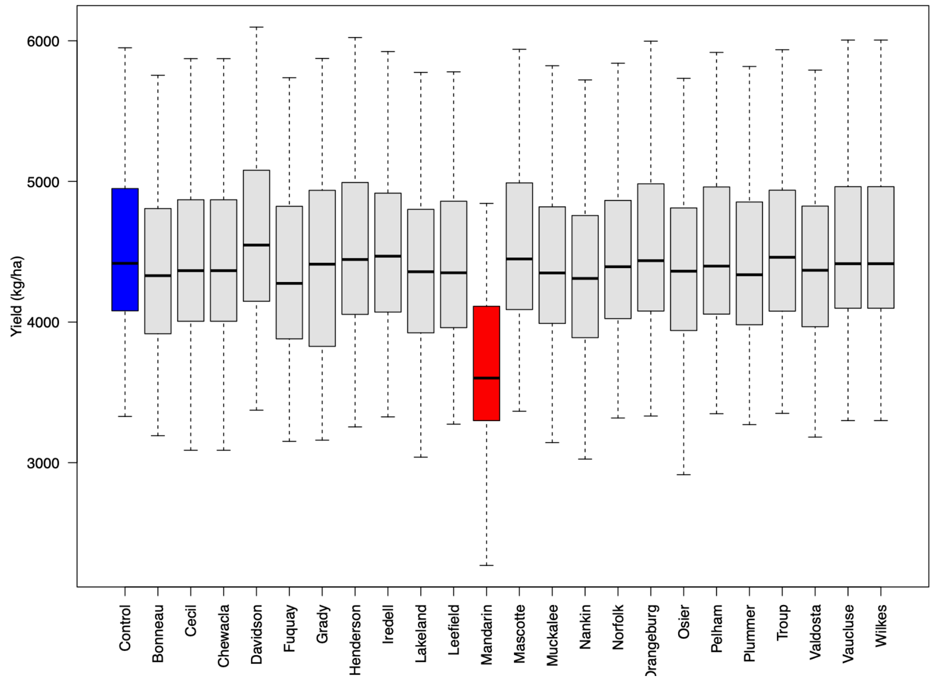


Figure 2.25. Average yield values (kg/ha) for each soil type tested over 27 years simulated under Checkbook Irrigation. Control soil is highlighted in blue and the significantly different soil (pval<0.05) is highlighted in red.

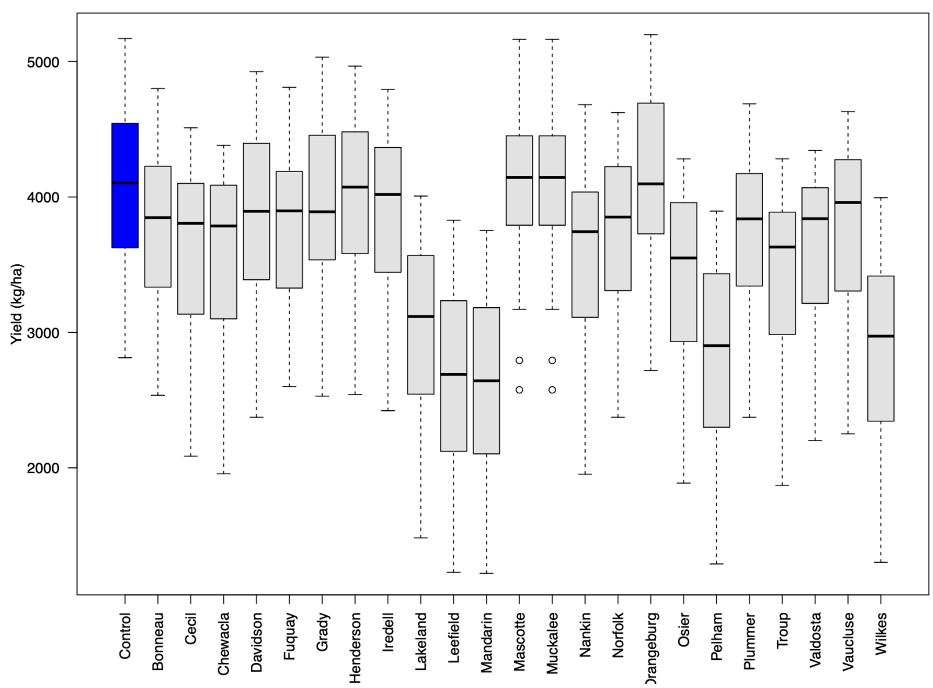


Figure 2.26. Average yield values (kg/ha) for each soil type tested over 27 years without irrigation, sorted by not statistically different to most statistically different soil (pval <0.05). Control is highlighted in blue and different soils are grouped by p-value.

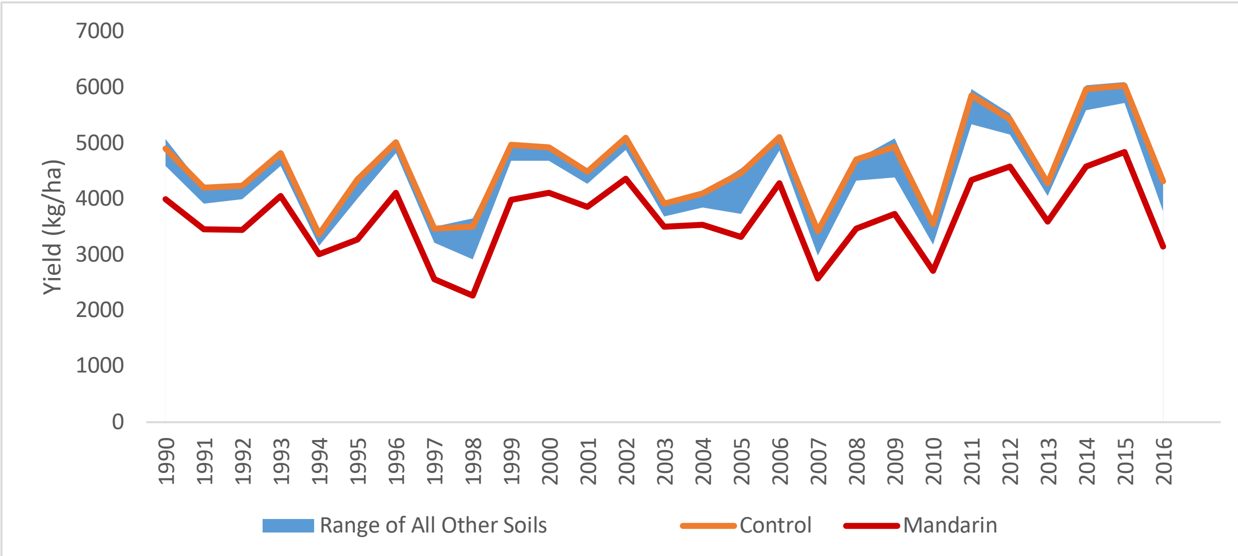


Figure 2.27. Average Annual yield (kg/ha) for all Georgia soils during the simulation period for a cotton-cotton-peanut rotation under UGA Checkbook irrigation, with the only statistically significant soil shown in red, control in orange, and all other soils in blue.

contributing factor in the overall distribution of soil moisture in the top layer 305mm little major differences can be seen with and without irrigation. Soil albeto seemed to have little effect on soil moisture or crop yields. Soils with more clayey textures in the soil profile and low hydraulic conductivity tended to have higher soil moisture in the top layer. This makes sense because soils with more clay will have fewer macropores and lower hydraulic conductivity will result in less percolation and thus less water lost in the soil profile.

However, some soils showed surprising trends with regard to irrigation and soil moisture content. For example, Chewacla and Wilkes had higher soil moisture content in the absence of irrigation. Chewacla has a very high silt content and high available water content, so it is unclear why less added water contributed to higher soil moisture (Table 2.4; Figures 2.5 and 2.6). However, Muckalee soil had a lower soil moisture content than the control, which could be

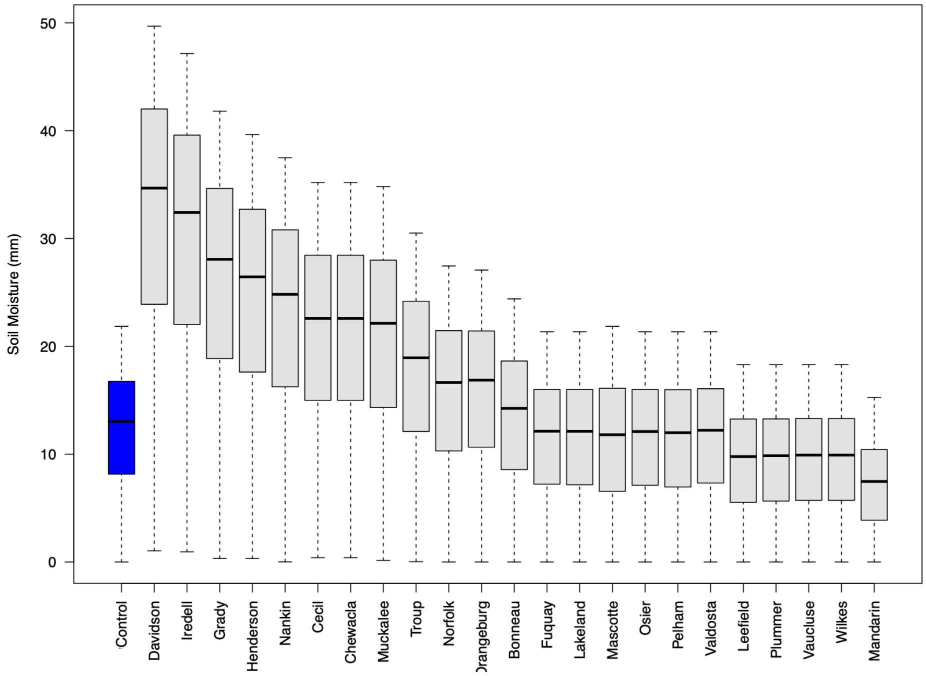


Figure 2.28. Average soil moisture values for each soil type tested over 27 years simulated under checkbook irrigation. Control soil is highlighted in blue and statistically similar soils after the multiple comparison analysis are grouped from least to most significantly different.

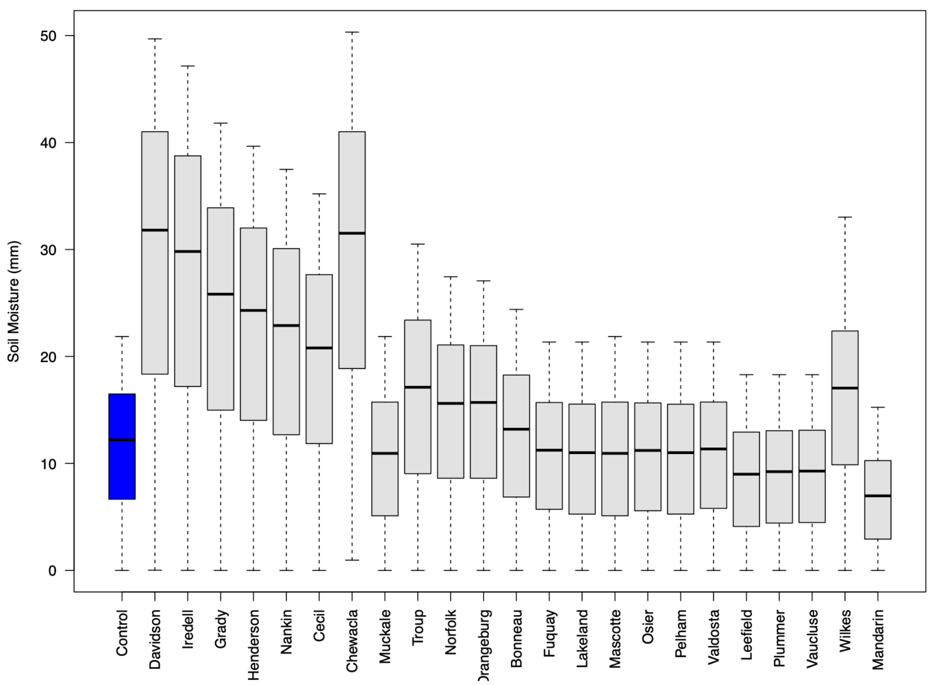


Figure 2.29. Average soil moisture (mm) values for each soil type tested over 27 years without irrigation. Control is highlighted in blue and the order is not changed from the ordering of from the previous figure so differences between irrigation scenarios are clear.

Table 2.6. List of soils followed by their respective important SSURGO database values. Information for the whole soil profile is shown followed by top layer values of bulk density (BD), available water content (AWC), hydraulic conductivity (K_{sat}), percent (%) active carbon content, percent (%) clay/silt/sand, and reflectivity (albeto).

Soil Name	Number of Layers	Hydro Soil Group	Profile Depth (mm)	Texture Distribution	Top Layer BD	Top AWC	Top K_{sat}	% Active Carbon	% Clay	% Silt	% Sand	Top Albeto
Tifton (control)	6	B	1830	LS-SL-SCL-SCL	1.2	0.06	331.2	0.44	5.5	9.2	85.3	0.3
Bonneau	2	A	1630	LS-SCL	1.5	0.08	331.2	0.73	10	4.3	85.7	0.3
Cecil	4	B	1910	SL-SCL-C-L	1.4	0.13	100.8	0.44	12.5	19.6	67.9	0.3
Chewacla	5	C	1780	L-SIL-L-SIL-SIL	1.45	0.2	32.4	1.45	22.5	37.7	39.8	0.37
Davidson	4	B	1830	CL-CL-C-C	1.43	0.16	32.4	0.73	27.5	37.8	34.7	0.16
Fuquay	3	B	2440	LS-SCL-SCL	1.65	0.07	331.2	0.73	6	9.1	84.9	0.3
Grady	3	D	1570	L-SCL-C	1.33	0.14	32.4	1.45	25	36.5	38.5	0.23
Henderson	3	B	1650	GR-SL-GR-C-C	1.4	0.13	82.8	0.73	18.5	15	66.5	0.3
Iredell	4	C	1570	SL-C-L-SL	1.5	0.14	100.8	0.73	15	19.1	65.9	0.3
Lakeland	2	A	2030	S-S	1.5	0.07	331.2	0.44	5	1.4	93.6	0.23
Leefield	3	C	1910	LS-SL-SCL	1.53	0.06	331.2	0.87	6.5	9.2	84.3	0.23
Mandarin	4	C	2030	S-FS-FS-FS	1.4	0.05	331.2	1.02	1.5	1.5	97	0.3
Mascotte	6	B	2030	FS-FS-FS-FS-SCL-LS	1.35	0.1	331.2	2.61	2.5	0.7	96.8	0.23
Muckalee	2	D	1570	L-SL	1.38	0.12	32.4	0.87	17.5	39.5	43	0.23
Nankin	4	C	1650	SCL-SCL-SC-SCL	1.53	0.12	32.4	0.44	25	18	57	0.3
Norfolk	3	B	1780	LS-SCL-SCL	1.63	0.09	331.2	0.73	5	15.8	79.2	0.37
Orangeburg	4	B	1630	LS-SL-SCL-SCL	1.45	0.08	100.8	0.44	7	9.2	83.8	0.3
Osier	3	A	1910	S-S-COS	1.48	0.07	331.2	2.03	5.5	1.6	92.9	0.23
Pelham	3	B	1730	LS-SCL-SCL	1.6	0.07	331.2	0.87	7.5	9	83.5	0.3
Plummer	2	B	1830	S-SCL	1.5	0.06	280.8	1.16	4	1.4	94.6	0.3
Troup	2	A	2030	LS-SCL	1.5	0.1	331.2	0.44	7	9.2	83.8	0.23
Valdosta	3	A	2510	S-LS-LS	1.43	0.07	331.2	0.44	5.5	1.6	92.9	0.3
Vaucluse	4	C	1830	LS-SCL-SCL-SL	1.45	0.06	331.2	0.44	6	9.1	84.9	0.3
Wilkes	3	C	1220	SL-CL-WB	1.4	0.13	100.8	0.73	12.5	19.6	67.9	0.37

because the overall soil thickness is not as high as the others (1570mm) but a similarly thick soil, Grady, did not have lower soil moisture. One possible explanation could lie in the textural distribution of the two soils down the soil profile. Muckalee has a low sand content in the top layers that increases farther into the earth, whereas Grady has the opposite trend and increasing clay content father from the surface. This indicates the lower soil layer parameterization could play an important role of surface soil moisture in SWAT.

The aforementioned parameters likely had an effect on soil moisture in the top 305 mm, but the most identifiable trend lies with available water content. As the available water content decreased, soil moisture also decreased. This too makes sense because available water content is directly related to how much water is in the soil layer in the SWAT equations (Neitsch et al., 2011). This trend can also be seen when comparing the soils average annual soil moisture and the seasonal soil moisture. Soils with lower available water content had less soil moisture and less variability throughout the 27 years simulated. All soils had higher soil moisture during the winter months and lower during the summer months, excepting the growing season when crop cover likely aided in water retention in the soil.

CONCLUSIONS

After testing 24 different Georgia soil types on a SWAT field scale model and running for 30 years (3 years warmup), crop yields had little response to the different soil types excepting for one very sandy soil under Checkbook irrigation, but the absence of irrigation showed decrease in yields and more sensitivity to soil parameters. This means even though yields showed slight variation, with irrigation other soil parameters likely have a smaller effect on crop yields in this SWAT model. However, soil moisture for the top layer showed much more variation and all soils were statistically significant compared to the control soil under both irrigation scenarios. Soil moisture tended to decrease as available water content decreased, clay content decreased, and hydraulic conductivity increased. Future research is needed to clearly identify which soil property in the SWAT-soil database is responsible for the changes in soil moisture and yields. A global sensitivity and uncertainty analysis on SWAT soil input parameters and both crop yields and soil moisture would be a likely next step. Also, observed field cotton and peanut yields per soil type would assist in checking to make sure SWAT simulated yields are consistent in the real world.

REFERENCES

Abbaspour, K. C. (2015). SWAT-CUP: SWAT Calibration and Uncertainty Programs- A User Manual,Department of Systems Analysis,Intergrated Assessment and Modelling (SIAM),EAWAG. Swiss Federal Institute of Aqualtic Science and Technology,Duebendorf,Switzerland. *User Manual*, 100p. https://doi.org/10.1007/s00402-009-1032-4

Agber, P., T., G., S., A. (2018). Soil Properties and Rainfed Maize Yield as Influenced by Tillage Practices Integrated With Soil Conservation Practices in Makurdi , Nigeria. *Sumerianz Journal of Agriculture and Veterinary*, *1*(2), 48–53.

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., Neitsch, S. L. (2012). *Soil and Water Assessment Tool (SWAT) User's Manual, Version 2012*. https://doi.org/10.1007/978-0-387-35973-1_1231

Brady, N., Weil, R. (2008). *The Nature and Properties of Soils*. (V. Anthony & K. Happell, Eds.) (14th ed.). Upper Saddle River: Pearson Prentice Hall.

Christopher, S. F., Schoenholtz, S. H., Nettles, J. E. (2015). Water quantity implications of regional-scale switchgrass production in the southeastern U.S. *Biomass and Bioenergy*, *83*, 50–59. https://doi.org/10.1016/j.biombioe.2015.08.012

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K. R., Zeckoski, R. W., Jeong, J., … Youssef, M. A. (2015). A recommended calibration and validation strategy for hydrologic and water quality models. *Transactions of the ASABE*, *58*(6), 1705–1719. https://doi.org/10.13031/trans.58.10712

Hoegenauer, K. L. (2014). *Conservation System Impacts on Soil Properties and Water-Use Efficiency in the Southeastern U.S. Coastal Plain*.

Karki, R., Srivastava, P., Kalin, L., Lamba, J., Bosch, D. D. (2019). Multi-variable sensitivity analysis, calibration, and validation of a field-scale SWAT model: Building Stakeholder Trust in Hydrologic/Water Quality Modeling. *ASABE Annual International Meeting*, (Presentation), 1–21.

Leroux, L., Castets, M., Baron, C., Escorihuela, M. J., Bégué, A., Lo Seen, D. (2019). Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. *European Journal of Agronomy*, *108*(July 2018), 11–26. https://doi.org/10.1016/j.eja.2019.04.007

Manevski, K., Børgesen, C. D., Li, X., Andersen, M. N., Zhang, X., Shen, Y., Hu, C. (2019). Modelling agro-environmental variables under data availability limitations and scenario managements in an alluvial region of the North China Plain. *Environmental Modelling and Software*, *111*(October 2018), 94–107. https://doi.org/10.1016/j.envsoft.2018.10.001

Maski, D., Mankin, K. R. D., Janssen, K. A., Tuppad, P., Pierzynski, G. M. (2010). MODELING NUTRIENT RUNOFF YIELDS FROM COMBINED IN-FIELD CROP MANAGEMENT PRACTICES USING SWAT, *53*(5), 1557–1568.

Moriasi, D. N., Gitau, M. W., Pai, N., Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R. (2011). Theoretical documentation SWAT.

Oelofse, M., Markussen, B., Knudsen, L., Schelde, K., Olesen, J. E., Stoumann, L., Bruun, S. (2015). Do soil organic carbon levels affect potential yields and nitrogen use efficiency ? An analysis of winter wheat and spring barley field trials. *European Journal of Agronomy*, *66*, 62–73. https://doi.org/10.1016/j.eja.2015.02.009

Reaves, D. W., Delaney, D. P. (2002). CONSERVATION ROTATIONS FOR COTTON PRODUCTION AND CARBON STORAGE. In *25TH SOUTHERN CONSERVATION TILLAGE CONFERENCE* (pp. 344–348).

Ruhl, J. B. (2005). Water Wars, Eastern Style: Divvying Up the Apalachicola-Chattahoochee-Flint River Basin. *Journal of Contemporary Water Research & Education*, *131*(131), 47–54. https://doi.org/10.1111/j.1936-704x.2005.mp131001008.x

SARE. (2007). *Managing Cover Crops Profitably*. (A. Clark, Ed.) (3rd ed.). University of Maryland: Sustainable Agriculture Research and Education (SARE) Program.

SARE. (2019). Crop Rotation with Cover Crops. Retrieved April 4, 2019, from https://www.sare.org/Learning-Center/Books/Managing-Cover-Crops-Profitably-3rd-Edition/Text-Version/Crop-Rotation-with-Cover-Crops

Srinivasan, R.; Zhang, X.; Arnold, J. (2010). SWAT UNGAUGED: HYDROLOGICAL BUDGET AND CROP YIELD PREDICTIONS IN THE UPPER MISSISSIPPI RIVER BASIN. *Transactions Of The Asabe*, *53*(5), 1533–1546.

Stevens, K. A., Ruscher, P. H. (2014). Large scale climate oscillations and mesoscale surface meteorological variability in the Apalachicola-Chattahoochee-Flint River Basin. *Journal of Hydrology*, *517*, 700–714. https://doi.org/10.1016/j.jhydrol.2014.06.002

Torak, L. J., Painter, J. A. (2006). Geohydrology of the Lower Apalachicola– Chattahoochee–Flint River Basin, Southwestern Georgia, Northwestern Florida, and Southeastern Alabama Scientific Investigations Report 2006-5070. Retrieved from https://pubs.usgs.gov/sir/2006/5070/pdf/sir06-5070.pdf

Van Gaelen, H., Tsegay, A., Delbecque, N., Shrestha, N., Garcia, M., Fajardo, H., … Raes, D.

(2015). A semi-quantitative approach for modelling crop response to soil fertility: Evaluation of the AquaCrop procedure. *Journal of Agricultural Science*, *153*(7), 1218–1233. https://doi.org/10.1017/S0021859614000872

van Lanen, H. A. J., Reinds, G. J., Boersma, O. H., Bouma, J. (1992). Impact of soil management systems on soil structure and physical properties in a clay loam soil, and the simulated effects on water deficits, soil aeration and workability. *Soil and Tillage Research*, *23*(3), 203–220. https://doi.org/10.1016/0167-1987(92)90101-G

Wang, X., Melesse, A. M. (2007). Effects of Statsgo and Ssurgo As Inputs on Swat Model'S Snowmelt Simulation1. *JAWRA Journal of the American Water Resources Association*, *42*(5), 1217–1236. https://doi.org/10.1111/j.1752-1688.2006.tb05296.x

Wang, Z., Zhang, T. Q., Tan, C. S., Taylor, R. A. J., Wang, X., Qi, Z. M., Welacky, T. (2018). Simulating crop yield, surface runoff, tile drainage and phosphorus loss in a clay loam soil of the Lake Erie region using EPIC. *Agricultural Water Management*, *204*(April), 212–221. https://doi.org/10.1016/j.agwat.2018.04.021

Wehr, J. (2014). THE CANARY IN THE COAL MINE: THE APALACHICOLA-CHATTAHOOCHEE-FLINT RIVER BASIN DISPUTE AND THE NEED FOR COMPREHENSIVE INTERSTATE WATER ALLOCATION REFORM. *Alabama Law Review*, *66*(1), 203–219.

Whetton, R., Zhao, Y., Shaddad, S., Mouazen, A. M. (2017). Nonlinear parametric modelling to study how soil properties affect crop yields and NDVI. *Computers and Electronics in Agriculture*, *138*, 127–136. https://doi.org/10.1016/j.compag.2017.04.016

CHAPTER 4: Thesis Conclusions

1. SWAT is capable of modelling surface runoff, soil moisture, crop biomass, crop yields, and crop nitrogen at the field scale
2. Integration of crop database parameters into the calibration and validation of the model resulted in a better simulation of soil moisture
3. SWAT simulated soil moisture and soil nitrate had great difficulty matching the observed data, especially for peanuts.
4. It is not clear whether these difficulties are because of problems with the model or problems with the observed data.
5. The scenario analysis conducted in calibration study revealed additional calibration of soil processes with low quality data could result in a model behaving differently than what is known of the study area.
6. Calibration of too many variables or with uncertain data could result in the model behaving differently than what is understood of a landscape
7. When under UGA Checkbook Irrigation, crop yields had little response to the different Georgia soil types tested in this study excepting for one very sandy soil.
8. Overall yields will be lower for all Georgia soils investigated without irrigation, but top 305mm of soil will have a larger response to soil parameterization.
9. Soil moisture for the top layer showed much more variation and all soils were statistically significant compared to the control soil. Soil moisture tended to decrease as available water content decreased, clay content decreased, and hydraulic conductivity increased.
10. Future research is needed to clearly identify which soil property in the SWAT-soil database is responsible for the changes in yields and soil moisture.

11. A global sensitivity and uncertainty analysis on SWAT soil input parameters and both crop yields and soil moisture would be a likely next step.

12. Also, observed field cotton and peanut yields per soil type would assist in checking to make sure SWAT simulated yields are consistent in the real world.

13. Analysis of other variables, such as surface runoff and leaching, would also assist in understanding how different soil types behave in a watershed

REFERENCES

Abbaspour, K.C. (2015). SWAT-CUP: SWAT Calibration and Uncertainty Programs- A User Manual,Department of Systems Analysis,Intergrated Assessment and Modelling (SIAM),EAWAG. Swiss Federal Institute of Aqualtic Science and Technology,Duebendorf,Switzerland. *User Manual*, 100p. https://doi.org/10.1007/s00402-009-1032-4

Abbaspour, Karim C., Vaghefi, S. A., Srinivasan, R. (2017). A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 international SWAT conference. *Water (Switzerland)*, *10*(1). https://doi.org/10.3390/w10010006

Agber, P., T., G., S., A. (2018). Soil Properties and Rainfed Maize Yield as Influenced by Tillage Practices Integrated With Soil Conservation Practices in Makurdi , Nigeria. *Sumerianz Journal of Agriculture and Veterinary*, *1*(2), 48–53.

Anand, S., Mankin, K. R., McVay, K. A., Janssen, K. A., Barnes, P. L., Pierzynski, G. M. (2007). Calibration and validation of ADAPT and SWAT for field-scale runoff prediction. *Journal of the American Water Resources Association*, *43*(4), 899–910. https://doi.org/10.1111/j.1752-1688.2007.00061.x

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., Neitsch, S. L. (2012). *Soil and Water Assessment Tool (SWAT) User's Manual, Version 2012*. https://doi.org/10.1007/978-0-387-35973-1_1231

Arnold, J. G., Youssef, M. A., Yen, H., White, M. J., Sheshukov, A. Y., Sadeghi, A. M., … Gowda, P. H. (2015). Hydrological Processes and Model Representation: Impact of Soft Data on Calibration. *Transactions of the ASABE*, *58*(6), 1637–1660.

https://doi.org/10.13031/trans.58.10726

Arundel, S. T., Archuleta, C.-A. M., Phillips, L. A., Roche, B. L., Constance, E. W. (2015). 1-Meter Digital Elevation Model specification. *Techniques and Methods*, 36. https://doi.org/10.3133/tm11B7

Ban, S., Irfan, Y., Lewell, F., Michael, E. (2007). Forecasting Irrigation Water Demand : A Case Study on the Flint River Basin in Georgia.

Behera, S., Panda, R. K. (2006). Evaluation of management alternatives for an agricultural watershed in a sub-humid subtropical region using a physical process based model. *Agriculture, Ecosystems and Environment*, *113*, 62–72. https://doi.org/10.1016/j.agee.2005.08.032

Boryan, C., Yang, Z., Mueller, R., Craig, M. (2011). Monitoring US agriculture: The US department of agriculture, national agricultural statistics service, cropland data layer program. *Geocarto International*, *26*(5), 341–358. https://doi.org/10.1080/10106049.2011.562309

Brady, N., Weil, R. (2008). *The Nature and Properties of Soils*. (V. Anthony & K. Happell, Eds.) (14th ed.). Upper Saddle River: Pearson Prentice Hall.

Chen, C., Pei, S., Jiao, J. J. (2003). Land subsidence caused by groundwater exploitation in Suzhou City, China. *Hydrogeology Journal*, *11*(2), 275–287. https://doi.org/10.1007/s10040-002-0225-5

Chen, Y, Marek, G. W., Marek, T. H., Brauer, D. K., Srinivasan, R. (2018). Improving SWAT auto-irrigation functions for simulating agricultural irrigation management using long-term lysimeter fi eld data. *Environmental Modelling and Software*, *99*(January), 25–38. https://doi.org/10.1016/j.envsoft.2017.09.013

Chen, Y, Marek, G. W., Marek, T. H., Gowda, P. H., Xue, Q., Moorhead, J. E., … He, K. R. (2019). Multisite evaluation of an improved SWAT irrigation scheduling algorithm for corn (Zea mays L .) production in the U . S . Southern Great Plains. *Environmental Modelling & Software*, *118*(April), 23–34. https://doi.org/10.1016/j.envsoft.2019.04.001

Chen, Yong, Marek, G. W., Marek, T. H., Brauer, D. K., Srinivasan, R. (2017). Assessing the efficacy of the SWAT auto-irrigation function to simulate irrigation, evapotranspiration, and crop response to management strategies of the texas high plains. *Water (Switzerland)*, *9*(7). https://doi.org/10.3390/w9070509

Chen, Yong, Marek, G. W., Marek, T. H., Moorhead, J. E., Heflin, K. R., Brauer, D. K., … Srinivasan, R. (2018). Assessment of Alternative Agricultural Land Use Options for Extending the Availability of the Ogallala Aquifer in the Northern High Plains of Texas. *Hydrology*, *53*(5), 2–16. https://doi.org/10.3390/hydrology5040053

Chen, Yong, Marek, G. W., Marek, T. H., Xue, Q., Brauer, D. K., Srinivasan, R. (2019). Assessing Soil and Water Assessment Tool Plant Stress Algorithms Using Full and Deficit Irrigation Treatments. *Agronomy Journal*, *111*(3), 1266–1280. https://doi.org/10.2134/agronj2018.09.0556

Christopher, S. F., Schoenholtz, S. H., Nettles, J. E. (2015). Water quantity implications of regional-scale switchgrass production in the southeastern U.S. *Biomass and Bioenergy*, *83*, 50–59. https://doi.org/10.1016/j.biombioe.2015.08.012

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K. R., Zeckoski, R. W., Jeong, J., … Youssef, M. A. (2015). A recommended calibration and validation strategy for hydrologic and water quality models. *Transactions of the ASABE*, *58*(6), 1705–1719. https://doi.org/10.13031/trans.58.10712

Dourte, D., Bartel, R. L., George, S., Marois, J. J., Wright, D. L. (2015). A sod-based cropping system for irrigation reductions, *31*(6), 14–17. https://doi.org/10.1017/S1742170515000393

Dourte, D. R., Fraisse, C. W., Uryasev, O. (2014). WaterFootprint on AgroClimate: A dynamic, web-based tool for comparing agricultural systems. *Agricultural Systems*, *125*, 33–41. https://doi.org/10.1016/j.agsy.2013.11.006

Gali, R. K., Cryer, S. A., Poletika, N. N., Dande, P. K. (2016). Modeling pesticide runoff from small watersheds through field-scale management practices: Minnesota watershed case study with chlorpyrifos. *Air, Soil and Water Research*, *9*, 113–122. https://doi.org/10.4137/ASWR.S32777

Hoegenauer, K. L. (2014). *Conservation System Impacts on Soil Properties and Water-Use Efficiency in the Southeastern U.S. Coastal Plain*.

Karki, R., Srivastava, P., Kalin, L., Lamba, J., Bosch, D. D. (2019). Multi-variable sensitivity analysis, calibration, and validation of a field-scale SWAT model: Building Stakeholder Trust in Hydrologic/Water Quality Modeling. *ASABE Annual International Meeting*, (Presentation), 1–21.

Leroux, L., Castets, M., Baron, C., Escorihuela, M. J., Bégué, A., Lo Seen, D. (2019). Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. *European Journal of Agronomy*, *108*(July 2018), 11–26. https://doi.org/10.1016/j.eja.2019.04.007

Llamas, R., Custodio, E., Lopez-Geta, J. A., de la Orden, J. A. (2003). *Intensive use of groundwater: challenges and opportunities*.

Maharjan, G. R., Prescher, A. K., Nendel, C., Ewert, F., Mboh, C. M., Gaiser, T., … Jiao, J. J. (2018). Approaches to model the impact of tillage implements on soil physical and nutrient properties in different agro-ecosystem models. *Soil and Tillage Research*, *180*(August 2017), 210–221. https://doi.org/10.1016/j.still.2018.03.009

Manevski, K., Børgesen, C. D., Li, X., Andersen, M. N., Zhang, X., Shen, Y., Hu, C. (2019). Modelling agro-environmental variables under data availability limitations and scenario managements in an alluvial region of the North China Plain. *Environmental Modelling and Software*, *111*(October 2018), 94–107. https://doi.org/10.1016/j.envsoft.2018.10.001

Marek, G. W., Gowda, P. H., Evett, S. R., Baumhardt, R. L., Brauer, D. K., Howell, T. A., … Point, I. (2016). Calibration and Validation of the SWAT Model for Predicting Daily ET over Irrigated Crops in the Texas High Plains Using Lysimetric Data. *Transactions of the ASABE*, *59*(2), 611–622. https://doi.org/10.13031/trans.59.10926

Marek, G. W., Gowda, P. H., Marek, T. H., Porter, D. O., Baumhardt, R. L., Brauer, D. K. (2017). Modeling long - term water use of irrigated cropping rotations in the Texas High Plains using SWAT. *Irrigation Science*, *35*(2), 111–123. https://doi.org/10.1007/s00271-016-0524-6

Maski, D., Mankin, K. R. D., Janssen, K. A., Tuppad, P., Pierzynski, G. M. (2010). MODELING NUTRIENT RUNOFF YIELDS FROM COMBINED IN-FIELD CROP MANAGEMENT PRACTICES USING SWAT, *53*(5), 1557–1568.

Migliaccio, K. W., Morgan, K. T., Vellidis, G., Zotarelli, L., Fraisse, C., Zurweller, B. A., … Rowland, D. (2015). Smartphone apps for irrigation scheduling. *Joint ASABE/IA Irrigation Symposium 2015: Emerging Technologies for Sustainable Irrigation*, *59*(1), 516–530. https://doi.org/10.13031/trans.59.11158

Moloney, C., Raj, C., Frankenberger, J., Chaubey, I. (2015). Using a Single HRU SWAT Model to Examine and Improve Representation of Field-Scale Processes. In *2015 Purdue SWAT*

Conference Material (Vol. Session C3).

Moriasi, D. N., Gitau, M. W., Pai, N., Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R. (2011). Theoretical documentation SWAT.

Oelofse, M., Markussen, B., Knudsen, L., Schelde, K., Olesen, J. E., Stoumann, L., Bruun, S. (2015). Do soil organic carbon levels affect potential yields and nitrogen use efficiency ? An analysis of winter wheat and spring barley field trials. *European Journal of Agronomy*, *66*, 62–73. https://doi.org/10.1016/j.eja.2015.02.009

Reaves, D. W., Delaney, D. P. (2002). CONSERVATION ROTATIONS FOR COTTON PRODUCTION AND CARBON STORAGE. In *25TH SOUTHERN CONSERVATION TILLAGE CONFERENCE* (pp. 344–348).

Rugel, K., Golladay, S. W., Jackson, C. R., Rasmussen, T. C. (2016). Delineating groundwater/surface water interaction in a karst watershed: Lower Flint River Basin, southwestern Georgia, USA. *Journal of Hydrology: Regional Studies*, *5*, 1–19. https://doi.org/10.1016/j.ejrh.2015.11.011

Ruhl, J. B. (2005). Water Wars, Eastern Style: Divvying Up the Apalachicola-Chattahoochee-Flint River Basin. *Journal of Contemporary Water Research & Education*, *131*(131), 47–54. https://doi.org/10.1111/j.1936-704x.2005.mp131001008.x

SARE. (2007). *Managing Cover Crops Profitably*. (A. Clark, Ed.) (3rd ed.). University of Maryland: Sustainable Agriculture Research and Education (SARE) Program.

SARE. (2019). Crop Rotation with Cover Crops. Retrieved April 4, 2019, from https://www.sare.org/Learning-Center/Books/Managing-Cover-Crops-Profitably-3rd-Edition/Text-Version/Crop-Rotation-with-Cover-Crops

Siebert, S., Burke, J., Faures, J. M., Frenken, K., Hoogeveen, J., Döll, P., Portmann, F. T. (2010). Groundwater use for irrigation - A global inventory. *Hydrology and Earth System Sciences*, *14*(10), 1863–1880. https://doi.org/10.5194/hess-14-1863-2010

Singh, S., Srivastava, P., Mitra, S., Abebe, A. (2016). Journal of Hydrology : Regional Studies Climate variability and irrigation impacts on streamflows in a Karst watershed — A systematic evaluation. *Biochemical Pharmacology*, *8*, 274–286. https://doi.org/10.1016/j.ejrh.2016.07.001

Soil Survey Staff. (2012). SSURGO Data Packaging and Use November 2012, (November).

Srinivasan, R.; Zhang, X.; Arnold, J. (2010). SWAT UNGAUGED: HYDROLOGICAL BUDGET AND CROP YIELD PREDICTIONS IN THE UPPER MISSISSIPPI RIVER BASIN. *Transactions Of The Asabe*, *53*(5), 1533–1546.

Stevens, K. A., Ruscher, P. H. (2014). Large scale climate oscillations and mesoscale surface meteorological variability in the Apalachicola-Chattahoochee-Flint River Basin. *Journal of Hydrology*, *517*, 700–714. https://doi.org/10.1016/j.jhydrol.2014.06.002

Teshager, A. D., Gassman, P. W., Secchi, S., Schoof, J. T., Misgna, G. (2016). Modeling Agricultural Watersheds with the Soil and Water Assessment Tool (SWAT): Calibration and Validation with a Novel Procedure for Spatially Explicit HRUs. *Environmental Management*, *57*(4), 894–911. https://doi.org/10.1007/s00267-015-0636-4

Torak, L. J., Painter, J. A. (2006). Geohydrology of the Lower Apalachicola– Chattahoochee–Flint River Basin, Southwestern Georgia, Northwestern Florida, and Southeastern Alabama Scientific Investigations Report 2006-5070. Retrieved from https://pubs.usgs.gov/sir/2006/5070/pdf/sir06-5070.pdf

Tripathi, M. P., Panda, R. K., Raghuwanshi, N. S. (2005). Development of effective management plan for critical subwatersheds using SWAT model. *Hydrological Processes*, *19*(3), 809–826. https://doi.org/10.1002/hyp.5618

Uniyal, B., Dietrich, J., Vasilakos, C., Tzoraki, O. (2017). Evaluation of SWAT simulated soil moisture at catchment scale by field measurements and Landsat derived indices. *Agricultural Water Management*, *193*, 55–70. https://doi.org/10.1016/j.agwat.2017.08.002

Van Gaelen, H., Tsegay, A., Delbecque, N., Shrestha, N., Garcia, M., Fajardo, H., … Raes, D. (2015). A semi-quantitative approach for modelling crop response to soil fertility: Evaluation of the AquaCrop procedure. *Journal of Agricultural Science*, *153*(7), 1218–1233. https://doi.org/10.1017/S0021859614000872

van Genuchten, M. T. (1980). Closed-Form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. *Soil Science Society of America Journal*. https://doi.org/10.2136/sssaj1980.03615995004400050002x

van Genuchten, M. T., Leji, F. J., Yates, S. R. (1991). *The RETC Cod for Quantifying the Hydraulic Functions of Unsaturated Soils*. Riverside.

van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., Srinivasan, R. (2006). A global sensitivity analysis tool for the parameters of multi-variable catchment models. *Journal of Hydrology*, *324*(1–4), 10–23. https://doi.org/10.1016/j.jhydrol.2005.09.008

van Lanen, H. A. J., Reinds, G. J., Boersma, O. H., Bouma, J. (1992). Impact of soil management systems on soil structure and physical properties in a clay loam soil, and the simulated effects on water deficits, soil aeration and workability. *Soil and Tillage Research*, *23*(3), 203–220. https://doi.org/10.1016/0167-1987(92)90101-G

Vellidis, G., Liakos, V., Perry, C., Porter, W. M., Tucker, M. A. (2016). Irrigation Scheduling for Cotton Using Soil Moisture Sensors, Smartphone Apps, and Traditional Methods, 772–780. Retrieved from http://vellidis.org/wp-content/uploads/2016/07/Vellidis-Beltwide-Paper-16779-Irrigation-Scheduling.pdf

Vellidis, G., Liakos, V., Porter, W., Tucker, M., Liang, X. (2016). A Dynamic Variable Rate Irrigation Control System. *Proceedings of the 13th International Conference on Precision Agriculture*, 1–9.

Viger, R. J., Hay, L. E., Markstrom, S. L., Jones, J. W., Buell, G. R. (2011). Hydrologic effects of urbanization and climate change on the flint river basin, Georgia. *Earth Interactions*, *15*(20), 1–25. https://doi.org/10.1175/2010EI369.1

Wallace, C. W., Flanagan, D. C., Engel, B. A. (2018). Evaluating the effects ofwatershed size on SWAT calibration. *Water (Switzerland)*, *10*(7), 1–27. https://doi.org/10.3390/w10070898

Wang, G., Barber, M. E., Chen, S., Wu, J. Q. (2014). SWAT modeling with uncertainty and cluster analyses of tillage impacts on hydrological processes, 225–238. https://doi.org/10.1007/s00477-013-0743-9

Wang, X., Melesse, A. M. (2007). Effects of Statsgo and Ssurgo As Inputs on Swat Model'S Snowmelt Simulation1. *JAWRA Journal of the American Water Resources Association*, *42*(5), 1217–1236. https://doi.org/10.1111/j.1752-1688.2006.tb05296.x

Wang, Z., Zhang, T. Q., Tan, C. S., Taylor, R. A. J., Wang, X., Qi, Z. M., Welacky, T. (2018). Simulating crop yield, surface runoff, tile drainage and phosphorus loss in a clay loam soil of the Lake Erie region using EPIC. *Agricultural Water Management*, *204*(April), 212–221. https://doi.org/10.1016/j.agwat.2018.04.021

Wehr, J. (2014). THE CANARY IN THE COAL MINE: THE APALACHICOLA-

CHATTAHOOCHEE-FLINT RIVER BASIN DISPUTE AND THE NEED FOR COMPREHENSIVE INTERSTATE WATER ALLOCATION REFORM. *Alabama Law Review*, *66*(1), 203–219.

Whetton, R., Zhao, Y., Shaddad, S., Mouazen, A. M. (2017). Nonlinear parametric modelling to study how soil properties affect crop yields and NDVI. *Computers and Electronics in Agriculture*, *138*, 127–136. https://doi.org/10.1016/j.compag.2017.04.016

Zhu, L., Gong, H., Li, X., Wang, R., Chen, B., Dai, Z., Teatini, P. (2015). Land subsidence due to groundwater withdrawal in the northern Beijing plain, China. *Engineering Geology*, (193), 243–255.

APPENDICES

APPENDIX 1 – Supplementary Information on Newton Lateral fields

Table A7. Management Schedule for modelled plots in Newton Lateral Fields

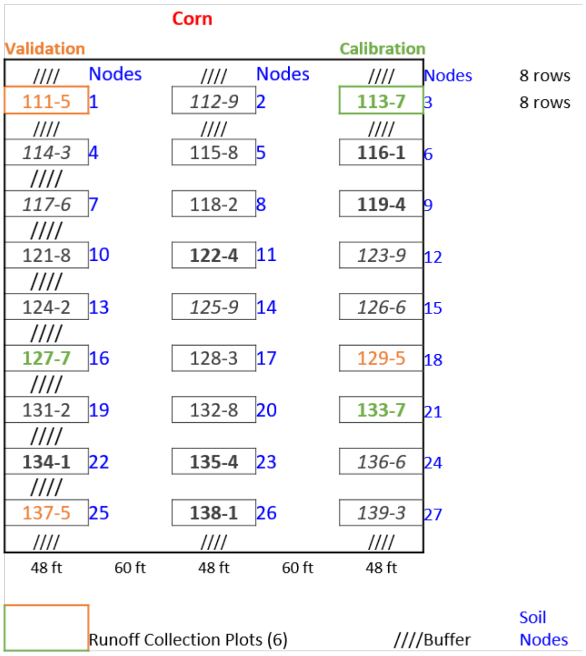
Corn			
Calibration Plot		*Validation Plot*	
Description	***Date***	***Description***	***Date***
56 kg/ha N from Urea dry blend	3/7/2018	56 kg/ha N from Urea dry blend	3/7/2018
89.6 kg/ha P from Urea dry blend	3/7/2018	89.6 kg/ha P from Urea dry blend	3/7/2018
Strip Till	3/9/2018	Strip Till	3/9/2018
50 kg/ha of mixture (Half 28-0-0 and half 20-17-0)	########	50 kg/ha of mixture (Half 28-0-0 and half 20-17-0)	########
Double check about Phosphorus	########	Double check about Phosphorus	########
Planting	########	Planting	########
57 kg/ha of N applied via fertigation to High N plots	5/9/2018	226 kg/ha of Urea applied via ground irrigation	5/7/2018
57 kg/ha of N applied via fertigation to High N plots	########	Harvested plots	########
57 kg/ha of N applied via fertigation to High N plots	########		
57 kg/ha of N applied via fertigation to High N plots	########		
Harvested plots	########		

Peanut			
Calibration Plot		*Validation Plot*	
Description	***Date***	***Description***	***Date***
Strip Till	########	Strip Till	########
22.4 kg/ha N	5/1/2018	22.4 kg/ha N	5/1/2018
56 kg/ha Phos	5/1/2018	56 kg/ha Phos	5/1/2018
Planted 110 lbs seed/ac 06G variety	########	Planted 110 lbs seed/ac 06G variety	########
Inverted	########	Inverted	########
Harvested	########	Harvested	########

Cotton			
Calibration Plot		*Validation Plot*	
Description	***Date***	***Description***	***Date***
Strip Till	########	Strip Till	########
22 kg/ha N	5/1/2018	22 kg/ha N	5/1/2018
56 kg/ha P	5/1/2018	56 kg/ha P	5/1/2018
Planting	########	Planting	########
33.6 kg/ha N applied to fertigation plots (28-0-0-5)	########	95 kg/ha N applied to traditional plots via side dress	########
33.6 kg/ha N applied to fertigation plots (28-0-0-5)	7/2/2018	Hurricane Michael	########
28 kg/ha N applied to fertigation plots (28-0-0-5)	7/9/2018	Harvested data	########
Hurricane Michael	########		
Harvested data	########		

Table A8. Irrigation schedule for modelled plots in Newton Lateral Fields

Corn			Peanut			Cotton		
Method:	Checkbook	SSA	Method:	NEW CB	Rainfed	Method:	App	Check- book
Plot:	Calibration	Validation	Plot:	Validation	Calibration	Plot:	Validation	Calibration
Date:	mm	mm	Date:	mm	mm	Date:	mm	mm
4/20/2018	19.05	19.05	4/20/2018	0	0	4/20/2018	0	0
4/30/2018	0	0	4/30/2018	0	0	4/30/2018	0	0
5/2/2018	0	0	5/2/2018	0	0	5/2/2018	0	0
5/4/2018	19.05	19.05	5/4/2018	0	0	5/4/2018	0	0
5/7/2018	7.62	7.62	5/7/2018	0	0	5/7/2018	0	0
5/10/2018	12.7	19.05	5/10/2018	0	0	5/10/2018	0	0
5/12/2018	19.05	0	5/12/2018	12.7	12.7	5/12/2018	12.7	12.7
5/14/2018	0	0	5/14/2018	12.7	12.7	5/14/2018	12.7	12.7
5/18/2018	0	19.05	5/18/2018	12.7	12.7	5/18/2018	12.7	12.7
5/21/2018	19.05	19.05	5/21/2018	0	0	5/21/2018	0	0
6/5/2018	0	19.05	6/5/2018	12.7	12.7	6/5/2018	12.7	12.7
6/7/2018	19.05	19.05	6/7/2018	0	0	6/7/2018	0	0
6/8/2018	0	19.05	6/8/2018	0	0	6/8/2018	0	0
6/13/2018	0	19.05	6/13/2018	0	0	6/13/2018	0	0
6/14/2018	0	19.05	6/14/2018	12.7	12.7	6/14/2018	0	0
6/15/2018	0	19.05	6/15/2018	0	0	6/15/2018	0	0
6/19/2018	0	19.05	6/19/2018	0	0	6/19/2018	0	0
6/21/2018	0	19.05	6/21/2018	0	0	6/21/2018	0	0
6/22/2018	0	19.05	6/22/2018	9.53	0	6/22/2018	0	15.24
7/11/2018	0	19.05	7/11/2018	9.53	0	7/11/2018	0	0
7/13/2018	0	0	7/13/2018	0	0	7/13/2018	19.05	0
7/16/2018	0	12.7	7/16/2018	0	0	7/16/2018	0	0
7/19/2018	19.05	19.05	7/19/2018	9.53	0	7/19/2018	19.05	19.05
7/30/2018	0	0	7/30/2018	9.53	0	7/30/2018	0	0
7/31/2018	0	0	7/31/2018	9.53	0	7/31/2018	0	19.05
8/7/2018	0	0	8/7/2018	9.53	0	8/7/2018	0	19.05
8/9/2018	0	0	8/9/2018	9.53	0	8/9/2018	88.9	19.05
Total	325.12	134.62	Total	130.21	63.5	Total	177.8	142.24



Block N 2018 Corn Treatments	Number
App x High N	1
App x Traditional	2
App x Low N	3
Checkbook x High N	4
Checkbook x Traditional	5
Checkbook x Low N	6
UGA SSA x High N	7
UGA SSA x Traditional	8
UGA SSA x Low N	9

Corn 2018 Fertilizer Treatments

Traditional: Yield goal = 250 bu/ac x 1.2 lb N/bu using as preplant granular, liquid starter at planting, and one liquid side-dress

High N - Fertigation : Yield goal is 250 bu/ac x 1.2 lb N/bu using preplant granular, liquid starter at planting, and up to 5 in-season applications via fertigation

Low N - Fertigation: Yield goal is 250 bu/ac x 1.0 lb N/bu using preplant granular, liquid starter at planting, and up to 5 in-season applications via fertigation

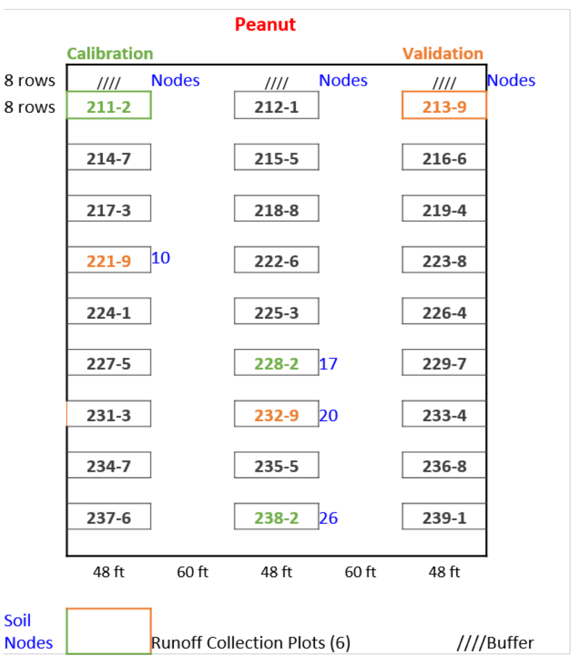
Corn 2018 Irrigation Treatments

App = Corn App Spreadsheet

Checkbook = UGA Extension Checkbook Method

UGA SSA = UGA Smart Sensor Array using 25-30 kPa triggering threshold and Porter weighted average method

Figure A1. Detailed plot map of the experimental corn field in 2018 with plot numbers and associated treatments



Block M 2018 Peanut Treatments	Number
Old Checkbook	1
New Checkbook	2
50% New Checkbook	3
Irrigator Pro (Temp)	4
Irrigator Pro (SSA)	5
SSA Dynamic VRI	6
SSA (Porter Method)	7
Peanut Farm	8
Rainfed	9

Peanut 2018 Irrigation Treatments

Old Checkbook = = UGA Extension Checkbook Method

New Checkbook = Porter's new weekly water use curve for peanut

50% New Checkbook = 50% of what is recommended by Porter's new weekly water use curve for peanut

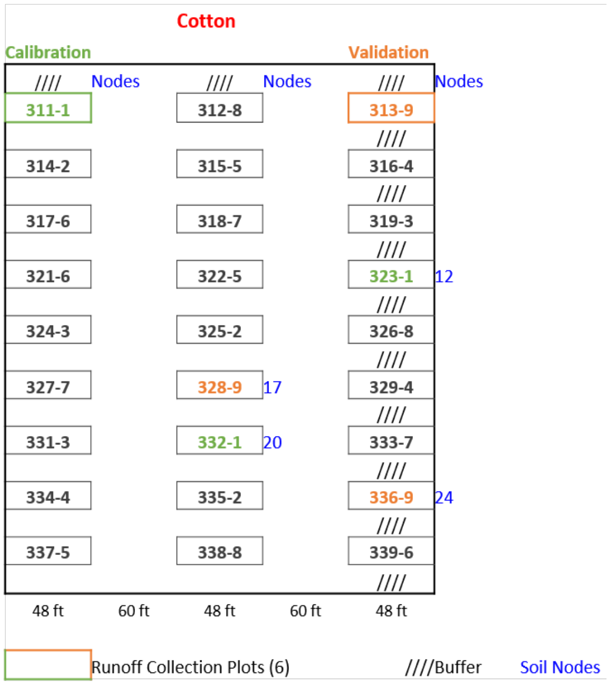
Irrigator Pro (Temp) = Traditional Irrigator Pro based on soil temperature readings. Fixed irrigation amount.

Irrigator Pro (SSA) = New version of Irrigator Pro using UGA SSA daily soil water tension values. Fixed irrigation amount.

SSA (Porter Method) = Porter's weighted average method with kPa threshold. Fixed irrigation amount.

SSA Dynamic VRI = Using Irrigator Pro (SSA) to determine when to irrigate and Van Genuchten method to decide how much to apply. Variable irrigation amount.

Figure A2. Detailed plot map of the experimental peanut field in 2018 with plot numbers and associated treatments



Block S 2018 Cotton Treatments	Number
App x Fertigation	1
App x NDVI	2
App x Traditional	3
UGA SSA x Fertigation	4
UGA SSA x NDVI	5
UGA SSA X Traditional	6
Checkbook x Fertigation	7
Checkbook x NDVI	8
Checkbook x Traditional	9

Cotton 2018 Ferilization Treatments (1500 lb lint/ac yield goal)

Fertigation = 20 lb/ac at planting, 85 lb/ac in 3 fertigation events (30 lb/ac, 30 lb/ac, 25 lb/ac)

NDVI = Use UAV or GreenSeeker and Clemson algorithm to calculate side-dress appplication. Apply liquid side-dress.
Traditional = One 85 lb/ac liquid side-dress application

Cotton 2018 Irrigation Treatments

App = Cotton App with 40% deficit threshold

UGA SSA = UGA Smart Sensor Array using 70 kPa triggering threshold until first flower and 40 kPa after first flower using Porter weighting method
Checkbook = UGA Extension Checkbook Method

Figure A3. Detailed plot map of the experimental cotton field in 2018 with plot numbers and associated treatments