COMPARING BIOPHYSICAL MODELS OF A CORN-COTTON-PEANUT FIELD EXPERIMENT

By

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To my family

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Agricultural nonpoint source (NPS) pollution is a leading source of water quality impacts on rivers and lakes and a major contributor to groundwater contamination. Excessive or poorly timed applications of irrigation and fertilizer can cause NPS pollution. However, impacts can be minimized using best management practices (BMPs).

DSSAT is a crop modeling tool that simulates growth of a crop over time along with soil water, carbon, and nutrient transport processes. SWAT is a watershed model whose primary use is to simulate the impacts of land use and management practices on crop, water, sediment, and nutrient yields at a watershed-scale. In this study, data from a 3-year corn-cotton-peanut experiment in Camilla, Georgia, was used to calibrate DSSAT and SWAT models. The first objective of this project was to quantify model accuracy for both models and evaluate SWAT's ability to model impacts at the field-scale. The second objective was to quantify the long-term effects of BMPs on crop yield, water use, and nutrient loss.

SWAT and DSSAT both simulated yields and soil moisture adequately at the field scale. The calibrated SWAT model was used to simulate three management scenarios with a range of irrigation, fertilization, and cover crop practices over a 20-year period. Use of soil moisture sensors for irrigation scheduling, a rye cover crop, and strip-tillage compared to more traditional

practices of calendar-based irrigation, no cover crop and conventional tillage resulted in lower irrigation and nitrogen leached to groundwater with no statistical differences in average yields of corn, cotton, or peanut.

CHAPTER 1
INTRODUCTION

Agricultural production has increased in recent decades to meet the demands of a growing global population, greatly expanding irrigation and fertilizer use (Pereira, 2017). Growing irrigation demand can lead to increased groundwater pumping, as many farmers rely on groundwater sources for water supply. Groundwater pumping can lower the water table and reduce the amount of water available to other users, including other farmers, municipalities, and ecosystems that depend on groundwater (Kendy, 2006). The environmental impacts of increased groundwater pumping include land subsidence, saltwater intrusion into aquifers, and reduced streamflow (Pfeiffer & Lin, 2012), which can affect aquatic habitats and the species that depend on them (Bawa & Dwivedi, 2019).

In addition to groundwater depletion, increased agricultural production often requires the use of fertilizers which can contaminate aquifers and surface waters. Nitrogen (N) and phosphorous (P) are key components of many fertilizers as they are important nutrients in crop growth (Burkart & Stoner, 2008). When applied to fields, these nutrients can leach into groundwater and contaminate water resources. Phosphorous contamination can be harmful in freshwater systems, while nitrogen contamination is an issue in both freshwater and coastal systems. Nitrogen leaching can contribute to the formation of harmful algal blooms in lakes and other bodies of water, which can have negative impacts on aquatic ecosystems and human health. Additionally, nitrate leaching can contribute to soil acidification, reduced soil fertility, and increased greenhouse gas emissions (Morrissy et al., 2021), further impacting the environment. These harmful effects can be reduced by implementing management practices that improve the efficiency and limit the amount of nitrogen applied on agricultural lands in order to minimize nitrate leaching and protect groundwater quality (Duda, 1993).

The National Water Quality Inventory reported that agricultural nonpoint source (NPS) pollution is the leading source of water quality impacts on surveyed rivers and lakes, the second largest source of impairments to wetlands, and a major contributor to contamination of surveyed estuaries and groundwater (US EPA, 2015). Improper, excessive, or poorly timed applications of pesticides, irrigation, and fertilizer can cause NPS pollution. However, impacts from these activities can be minimized using best management practices (BMPs) that are adapted to local conditions. BMPs are intended to reduce NPS pollution while simultaneously maintaining agricultural production in an economically feasible manner.

The Floridan Aquifer supplies drinking water for over 10 million people throughout the entire state of Florida as well as parts of Alabama, Georgia, and South Carolina. The Floridan Aquifer also provides water to Florida's extensive system of over one thousand freshwater springs (USGS Floridan Aquifer System Groundwater Availability Study, n.d.). The aquifer contributes directly to the health of Florida's springs, impacting Florida's aquatic species and ecosystem as well as its economy. In many areas, the Floridan aquifer is unconfined, and highly porous, which allows contaminants to travel long distances quickly. As a result, Florida's natural springs and their associated spring-sheds are directly impacted by land use, development, and management practices implemented by landowners in the region. Florida Department of Environmental Protection (FDEP) has identified many substantial threats to the system, such as over-pumping and nutrient loading of the springs system (Mattson, 2022).

Biophysical models are useful tools in predicting crop growth under varying environmental factors and management practices and can also be used in predicting the effects of agricultural practices on soil and water quality. Models can serve as vital tools in analyzing the efficacy of BMPs beyond the original experimental site. The Decision Support System for

Agrotechnology Transfer (DSSAT) is a commonly used tool for modeling crops and simulating growth, development, and yield as a function of soil-plant-atmosphere dynamics. The Soil and Water Assessment Tool (SWAT) is a physically based, watershed-scale model designed to simulate flow, sediment, nutrient, pesticide, and bacterial transport within watersheds. These models have been used to predict many scenarios which can range from evaluating impacts of BMPs on soil and water quality in a field to predicting the impacts of climate change on crop growth in specific regions. Using calibrated models the impacts of BMPs can be evaluated beyond the original experimental site and over longer time periods (Yingqi Zhang, 2022). Biophysical models can also serve an important role in estimating values for metrics that are difficult to measure in the field, such as leached nitrogen or aquifer recharge. Although models have been used by scientists for decades, stakeholder trust in them is still low (Voinov & Gaddis, 2008). An important step in improving stakeholder confidence in these biophysical models is to evaluate their accuracy in different scenarios, often in participatory modeling processes that incorporate stakeholders in the modeling process (Alharbi et al., n.d.; Cabrera et al., 2008; Mer et al., 2020).

SWAT and DSSAT are both powerful modeling tools used in the field of agriculture, but they each have different strengths and applications. SWAT is primarily used for watershed-scale analysis of soil and water management practices, and it is particularly useful for simulating the impacts of land use and climate change on hydrology and water quality. It is designed to model the processes of water balance, erosion, sedimentation, and nutrient, pesticide, and bacterial transport within a river basin. SWAT can simulate the effects of land use changes, such as urbanization or agricultural expansion, on streamflow and water quality parameters, such as total suspended solids, nitrate, and phosphorus. It can also be used to evaluate the effectiveness of management practices, such as conservation tillage, cover crops, irrigation management, or nutrient management, in reducing nutrient and sediment loads to water bodies.

Conversely, DSSAT is a comprehensive crop modeling system that can simulate the growth and development of over 40 crops under a wide range of environmental and management conditions, but it operates on a land parcel scale. It can model the effects of factors such as soil type, weather, irrigation, fertilization, and pest management on crop growth, yield, and water quality. DSSAT incorporates models for crop phenology, photosynthesis, water uptake, nutrient uptake, biomass partitioning, and many other processes. It also allows for the testing of different crop management strategies, such as planting dates, irrigation schedules, and fertilizer rates, to determine their effects on crop performance. As of 2019, DSSAT has been used by more than 16,500 researchers, growers, and policy makers in over 187 countries worldwide. Its user-friendly interface aids agricultural decision-makers by reducing the time and resources required for analyzing complex decisions. The most recent version of DSSAT (v4.7.5) includes at least one real world experiment for each crop that was used in model development, calibration, or evaluation. It has been shown to accurately simulate yield, soil nutrient dynamics, and water balance (Abayechaw, 2021).

SWAT, on the other hand, is a hydrological model whose purpose is to simulate water quality and quantity at the watershed-scale. SWAT is widely used to study the interactions between crop growth and hydrological processes in agricultural watersheds. Although SWAT is typically used to simulate processes at the watershed scale, it has been shown to adequately simulate processes at the field scale (Chen et al., 2017; M. W. Gitau et al., 2008, Karki et al. 2021). Importantly, SWAT's spatial unit for all calculations is the hydrologic response unit (HRU). The HRU is a conceptual unit that represents a portion of the watershed or catchment that has homogeneous land use, soil type, and slope characteristics. This lumped approach allows SWAT to efficiently simulate hydrological processes such as surface runoff, groundwater recharge, and baseflow at the watershed scale. However, since HRUs do not have a specific spatial location, it can be difficult to evaluate conservation practices at the field scale. Since BMPs are implemented at the field scale, it is crucial to assess and authenticate the SWAT model's capability to replicate various management techniques at this scale. Validation of model accuracy helps in presenting the findings to farmers and other stakeholders, which ultimately leads to establishing trust in the model's predictions (Voinov & Gaddis, 2008).

Many studies have analyzed alternate management practices in different crop rotations and their impact on yield as well as hydrological, sedimentary, and nutrient processes. Karki et al. (2020), Rath et al. (2021), and Zamora et al. (2020) conducted similar studies in which they calibrated SWAT or DSSAT to experimental crop rotations in areas impacted by the Floridan Aquifer and evaluated the effects of management practices on cotton-peanut or corn-peanut rotations. Understanding the effects of irrigation and fertilizer practices on crop yield, water use, and nitrogen use is crucial for farmers and stakeholders. Corn, cotton, and peanuts are major crops in the state of Georgia, and they contribute significantly to the agricultural economy. According to the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), the combined estimated value of production for these crops in Georgia in 2020 was approximately $2.27 billion (USDA/NASS 2022 State Agriculture Overview for Georgia, n.d.). Therefore, being able to optimize crop yield while limiting water and nutrient loss is important for farmers in improving profits and promoting economic sustainability while simultaneously protecting water quality, quantity, and habitat in the Upper Floridan Aquifer.

In this study, data from a 3-year corn-cotton-peanut experiment in Camilla, Georgia, was used to calibrate and validate DSSAT and SWAT models. The outputs of these simulations were compared to observed data and evaluated for accuracy. The calibrated SWAT model was then used to evaluate the effects of different management systems over a long-term historic climate record. Future studies will use the SWAT model to perform watershed scale analyses using these scenarios to determine how nitrogen and irrigation application affects surface and ground water quality in the watershed.

The first objective of this study was to observe and quantify model accuracy for both DSSAT and SWAT, evaluate SWAT’s ability to model at the field-scale, and identify whether there are significant differences in the performances of these models. The second objective was to quantify the effects of BMPs on crop yield, water use, and nutrient loss for corn, cotton, and peanut production over a multi-decadal historic weather record. Achieving these objectives is important to build confidence in use of the SWAT model to evaluate regional tradeoffs among yield, producer profits and receiving water quality and quantity.

CHAPTER 2
COMPARING DSSAT AND SWAT MODELS OF A CORN-COTTON-PEANUT FIELD EXPERIMENT IN CAMILLA, GEORGIA, AND APPLICATION OF THE CALIBRATED SWAT MODEL BEYOND THE FIELD EXPERIMENT

Materials and Methods

Experimental Site and Design

A three-year corn-cotton-peanut rotation near Camilla, Georgia, was used to evaluate management practices that could lead to improved water and nitrogen use efficiencies while maintaining crop yields. Different fertilization and irrigation treatments were applied to the cotton and corn crops, giving each crop a total of nine unique treatments for each planting year. Since nitrogen fertilizer is not applied to peanut during the growing season, the peanut crops received nine irrigation treatments. Crops yields, nutrient uptake, soil water content and soil moisture were observed during the field experiment.

The experiment took place in a 4-hectare research field at the Stripling Irrigation Research Park in Camilla, Georgia, known as the Newton Lateral Field (Figure 2-1) from 2018 - 2020. The soil in the Newton Lateral field is classified as a Lucy Loamy Sand. Soil texture varied slightly across the field with 83% Sand, 10% Silt and 7% Clay in the South block to 86% Sand, 8% Silt, and 6% Clay in the North block. Soil samples were collected to 36 inches, and soil texture was reported in six individual 6-inch layers. The experimental field was divided into three blocks (North, Middle, South) and each block was divided into 27 completely randomized plots with three replicates of each treatment. The plots were each 14.5 × 14. 5 m. The eight middle rows in each plot were used for data collection and the four rows on either side of the middle eight served as buffers. The North field hosted a corn-cotton-peanut rotation, the Middle field a peanut-corn-cotton-peanut rotation, and the South field a cotton-peanut-corn-cotton rotation.

Planting and harvesting dates for each field are detailed in Table 2-1. Due to extreme weather conditions resulting from Hurricane Michael, yield data was not available for the cotton season of 2018.

Irrigation treatments

Various irrigation scheduling methods for cotton and corn were compared to the traditional calendar scheduling method.

Corn: The three methods used were an app-based method, UGA Smart Sensor Arrays (SSA), and Checkbook. The app-based method involved an online corn application (smartirrigationapps.org) which calculated water deficit using precipitation, root depth, and evapotranspiration to estimate irrigation needs. The UGA SSA method used a 25-30 kPa soil tension threshold to trigger irrigation. The Checkbook method was developed by the UGA Extension which predicts irrigation requirements for crops throughout each stage of growth based on historical evapotranspiration patterns. This method treats the soil as a checking account: rain and irrigation are deposits while plant water use and evapotranspiration are withdrawals. If rain occurs close to an irrigation event, that amount of water is removed from irrigation.

Cotton: Similar irrigation treatments were applied for the cotton crop as was applied for corn, with a few alterations. The cotton app accounted for a 40% deficit threshold on irrigation. The UGA SSA method for cotton utilized a 70 kPa soil tension triggering threshold until the first flower and 40 kPa after the flower.

Peanut: Nine unique irrigation treatments were applied to the peanut crop. The Old Checkbook refers to the UGA Extension Checkbook method, while the New Checkbook method involved a slight increase in irrigation from the Old Checkbook Method. The 50% New Checkbook method involves using 50% of what is recommended by the checkbook method. The Irrigator Pro (Temp) method refers to a traditional irrigation method based on soil temperatures, while the Irrigator Pro (SSA) method refers to an irrigation method utilizing daily soil water tension values. The SSA Dynamic VRI uses Irrigator Pro to determine when to irrigate. The SSA Porter Method involves using a kPa threshold to determine how much to irrigate. Peanut Farm refers to an irrigation method where only 1 inch of irrigation is applied and the rest is rainfed, and the Rainfed treatment refers to applying no irrigation and only using rain. Irrigator Pro (Temp), Irrigator Pro (SSA), and SSA Porter Method all had fixed amounts of irrigation that were predetermined, while the SSA Dynamic VRI implemented a variable irrigation amount.

Nitrogen treatments

Corn: Fertilizer applications in corn were not consistent each year. In 2018, three nitrogen fertilizer rates were applied and evaluated in corn: high nitrogen, traditional, and low nitrogen. A yield goal of 250 bu/ac was set prior to planting and was used to calculate how much nitrogen would be applied in each treatment. The high nitrogen application applied 300 kg N/ha as pre-plant granular, a liquid starter at planting, and 4 in-season applications via fertigation. The traditional nitrogen treatment also applied 300 kg N/ha, but only applied as pre-plant granular, a liquid starter at planting, and one in-season liquid side dress. The low nitrogen application applied 280 kg N/ha and used the same schedule as the high N treatment, with applications as pre-plant granular, a liquid starter at planting, and 4 in-season fertigation applications.

In 2019, the traditional fertilizer method remained the same, but the other two treatments were replaced with a scheduled fertigation method and an app-based fertigation method. The scheduled fertigation method reflected the low nitrogen application from the previous year, with 280 kg N/ha applied as preplant granular, a liquid starter at planting, and 5 in-season applications via scheduled fertigation. The app-based fertigation method was similar, except that fertilizer applications were scheduled using the Corn App model.

In 2020, the app-based fertigation method was replaced with a second scheduled fertigation treatment. That treatment applied 280 kg N/ha of fertilizer as preplant granular, a liquid starter at planting, and 4 in-season applications, rather than 5. The other two treatments remained unchanged.

Cotton: Cotton fertilizer applications from 2018 - 2020 involved a fertigation treatment, a normalized difference vegetation index (NDVI) treatment, and a traditional treatment. The fertigation treatment applied 22 kg N/ha at planting and 95 kg/ha split up into 3 fertigation events (33 kg/ha, 33 kg/ha, 28 kg/ha). The NDVI treatment implemented an algorithm to calculate liquid side dress application amounts and timing. Fertilizer applications ranged from 81 - 94 kg N/ha in a one-time application. The traditional treatment was a one-time 95 kg/ha liquid side dress application.

Peanut: In each treatment, 22 kg N/ha were applied 12 days before planting.

Each fertilizer application was paired with an irrigation application to create nine unique treatments. Table 2-2 shows the fertilizer schedule for the north field, Table 2-3 shows the cumulative irrigation for corn and cotton, and Table 2-4 shows the cumulative irrigation for each peanut irrigation treatment. Tables 2-5, 2-6, and 2-7 provide a summary of when observations were recorded in the north, middle, and south fields, while Tables 2-8, 2-9, and 2-10 show the summary of treatments across each field.

Model Description

DSSAT simulation models

DSSAT is a collection of independent programs that operate together, with crop growth at its center (Jones et al., 2003). The CERES-Maize, CROPGRO-Cotton, and CROPGRO-Peanut simulation models within DSSAT were used to evaluate soil and water dynamics in the corn-cotton-peanut rotation. To simulate crop growth, DSSAT calculates growing degree days using the average daily maximal and minimal temperatures recorded at the onsite weather station, from which a base temperature is subtracted that varied based on crop cultivar. Accumulated thermal units equal zero when average temperatures were below the base temperature. These accumulated heat units are used to drive a model to calculate crop development under the absence of water, nitrogen, or phosphorous stress in daily time steps (Arshad et al., 2017; Garibay et al., 2019). DSSAT's crop growth parameters incorporate phenology into its simulation by taking into account the physiological day durations for respective life cycle phases. A crop's life cycle progress at any phase is highly dependent on the accumulation of heat units as a function of temperature and day length, as some crops are sensitive to day length while others are not. When the growing degree day accumulator reaches a value defined by a threshold determined by the crop parameters, a new growth stage is triggered.

The one-dimensional tipping-bucket method is used to simulate water movement through the soil in DSSAT to predict infiltration, drainage of water through the root zone, and soil water evaporation and plant transpiration in order to predict actual evapotranspiration (ET). The soil N balance includes processes such as daily N uptake, N2-fixation (CROPGRO-Peanut), mobilization, the decay of crop residues, N leaching in drainage, and denitrification (Zamora Re et al., 2020).

SWAT simulation model

SWAT simulates plant growth by using a simplified version of EPIC's generic crop growth model (Williams et al., 1984 Williams, 1995). Crop growth simulation begins with an atmospheric-CO2-dependent radiation use efficiency factor which intercepts photosynthetically active radiation daily. The daily accumulation of this factor accounts for total plant biomass, which can be inhibited due to insufficient water, N, or P. Plant stress can also result from low temperature. Leaf area index (LAI), leaf area per unit land area, is incremented daily and is simulated by the accumulation of potential heat units (PHUs). Each crop has its own specific maximum LAI; LAI increases until this value is reached, and then remains constant until harvest. Along with total plant biomass, SWAT simulates root biomass daily as a crop-dependent fraction of total plant biomass; root depth is simulated daily according to the accumulation of PHUs until maximum root depth is achieved. The harvest index is a crop-dependent fraction that determines how much of the final biomass is harvested as yield and how much is left on the field as residue (Sumathy Sinnathamby, 2016). SWAT's module for soil moisture simulates saturated soil water flow between soil layers using a cascading approach, uniformly distributing water within a given layer. Soil water percolates between layers only when the water content exceeds field capacity within that specific layer.

Model Inputs

DSSAT model inputs

Weather data was obtained for 1997 to 2020, including daily maximum and minimum temperature values, precipitation levels, and solar radiation values. Relative humidity and wind velocity were simulated based on site location. Potential ET values were calculated by the Penman-Monteith method, using daily temperature, solar radiation, relative humidity, and wind velocity as inputs.

Observed physical soil characteristics such as percent silt, percent clay, and bulk density, along with chemical characteristics such as initial nitrate (NO_3), ammonia (NH_4), and total Kjeldahl nitrogen (TKN), pH, and organic matter were used as inputs into the soil model. DSSAT estimated values for the lower limit of soil extractable water (SLLL), soil drained upper limit (DUL), and soil available water capacity (AWC) using the Rawls et al. (1982) method in which soil water retention at -0.33 and -15 bar tension are calculated via Brooks-Corey parameters.

The cultivars McCurdy 84aa, Georgia King, and Georgia Green were assumed for corn, cotton, and peanut, respectively. The genetic coefficients for the McCurdy 84aa cultivar were based on the calibrated values used in Rath, et al (2021) as shown in Table 2-11, and the coefficients for Georgia King were based on the values used in Sangster (2022) as shown in Table 2-12. Cultivars from these experiments were chosen as they utilized the same crop variety in similar weather conditions and soil. The standard Georgia Green cultivar coefficients for peanut provided in DSSAT were utilized. DSSAT does not currently have a crop file for rye, so a wheat crop file was used instead as the cover crop. Management practices such as irrigation and fertilizer application were input manually in DSSAT consistent with recorded experimental data.

SWAT model inputs

A unique SWAT simulation was set up for each field (north, middle, south), with 9 HRUs each representing a separate treatment. Climate data entered into the model included daily max and minimum temperature, precipitation, and solar radiation from 2015 to 2020. The warmup period for the model was 2015 to 2017. Relative humidity and wind speed were simulated by SWAT for the calculation of evapotranspiration using the Penman-Monteith method. Humidity was calculated using the method developed by J.R Williams for the EPIC model (Williams, 1990), while wind speed was calculated using the method developed by Haltiner and Martin (Sharpley et al., 1990, Haltiner and Martin, 1957).

Observed soil characteristics such as percent sand, silt, clay, and bulk density, as well as chemical characteristics such as organic carbon were input into SWAT’s soil file. Measurements of available water capacity (AWC) and saturated hydraulic conductivity (SOLK) were not available and were calibrated by SWATCUP.

Crop parameters for corn, cotton, and peanut were obtained by calibration of the model via SWATCUP. Management practices such as irrigation and fertilizer application were input manually in SWAT consistent with recorded experimental data.

Calibration

After adjusting crop parameters based on values found in literature as described above, the DSSAT model predicted yields for corn and peanut were classified as good (nRMSE < 15%) and classified as moderate for cotton (15% < nRMSE < 30%). Soil moisture prediction was classified as moderate (15% < nRMSE < 30%) without calibration. Therefore, calibration of the DSSAT model parameters outside of the adjustment of crop parameters from literature was not necessary.

The SWAT model yield and soil moisture predictions using default parameters were poor (nRMSE >30%), so calibration was necessary. For SWAT calibration, the south field rotation was used for calibration while the north and middle field rotations were used for validation. Soil moisture, biomass, and crop yield from 2018 to 2020 were used for calibration of the south field. The model was validated using crop yield, biomass, soil moisture, and soil nitrogen in the north and middle fields. Calibration was performed using the Sequential Uncertainty Fitting Algorithm Version 2 (SUFI-2), within SWAT-CUP, an automated calibration and uncertainty program developed for SWAT (Khalid et al., 2016). Soil moisture parameters were calibrated first, followed by crop parameters for the calibration of yield and biomass, in accordance with the sequence adopted by (Nair et al., 2011).

Experimental data reflecting soil moisture values in the field were available for the first 900mm of the soil profile. Therefore, SWAT model calibration could only be performed on this top 900mm of soil. This proved to be a challenge as the SSURGO soil profile extended to 1875mm and SWAT default configuration outputs soil moisture for the whole soil column. In order to accurately calibrate the model for the measured soil depth, the SWAT hruday.f90 subroutine source code modified by (Karki et al., 2020) was used and new SWAT executable was compiled such that the total simulated soil moisture for the top 900mm was exported as an additional variable in the .hru output file.

Model Evaluation

To evaluate the performance of the models, outputs for yield, soil water content, soil nitrate, and N uptake from the calibrated models were compared with observed data collected in all nine treatments. After evaluating model performance, simulated water and N balances were compared.

Model performance was evaluated using the normalized root mean squared error (nRMSE). The root mean squared error (RMSE) measures the differences between values predicted by a model and the observed values. It is calculated as the square root of the variance of the differences between the predicted and observed values. However, RMSE is scale dependent. In order to facilitate comparisons between different datasets and models with different scales, the non-dimensional nRMSE, defined as the RMSE divided by the mean of the observed values, was used. An nRMSE value between 0% and 15% is considered a "good" prediction, an nRMSE value between 15% and 30% is considered a "moderate" prediction, and higher than 30% is considered "poor" (Liu et al., 2019).

Percent bias, or PBIAS, was also evaluated to understand trends in model prediction. PBIAS measures the average tendency of the model to either overestimate (positive PBIAS) or underestimate (negative PBIAS) the observed values. An absolute PBIAS value between 0% and 15% is considered a good prediction, a value between 15% and 25% is considered "satisfactory", and greater than 25% is "unsatisfactory" (Moriasi et al., 2007).

Differences in experimental treatment yields were evaluated for cotton and peanut over all three years and corn over each year using one-way ANOVA with post-hoc Tukey test at 95% confidence interval (Michael R. Stoline, 2012). The Tukey test was used to determine if the use of fertigation or soil moisture sensors produced statistically different yields than traditional methods. Model predictions for yield, biomass, soil moisture, soil nitrogen, and N uptake were evaluated in all fields. However, for the sake of conciseness, only results for the north field will be presented in the results section, except in the case of examining calibrated and validated data such as for yield, biomass, and soil moisture. Results were consistent across all fields.

Nitrogen balance

A nitrogen balance was calculated to evaluate differences in the simulated soil-dynamics between the two models and to evaluate the effects of different irrigation practices on the nitrogen balance. In DSSAT, N balance outputs are applied N fertilizer, mineralized N, immobilized N, leached N, N uptake from soil, and any nitrogen loss that could be attributed to atmospheric losses. SWAT's N balance outputs are applied N fertilizer, net mineralized N, leached N, N uptake from soil, and N loss due to atmospheric losses.

SWAT's mineralization algorithm is a "net mineralization" algorithm, which incorporates immobilization (i.e., immobilized nitrogen is subtracted from mineralized nitrogen). DSSAT's algorithm, however, simulates mineralization and immobilization separately. For the purpose of model comparison, mineralization in this N balance was computed as net mineralization. Default parameters for humus mineralization, nitrogen percolation, and nitrogen uptake distribution were used in both models.

The treatments presented for the nitrogen balance for corn are the "Traditional x Checkbook" (T5) and the "UGA SSA x Traditional" (T8). The "Traditional x Checkbook" (T9) method and the “UGA SSA x Fertigation” (T4) method are presented for cotton. Similarly, treatments presented for peanut are the Irrigator Pro (SSA) (T5) method as well as the Old Checkbook method (T1). These treatments were examined in order to determine if the use of soil moisture sensors for irrigation scheduling has an effect on the N balances compared to the traditional checkbook method. It is important to note that these management systems do not all occur consecutively on the same plot, as they all correspond to different treatment numbers.

In DSSAT, rye is not available as a crop file, and so instead wheat was used in the cover crop simulation. Due to the differences in N mineralization between wheat and rye, mass balances were not shown for cover crops, but initial nitrate in the soil at the beginning of the cropping season is shown.

Water balance

A water balance was calculated to evaluate differences in the way the two models simulate water movement throughout the soil and to identify whether the use of soil moisture sensors in irrigation applications impacted the amount of water that is drained to groundwater. Inputs to the water balance include precipitation and irrigation while the outputs are drainage, evapotranspiration, and runoff. Drainage refers to water leaving the root zone vertically as a result of excess water in the soil profile. Runoff refers to surface runoff in which precipitation or irrigation falls on the land and flows overland. The same treatments evaluated in the N balance were evaluated for the water balance to identify whether the use of soil moisture sensors had an impact on the water balance. Both models utilized the Penman-Monteith method for predicting evapotranspiration.

Development of Long-Term Scenarios

Three management systems developed with stakeholders in a participatory modeling process (Bartels & Furman, 2023) were used to simulate 20 year corn-cotton-peanut rotations in

SWAT using the calibrated parameters from the modeled experiment.. Summaries of the three management systems are listed in Table 2-13. There were similarities in the management systems, such as all peanut receiving 1/2 ton of lime and 1/2 ton of gypsum, all cotton receiving ⅓ ton of lime, and all corn receiving ½ ton of lime. Management system (MS) 1 utilized strip tillage, a rye cover crop, and soil moisture sensors for the purpose of triggering irrigation. MS 2 utilized conventional tillage, no cover crop, and the UGA checkbook method for irrigation. MS 3 also implemented conventional tillage, no cover crop, and a traditional calendar irrigation method.

The calibrated model was run for 23 years (1997-2020) with a three-year warm up period (1997-2000) for the three management systems. Mean differences in annual yield, applied irrigation, soil drainage, surface runoff, and leached nitrate between the three systems were evaluated using one-way ANOVA with post-hoc Tukey test at 95% confidence interval. When a crop's growth is reduced due to insufficient water or nitrogen, SWAT reports that value as water stress or nitrogen stress. Water stress and nitrogen stress were compared between management systems to identify why yields were different among management systems.

Results

Field Experiment Simulations

Yield and biomass calibration and validation

A one-way ANOVA with post-hoc Tukey test at 95% confidence interval revealed that there was no statistically significant difference between experimental yields for any crop across all nine treatments for any year. Experimental treatments that used soil moisture sensors in their irrigation methods applied 51%, 54%, and 57% less water in corn, cotton, and peanut, respectively. Thus, implementation of SMS irrigation decreased applied irrigation while maintaining yields. Fertigation used 17% less nitrogen in experimental corn treatments than the traditional treatment, while fertigation in cotton used the same amount of nitrogen as all other treatments, with no statistical difference in yield.

A sensitivity analysis showed that the sensitive SWAT parameters for predicting yield and biomass were harvest index (HVSTI), biomass to energy ratio (BIO_E), and maximum leaf area index (BLAI) for all three crops ($p < 0.05$). Calibrated values for crop parameters can be found in Table 2-14. Following calibration, simulated values for yield were generally in good agreement with the observed data for both DSSAT and SWAT (Table 2-15). The nRMSE values for corn and peanut were below 15% for both SWAT and DSSAT calibration and validation results, showing good fit. Cotton showed moderate performance for both models according to the nRMSE criteria. Karki et al. (2020) and Chen at al. (2016) reported similar difficulty in simulating irrigated cotton yields using SWAT, and Sangster (2022) reported similar results in predicting cotton yield using DSSAT. Model performance did not vary across treatments. (Figures 2-2, 2-3, 2-4, 2-5, 2-6)

Of note, the corn 2020 season had overall lower observed yields than 2018 and 2019 (Figures 2-4). Average corn yield in 2020 was 11,367 kg/ha, considerably lower than yields of 15,379 and 15,994 kg/ha in 2018 and 2019, respectively. Neither model was able to simulate lower yields in 2020, instead predicting corn yields similarly to the previous two years. It is possible the observed yield reduction could be attributed to pests or disease in the middle field, neither of which are simulated by SWAT or DSSAT.

Simulations of corn, cotton, and peanut yielded more consistently similar results among years in DSSAT than in SWAT. PBIAS values for corn in 2018 and 2019 were -5.9% and -5.1% in DSSAT (Table 2-16), indicating a small, but consistent, underprediction. In contrast, PBIAS values for SWAT in those same years were more variable (-6.9% and -0.3%). Similar trends were observed in cotton and peanut simulations, with PBIAS values of -2.5% and -5.5% for cotton in 2019 and 2020 in DSSAT, compared to PBIAS of -1% and 5.3% for the same years in SWAT. While DSSAT's predictions tended to be more consistent, SWAT's average predictions were overall more accurate. The average PBIAS values for both models fell within the "good" range for all crops.

DSSAT and SWAT's simulation of biomass generally followed observed trends for corn but showed fairly large differences in the simulation of cotton, particularly in mid-season (Figures 2-7, 2-8). There were very few biomass observations for peanut, so an evaluation of model accuracy was not conducted for this crop. nRMSE values for calibration of biomass in the south field indicated poor fit in both corn and cotton. PBIAS values indicated that DSSAT's calibration of cotton was good, but SWAT's calibration of cotton was unsatisfactory. PBIAS values for both models showed good calibration of corn biomass. Poor nRMSE values could be due to few observational data points, especially towards the end of the harvesting season. Validation results for corn biomass in the north field in SWAT and DSSAT yielded nRMSE values of 18% and 28% (Table 2-17), indicating a moderate fit. PBIAS values were 5.3% for SWAT and 20.6% for DSSAT, indicating good prediction in SWAT and satisfactory prediction in DSSAT. These results are consistent with Tojo Soler et al. (2007) who reported moderate to poor performance in DSSAT's prediction of irrigated maize biomass. However, Rath et al. (2020) reported good prediction (nRMSE < 15%) of aboveground biomass in a SWAT simulation of corn biomass.

Both models underestimated biomass in cotton. In the north field, DSSAT overestimated cotton biomass in the App x High N and UGA SSA x High N treatments and underestimated biomass in the Checkbook x High N treatment (Figure 2-8). SWAT, however, consistently underestimated cotton biomass early in the planting season but was able to accurately simulate biomass near the end of the harvesting season. Cotton nRMSE values across treatments 3, 6, and 9 in the north field for SWAT and DSSAT were 40% and 34%, indicating poor fit. PBIAS values for SWAT and DSSAT were -24% and -2%, showing satisfactory fit in SWAT and good fit in DSSAT. Overall, analysis of biomass validation showed moderate performance in corn for both models, while showing poor nRMSE values and satisfactory PBIAS values in cotton.

Nitrogen uptake

Modeled N uptake dynamics generally followed observed trends for corn in both models, however both models underpredicted N uptake in cotton toward the end of the harvesting season (Figure 2-9). The nRMSE values for N uptake in corn during the 2018 season for SWAT and DSSAT were 22% and 20%, respectively, indicating moderate fit (Table 2-18). PBIAS values for SWAT and DSSAT were 18% and 8%, respectively indicating satisfactory and good prediction. The nRMSE values for simulating N uptake in cotton were 38% (SWAT) and 40%, (DSSAT) indicating poor fit. PBIAS values for SWAT and DSSAT were -18% and -24%, indicating satisfactory fit. Overall, analysis of simulations indicates satisfactory results in representing N uptake values in corn, while indicating moderate to poor results in cotton.

Soil moisture calibration and validation

Sensitivity analysis showed that available water content and hydraulic conductivity were the most sensitive parameters in predicting soil moisture content ($p < 0.05$). Calibrated soil parameters can be found in Table 2-19.

Soil moisture nRMSE values fell between 15%-30% (Table 2-20), indicating moderate fit. Treatments 3, 6, and 9 from the south field and treatments 1, 4, and 7 from the north field are displayed in Figure 2-10 as soil samples from those treatments occurred most often. Average absolute values for PBIAS ranged between 0% and 12%, indicating good prediction of soil moisture in both models. DSSAT's algorithm calculated its field capacity and wilting point to be 251.3 and 131.3 mm, respectively. SWAT's calibrated soil led to a field capacity and wilting point of 319.5 and 193.4 mm, respectively. Consequently, while DSSAT and SWAT soil moisture values showed similar temporal behavior, PBIAS values show that DSSAT typically underpredicts soil moisture values while SWAT typically overpredicts (Figure 2-10 and Table 2-21).

Soil nitrogen

In general, simulated values for SWAT and DSSAT soil nitrogen followed trends in observed data and fell within the range of variability of observations (Figure 2-11). However, soil N was simulated with poor fit (nRMSE > 30% and PBIAS >25%) in both models (Tables 2-22, 2-23). This is consistent with studies such as Zamora et al. (2020), and Rath et al. (2020), which found that observed seasonal soil N fluctuations occurred at a smaller magnitude than the models predicted, perhaps due to the low frequency of observations.

Both models tended to overestimate the amount of soil nitrogen in the days immediately following a fertilizer application, but underestimated soil nitrogen in the weeks following. It is possible that greater soil nitrogen values would have been captured if there had been a higher sampling frequency. It was difficult to isolate simulation trends among differing treatments as the treatments varied among fields and within years. Overall, SWAT consistently predicted less nitrate in the soil than DSSAT preceding large fertilization events but tended to predict higher soil N during and immediately following these events. Differences in model simulation of N are discussed in greater detail in the following section.

Nitrogen balance

The nitrogen balance comparison brings to light differences in model nitrogen dynamics. In the corn season, SWAT predicted higher leached N and more N uptake than DSSAT (Table 2-

24 and Figure 2-12). In the cotton season, SWAT simulated less N uptake than DSSAT (Table 2-25 and Figure 2-13). In peanut, SWAT predicted lower leached N and lower N uptake than DSSAT (Table 2-26 and Figure 2-14). The N uptake model performance evaluation showed that DSSAT displayed better simulation of N uptake in corn than SWAT (PBIAS 8% vs 18%), while SWAT displayed better simulation of N uptake in cotton (PBIAS -18% vs -25%). Across crops SWAT consistently simulated less mineralized N than DSSAT. Possible explanations for this include the fact that SWAT and DSSAT simulate N mineralization differently. SWAT requires a C:N ratio less than 20:1 for N to mineralize, while DSSAT requires a C:N ratio less than 25:1 in order for N to mineralize (Godwin & Singh, 1998).

When comparing the differences in soil N balance due to different treatments, there are a few notable findings. In the corn 2018 season, the UGA SSA irrigation treatment decreased N leaching over the checkbook method by 35% according to DSSAT and 25% according to SWAT while maintaining the same amount of applied N fertilizer. The cotton 2019 season showed a 40% decrease in leached N in DSSAT and a 70% decrease in SWAT due to use of SMS compared to the checkbook method. Use of SMS produced a 5% increase in leached N during the peanut 2020 season in both models compared to the old checkbook method.

Water balance

Differences in the water balance between SWAT and DSSAT were minimal in the 2018 corn season (Table 2-27 and Figure 2-15), with no differences in water balance outputs greater than 10%. Implementation of UGA SSA decreased the amount of irrigation applied by 58% over the traditional checkbook method, which subsequently decreased simulated drainage by 29% in DSSAT and 27% in SWAT. However, DSSAT's water balance produced noticeably different results from SWAT during the 2109 cotton season (Table 2-28 and Figure 2-15). SWAT's simulations produced higher ET and lower drainage than DSSAT, while producing similar values for runoff. UGA SSA irrigation in the cotton 2019 season decreased applied irrigation by 57% compared to the checkbook irrigation method, which decreased drainage by 30% in DSSAT and 78% in SWAT.

Counterintuitively, when comparing the Old Checkbook irrigation method to the Irrigator Pro (SSA) method in peanut 2020 (Table 2-29 and Figure 2-16), the use of soil moisture sensors actually led to an increase in applied irrigation by 55% compared to the traditional method. This increased drainage by 27% in DSSAT and 57% in SWAT. During the peanut 2020 season, SWAT predicted less drainage than DSSAT resulting in higher runoff predictions.

Overall, the use of soil moisture sensors decreased water use and drainage in both corn and cotton while maintaining similar yields in both models. The implementation of soil moisture sensors in the peanut crop showed an increase in irrigation, runoff, and drainage while also predicting similar yields in both models.

Long Term Simulation

Mean yields between management systems were not significantly different for any of the three crops. Corn yield evaluation for the three management levels showed an average of 15328 kg/ha for MS 1, an average of 15086 kg/ha for MS 2 and an average of 15917 kg/ha for MS 3. (Figure 2-18). Corn experienced the highest simulated water stress in MS 2 and the lowest water stress in MS 3, and the same level of simulated N stress in all three management systems. Average annual cotton yield for MS 1, MS 2, and MS 3 were 3588 kg/ha, 4809 kg/ha, and 4888 kg/ha respectively. Cotton experienced its highest water stress in MS 2 and lowest in MS 1; conversely, cotton's highest N stress occurred during MS 1 and its lowest N stress occurred in MS 2, likely due to the lack of poultry litter application before planting in MS1. Average yield in peanut was similar in all three management systems (10041 kg/ha, 9933 kg/ha, and 10029 kg/ha for MS 1, 2, and 3), with less variation occurring in MS 3 compared to MS 1 and 2. MS 3 exhibited the most water stress for peanut and MS 1 showed the least. Peanuts are legumes and SWAT does not allow legumes to experience nitrogen stress, thus any variability in yield in peanut is due to water stress.

The traditional irrigation method used in MS 3 led to higher irrigation application in all three crops and higher surface runoff and drainage in cotton and peanut. In all three crops, applied irrigation was not statistically different for MS1 and MS2, while irrigation applied in MS 3 was 81% higher in corn, 52% higher in cotton, and 80% higher in peanut (Figure 2-19). For corn, average annual drainage and average annual surface runoff were not significantly different among management systems. For cotton, both average annual drainage and average annual surface runoff were statistically significantly lower for MS 1 compared to MS 2 and MS 3 (Figure 2-20). For peanut drainage was statistically significantly higher in MS 3 compared to the other two management systems, but there was no statistically significant difference in surface runoff among the management systems.

MS 1 led to statistically significant reductions in N leaching in all three crops. In corn, MS 1 leached 38% and 60% less N than MS 2 and MS 3, respectively. For cotton, MS 1 produced 69% and 67% less N leaching than MS 2 and MS 3 respectively. For peanut MS 1 showed sees 82% and 88% less leached N than MS 2 and MS 3, respectively (Figure 2-22). SWAT simulated extremely low values for N loss via surface runoff, so N runoff was not included in the evaluation of nutrient loss between management systems.

Overall, MS 1 applied less irrigation than MS 3, produced the lowest amount of leached N, and showed a decrease in drainage and surface runoff when compared to MS 3, while maintaining similar yields. MS 2 is currently practiced by many farmers in southern Georgia; model results indicate that transitioning to MS 1 from MS 2 could potentially reduce nitrate pollution and conserve water resources without a significant change in yield. However, the expenses associated with installing SMS systems and applying winter cover crops could potentially dissuade farmers from transitioning to MS 1. Financial incentive programs implemented by federal and state agencies could play a role in persuading producers to make this change.

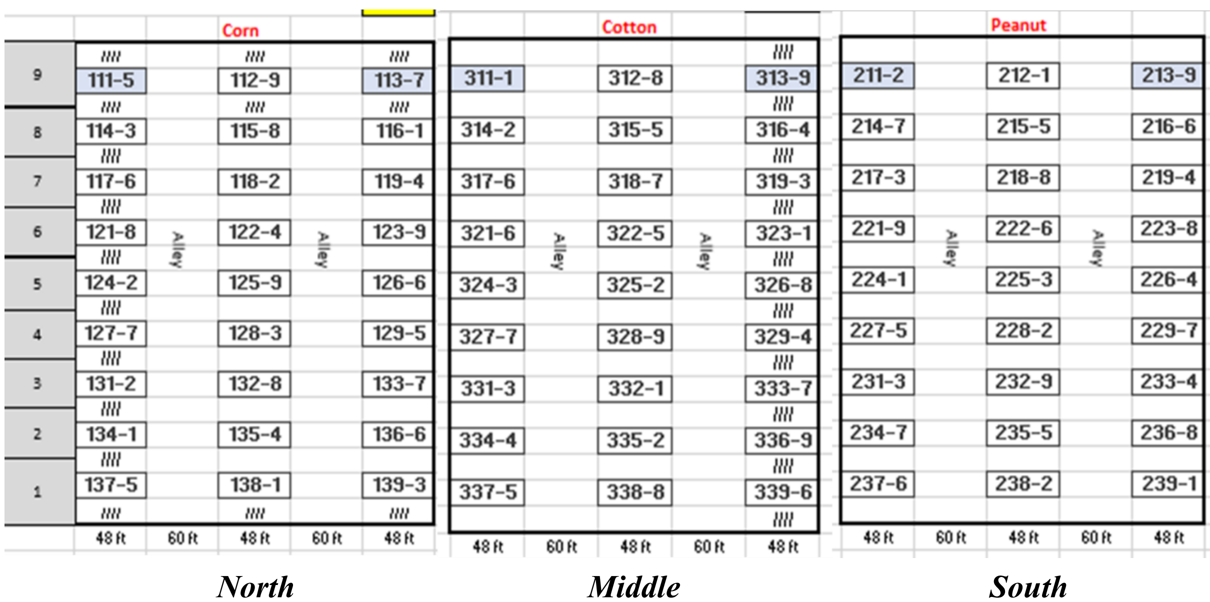

Figure 2-1. Layout of the experimental site with corresponding plot and treatment numbers. The first three numbers preceding the dash refer to the plot identification number while the fourth number following the dash refers to the plot's treatment number.

Table 2-1. Planting and harvesting schedule for north, middle, and south fields.

Field	Crop	Planting Date	Harvesting Date
North	Corn	3/29/2018	8/28/2018
	Rye	8/30/2018	4/16/2019
	Cotton	5/3/2019	9/27/2019
	Rye	9/30/2019	4/9/2020
	Peanut	5/7/2020	10/7/2020
Middle	Cotton	5/10/2018	10/24/2018
	Rye	10/26/2018	4/16/2019
	Peanut	5/10/2019	9/24/2019
	Rye	9/26/2019	3/2/2020
	Corn	3/20/2020	8/12/2020
South	Peanut	5/22/2018	10/2/2018
	Rye	10/4/2018	3/2/2019
	Corn	3/27/2019	8/22/2019
	Rye	8/24/2019	2/1/2020
	Cotton	5/6/2020	11/2/2020

Table 2-2. Fertilizer application scheduling for north field

Crop and Year	Date	Fertilizer Composition	Nutrients	N Fertilizer Treatment (kg/ha)		
				High N	Traditional	Low N
Pre - Planting 2018	03/07/2018	Urea Based Dry Blend Formulation	N	56	56	56
			P	89.6	89.6	89.6
			K	201.6	201.6	201.6
Corn 2018	03/29/2018	50% 28-0-0-5 50% 20-17-0-2.5	N	50	50	50
			K	36.96	36.96	36.96
	05/07/2018	Urea Based Dry Blend Formulation	N	0	226	0
	05/09/2018	28-0-0-5	N	57	0	43
	05/16/2018	28-0-0-5	N	57	0	43
	05/23/2018	28-0-0-5	N	57	0	43
	05/30/2018	28-0-0-5	N	57	0	43
			Total N	334	332	278
Rye 2018 - 2019		Harrow				
				Fertigation	NDVI	Traditional
Cotton 2019	04/25/2019		N	34	34	34
			P	78	78	78
			K	101	101	101
	06/19/2019		N	34	84	95
	07/02/2019		N	34	0	0
	07/17/2019		N	28	0	0
			Total N	130	118	129
Rye 2019 - 2020		Harrow				
Peanut 2020	04/20/2020		N	22	22	22
			P	78	78	78
			K	90	90	90

Table 2-1. Cumulative irrigation for corn and cotton treatments in north field

Year	Crop	Planting Date	Harvest Date	Cumulative Irrigation (mm) App	Checkbook	UGA SSA	Cumulative Rainfall (in)
2018	Corn	March 29, 2018	August 28, 2018	140.97	325.12	134.62	770.128
2019	Cotton	May 3, 2019	September 27, 2019	152.67	226.06	114.3	331.724
2020	Peanut	May 7, 2020	October 7, 2020	-	-	-	137.922

Table 2-2. Cumulative irrigation for peanut treatments in north field

Treatment	Old Checkbook	New Checkbook	50% Checkbook
Cumulative Irrigation	89.91	98.29	72.64
Treatment	Irrigator Pro (Temp)	Irrigator Pro (SSA)	SSA Dynamic VRI
Cumulative Irrigation	101.6	139.7	63.5
Treatment	SSA (Porter Method)	Peanut Farm	Rainfed
Cumulative Irrigation	63.5	25.4	25.4

Table 2-3. Timeline of recorded observations in north field

		North Field	
Crop	Data Collected	Treatments	How Often
Corn 2018	Soil Nutrients	All	Once a month
	Soil Moisture	All	Once a month
	Biomass	All	Once a month
	Tissue TKN	All	Once a month
Cotton 2019	Soil Nutrients	1, 4, 7	Once every two months
	Soil Moisture	1, 4, 7	Once every two months
	Biomass	1, 4, 7	Once every two months
	Tissue TKN	1, 4, 7	Once every two months
Peanut 2020	Soil Nutrients	All	Once, one month before planting
	Soil Moisture	All	Once, one month before planting
	Biomass	None	-
	Tissue TKN	None	-

Table 2-4. Timeline of recorded observations in middle field

		Middle Field	
Crop	Data Collected	Treatments	How Often
Cotton 2018	Soil Nutrients	All	Once a month
	Soil Moisture	All	Once a month
	Biomass	All	Once a month
	Tissue TKN	All	Once a month
Peanut 2019	Soil Nutrients	None	-
	Soil Moisture	1, 4, 5	Once, one month before planting
	Biomass	None	-
	Tissue TKN	None	-
Corn 2020	Soil Nutrients	All	Once a month
	Soil Moisture	All	Once a month
	Biomass	All	Once a month
	Tissue TKN	All	Once a month

Table 2-5. Timeline of recorded observations in south field

	South Field		
Crop	Data Collected	Treatments	How Often
Peanut 2018	Soil Nutrients	All	Once a month
	Soil Moisture	All	Once a month
	Biomass	None	-
	Tissue TKN	None	-
Corn 2019	Soil Nutrients	3, 6, 9	Once a month until June
	Soil Moisture	3, 6, 9	Once a month until June
	Biomass	3, 6, 9	Once a month until June
	Tissue TKN	3, 6, 9	Once a month until June
Cotton 2020	Soil Nutrients	All	Once in July and once in October
	Soil Moisture	All	Once every two months
	Biomass	All	Once a month, beginning in July
	Tissue TKN	All	Once a month, beginning in July

Table 2-6. Summary of treatment numbers in north field

Treatment	2018 Corn Treatments	2019 Cotton Treatments	2020 Peanut Treatments
1	App x High N	App x Fertigation	Old Checkbook
2	App x Traditional	App x NDVI	New Checkbook
3	App x Low N	App x Traditional	50% New Checkbook
4	Checkbook x High N	UGA SSA x Fertigation	Irrigator Pro (Temp)
5	Checkbook x Traditional	UGA SSA x NDVI	Irrigator Pro (SSA)
6	Checkbook x Low N	UGA SSA X Traditional	SSA Dynamic VRI
7	UGA SSA x High N	Checkbook x Fertigation	SSA (Porter Method)
8	UGA SSA x Traditional	Checkbook x NDVI	Peanut Farm
9	UGA SSA x Low N	Checkbook x Traditional	Rainfed

Table 2-7. Summary of treatment numbers in middle field

Treatment	2018 Cotton Treatments	2019 Peanut Treatments	2020 Corn Treatments
1	App x Fertigation	Old Checkbook	Checkbook x Scheduled Fertigation 1
2	App x NDVI	New Checkbook	App x Traditional
3	App x Traditional	50% New Checkbook	App x Scheduled Fertigation 2
4	UGA SSA x Fertigation	Irrigator Pro (Temp)	Checkbook x Scheduled Fertigation 2
5	UGA SSA x NDVI	Irrigator Pro (SSA)	App x Scheduled Fertigation 1
6	UGA SSA X Traditional	SSA Dynamic VRI	UGA SSA x Scheduled Fertigation 1
7	Checkbook x Fertigation	SSA (Porter Method)	UGA SSA x Scheduled Fertigation 2
8	Checkbook x NDVI	Peanut Farm	UGA SSA x Traditional
9	Checkbook x Traditional	Rainfed	Checkbook x Traditional

Table 2-8. Summary of treatment numbers in south field

Treatment	2018 Peanut Treatments	2019 Corn Treatments	2020 Cotton Treatments
1	Old Checkbook	Checkbook x Scheduled Fertigation	App x Fertigation
2	New Checkbook	App x Traditional	App x Fert #2
3	50% New Checkbook	App x App Fertigation	App x Traditional
4	Irrigator Pro (Temp)	Checkbook x App Fertigation	UGA SSA x Fertigation
5	Irrigator Pro (SSA)	App x Scheduled Fertigation	UGA SSA x Fert #2
6	SSA Dynamic VRI	UGA SSA x Scheduled Fertigation	UGA SSA X Traditional
7	SSA (Porter Method)	UGA SSA x App Fertigation	Checkbook x Fertigation
8	Peanut Farm	UGA SSA x Traditional	Checkbook x Fert #2
9	Rainfed	Checkbook x Traditional	Checkbook x Traditional

Table 2-9. Calibrated McCurdy84aa cultivar coefficients for corn

	Cultivar Code	Cultivar Name	Ecotype Code	P1	P2	P5	G2	G3	PHINT
Original Cultivar	IB0035	McCurdy 84aa	IB0001	260	0.3	955	700	8.5	43
Calibrated Cultivar	IB0035	McCurdy 84aa	IB0001	260	0.3	1100	800	10	43

Table 2-10. Calibrated Georgia King cultivar for cotton

	VRNAME	EXPNO	ECO#	CSDL	PPSEN	EM-FL	FL-SH	FL-SD	SD-PM	FL-LF
Original Cultivar	Georgia King	10	CO0005	23	0.01	44	11	16	38	75
Calibrated Cultivar	Georgia King	5	CO0005	23	0.01	37	11.2	15.1	40	72.89
LFMAX	SLAVR	SIZLF	XFRT	WTPSD	SFDUR	SDPDV	PODUR	THRSH	SDPRO	SDLIP
1.05	170	300	0.61	0.18	35	27	12	70	0.153	0.12
1.1	170	273.3	0.63	0.18	24.6	26.08	13.9	70	0.153	0.12

Table 2-13. Description of three management systems

Crop	Operation	Management System 1	Management System 2	Management System 3
Corn	Tillage	Strip Tillage	Conventional Tillage	Conventional Tillage
	Irrigation	Soil Moisture Sensor	UGA Checkbook	Minimum 1 ac-in every week (up to week 6) Minimum 2 ac-in every week (7th week to harvest)
	Fertilizer	60 lbs N at planting	60 lbs N at planting	60 lbs N at harvest
		180 lbs N applied over 5 applications every two weeks beginning 5 weeks after planting	180 lbs N applied over 3 applications every two weeks beginning 8 weeks after planting	180 lbs N applied in 1 application, 12 weeks after planting
	Cover Crop	Rye	None	None
	Operation	Management System 1	Management System 2	Management System 3
Cotton	Tillage	Strip Tillage	Conventional Tillage	Conventional Tillage
	Irrigation	Soil Moisture Sensor	UGA Checkbook	Minimum 1 ac-in every week
	Fertilizer	20 lb N starter	2 ton chicken litter	2 ton chicken litter
		90 lb N side dress applied over three applications	70 lb N side dress applied in one application	30 lb N after planting, 90 lb N side dress applied in one application
	Cover Crop	Rye	None	None
	Operation	Management System 1	Management System 2	Management System 3
Peanut	Tillage	Strip Tillage	Conventional Tillage	Conventional Tillage
	Irrigation	Soil Moisture Sensor	UGA Checkbook	Minimum 1 ac-in every week
	Fertilizer	-	-	-
	Cover Crop	Rye	None	None

Table 2-14. Adjusted crop parameters for yield calibration in south field

Parameter	Crop	Adj	Initial Parameter Range	Fitted Parameter	Original Parameter	Calibrated Parameter
HVSTI	Peanut	r	-0.3 to 0.3	0.4672	0.40	0.5868
BIO_E	Peanut	r	-0.3 to 0.3	0.5044	20.00	30.0800
HVSTI	Corn	v	0.3 to 0.9	0.9000	0.50	0.9000
BIO_E	Corn	r	-1 to -0.2	-0.3029	39.00	27.1866
BLAI	Corn	r	-0.3 to 0.3	-0.0028	6.00	5.9834
HVSTI	Cotton	v	0.3 to 0.6	0.6766	0.40	0.6766
BIO_E	Cotton	r	-0.3 to 0.3	-0.2626	15.00	11.0610
BLAI	Cotton	r	-0.3 to 0.3	0.0653	4.00	4.2613
ESCO		r	-0.2 to 0.2	-0.2391	0.95	0.7228
EPCO		r	-0.2 to 0.2	-0.1980	1.00	0.8020

Table 2-15. nRMSE values for yield across all treatments across all years.

nRMSE	Corn	Cotton	Peanut
SWAT (calibration)	11.37%	15.53%	11.20%
SWAT (validation)	12.92%	13.49%	6.88%
DSSAT	11.22%	17.32%	11.58%

Table 2-16. PBIAS values for yield across all treatments.

PBIAS	Corn		Cotton		Peanut	
Model	SWAT	DSSAT	SWAT	DSSAT	SWAT	DSSAT
2018	-6.90%	-5.90%	-	-	-6.30%	0.80%
2019	-0.30%	-5.1	-1%	-2.50%	3.70%	1%
2020	20%	23.80%	5.30%	-5.50%	1.50%	-0.20%
Average	4.27%	4.27%	1.95%	-4.00%	-0.37%	0.53%

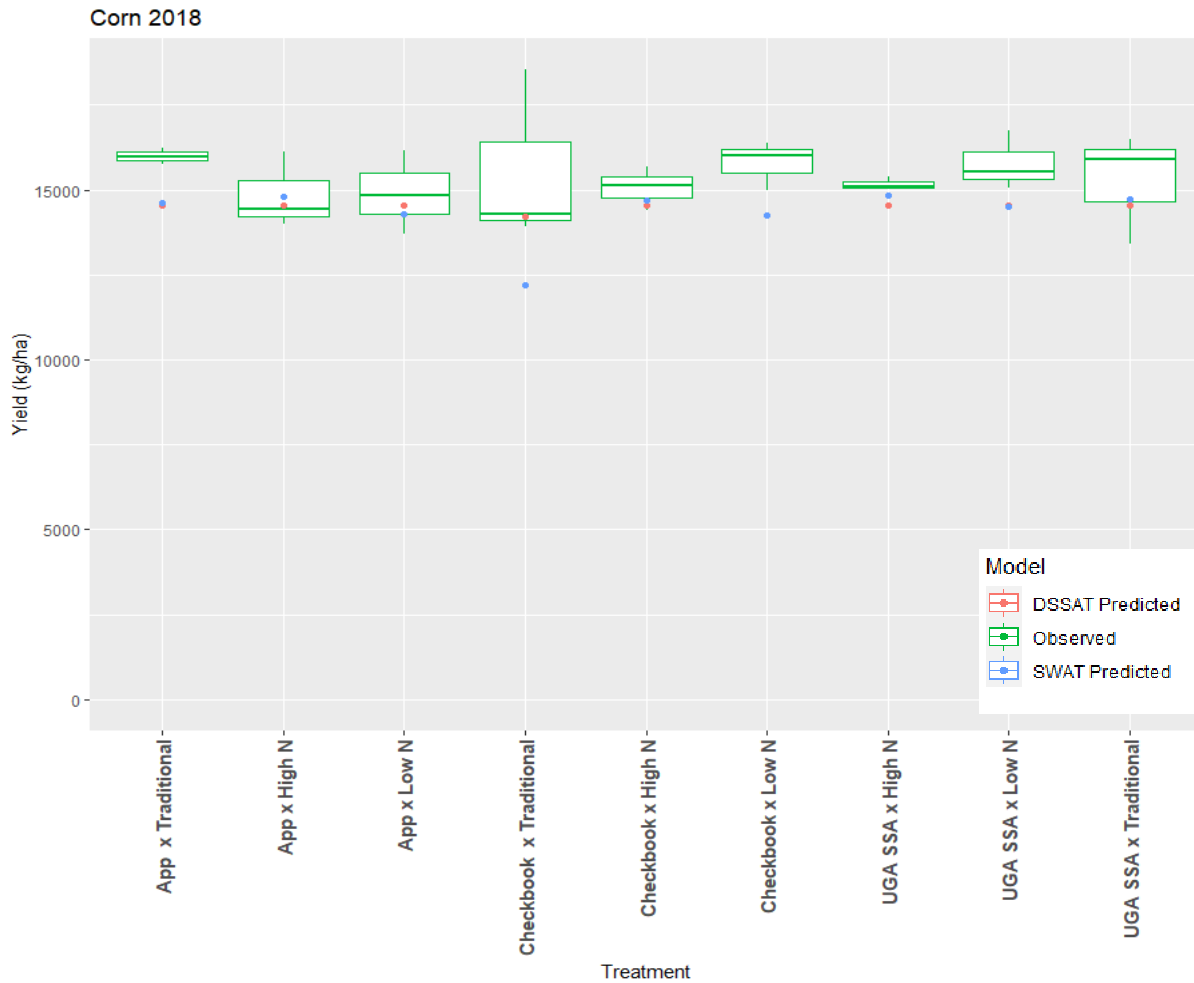

Figure 2-2. Observed versus simulated yield for corn 2018. Yield differences among treatments between observed values were not statistically significant.

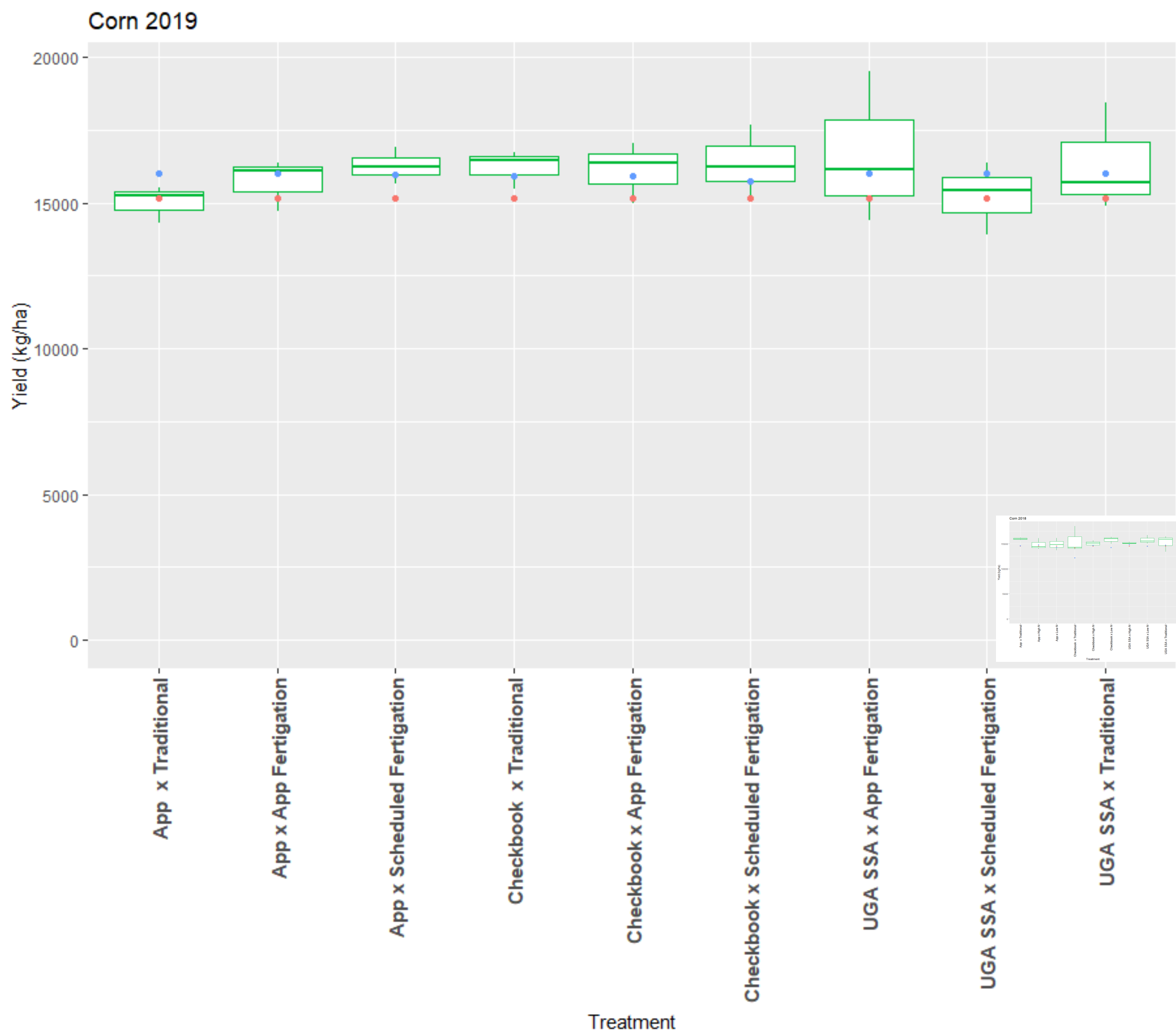

Figure 2-3. Observed versus simulated yield for corn 2019. Yield differences among treatments between observed values were not statistically significant.

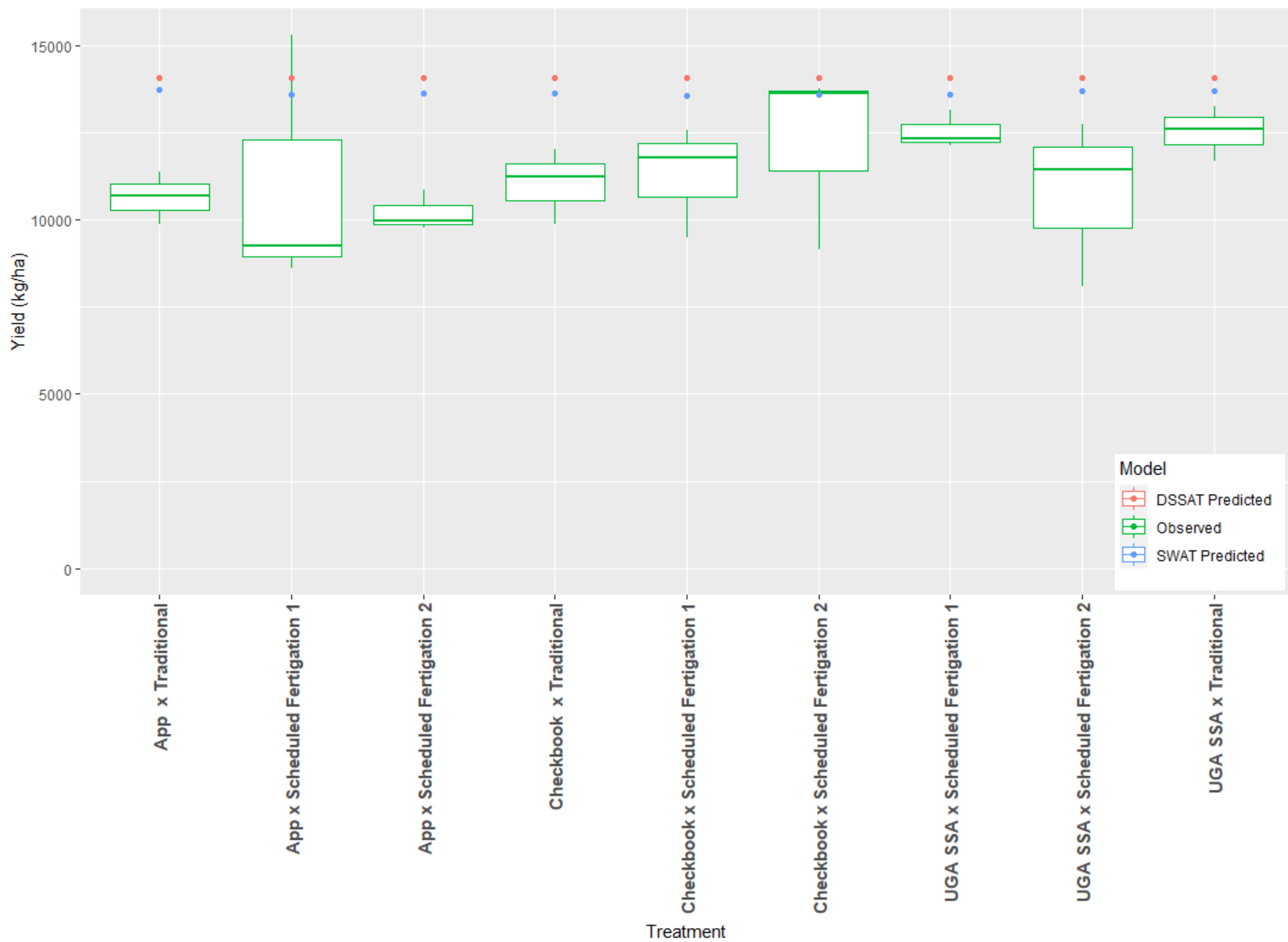

Figure 2-4. Observed versus simulated yield for corn 2020. Yield differences among treatments between observed values were not statistically significant.

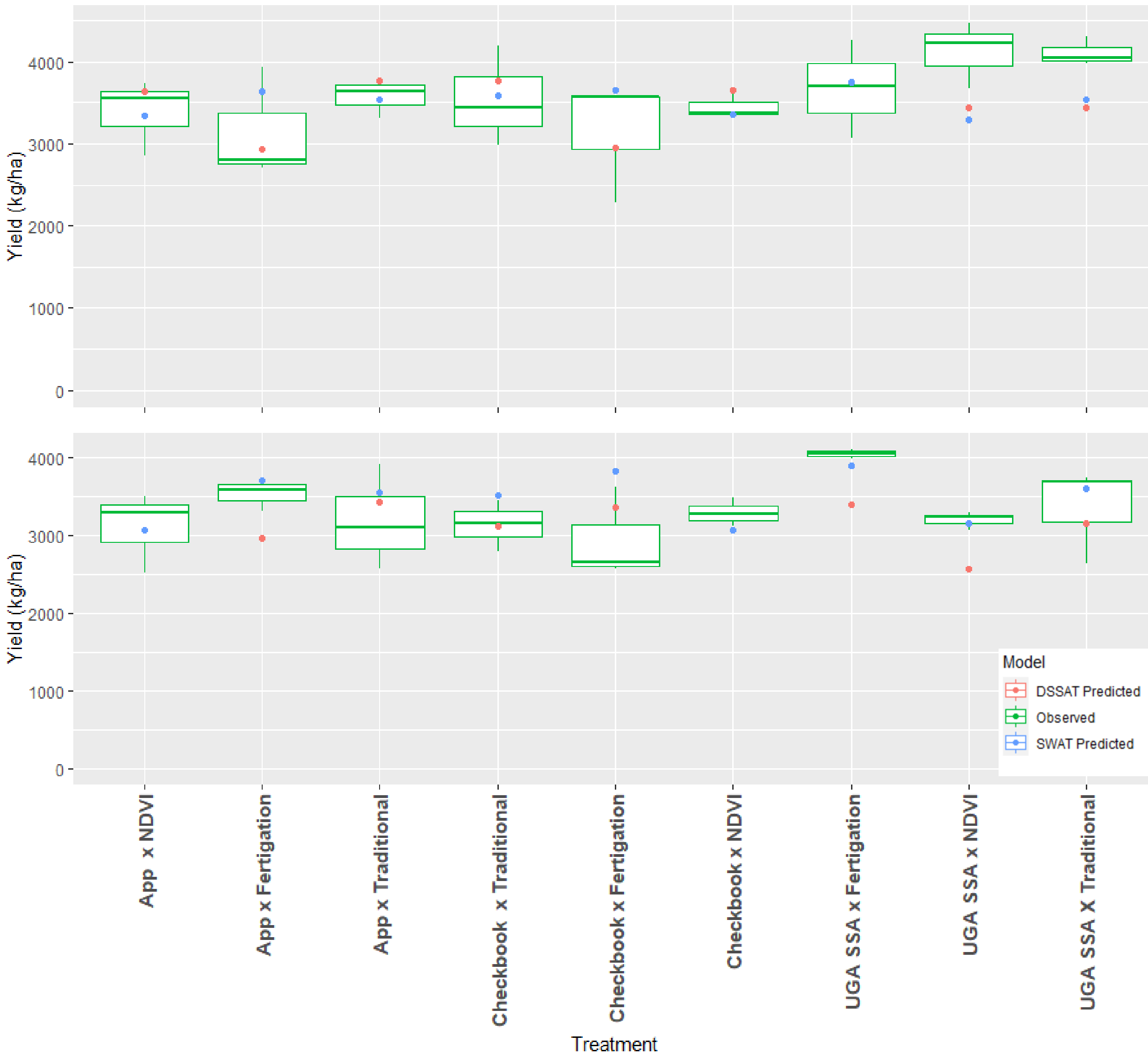

Figure 2-5. Observed versus simulated yield for cotton 2019 (top) and cotton 2020 (bottom). Yield differences among treatments between observed values were not statistically significant.

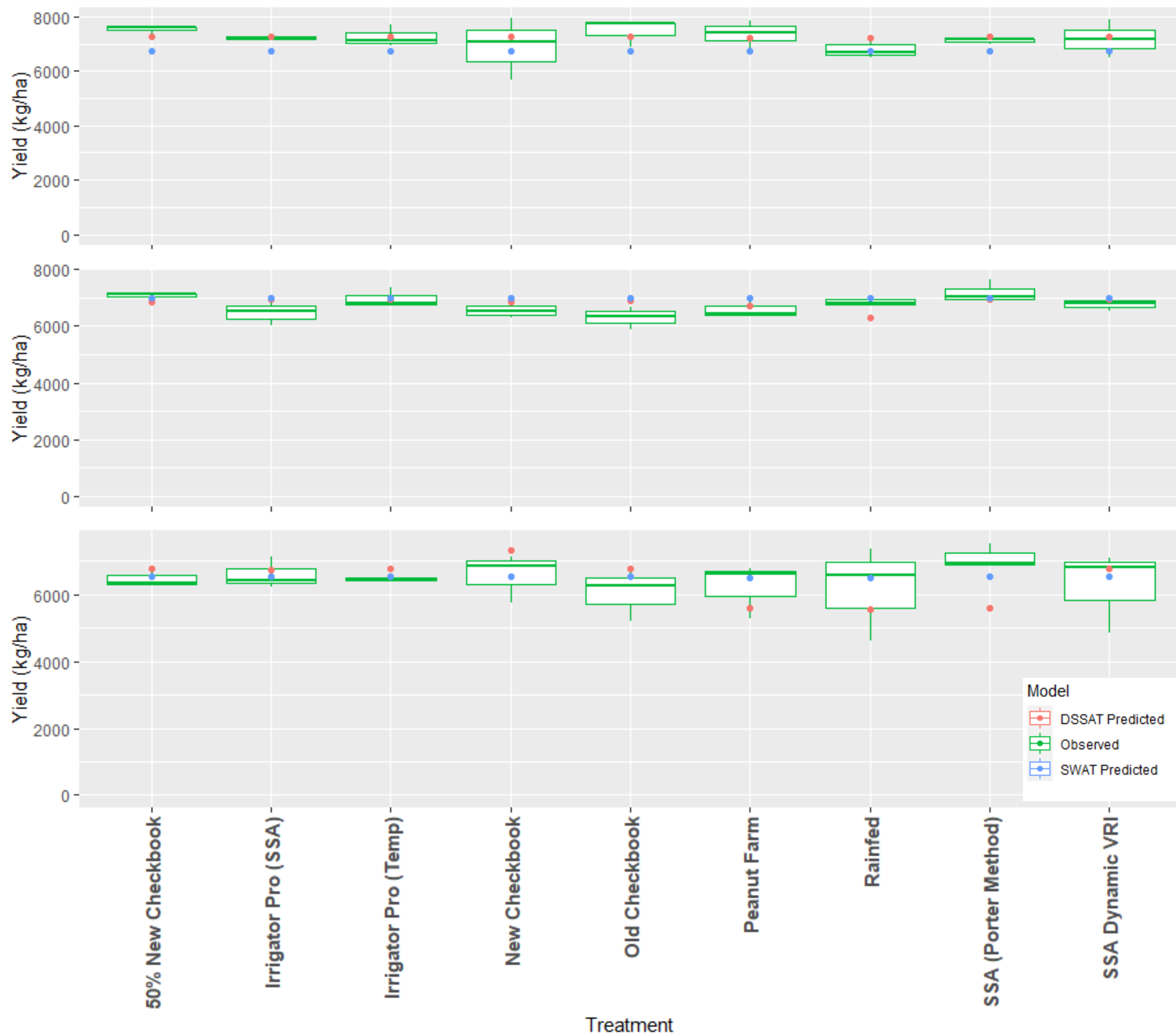

Figure 2-6. Observed versus simulated yield for peanut 2018 (top), peanut 2019 (middle) and peanut 2020 (bottom). Yield differences among treatments between observed values were not statistically significant.

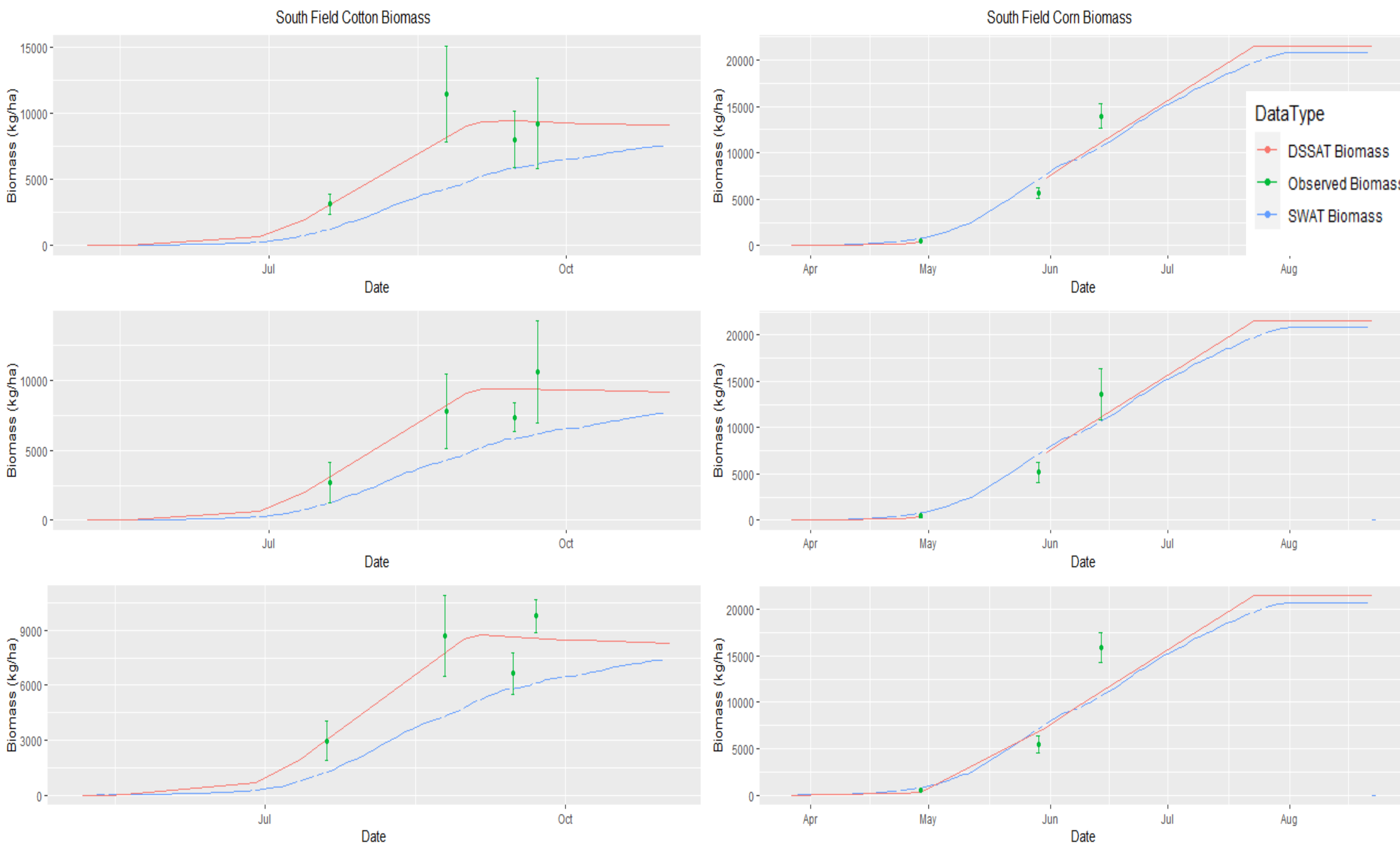

Figure 2-7. Observed and simulated corn (top) and cotton (bottom) biomass in the south field for treatments 3 (top), 6 (middle), and 9 (bottom)

Table 2-17. Model performance indices for biomass in corn and cotton

		Corn		Cotton	
Field	Model	nRMSE	PBIAS	nRMSE	PBIAS
South (calibration)	SWAT	38.90%	-8.20%	65%	-53.20%
South (calibration)	DSSAT	45.70%	-14.20%	47%	-22.30%
North (validation)	SWAT	17.63%	5.30%	40.67%	-24.80%
North (validation)	DSSAT	27.76%	20.60%	34.80%	-1.80%

Table 2-18. Model performance indices for N uptake in corn and cotton in the north field.

Corn	PBIAS	nRMSE	Cotton	PBIAS	nRMSE
SWAT	18.3%	22.35%	SWAT	-17.8%	38%
DSSAT	7.6%	20.2%	DSSAT	-24.5%	40%

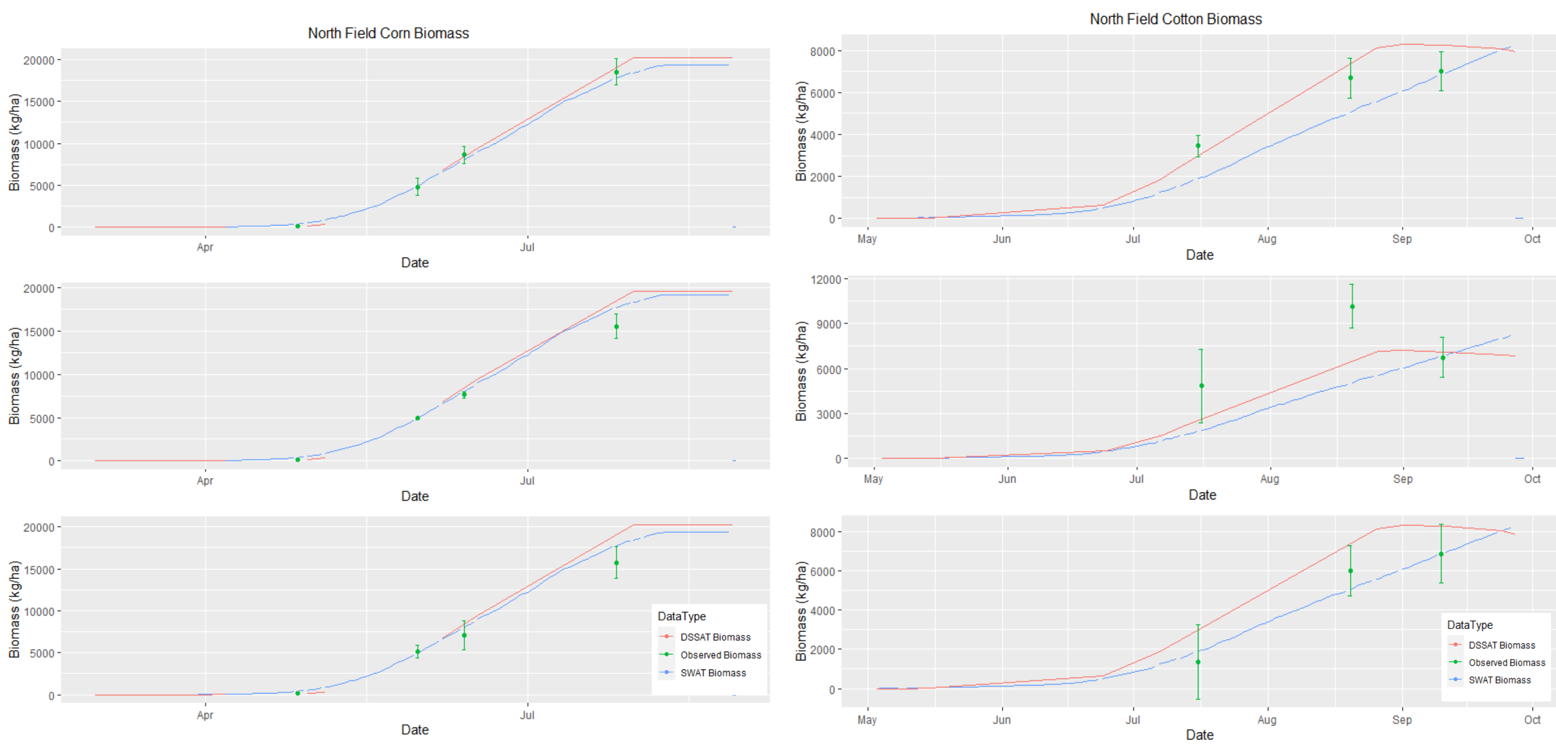

Figure 2-8. Observed and simulated corn (left) and cotton (right) biomass in the north field for treatments 1 (top), 4 (middle), and 7 (bottom)

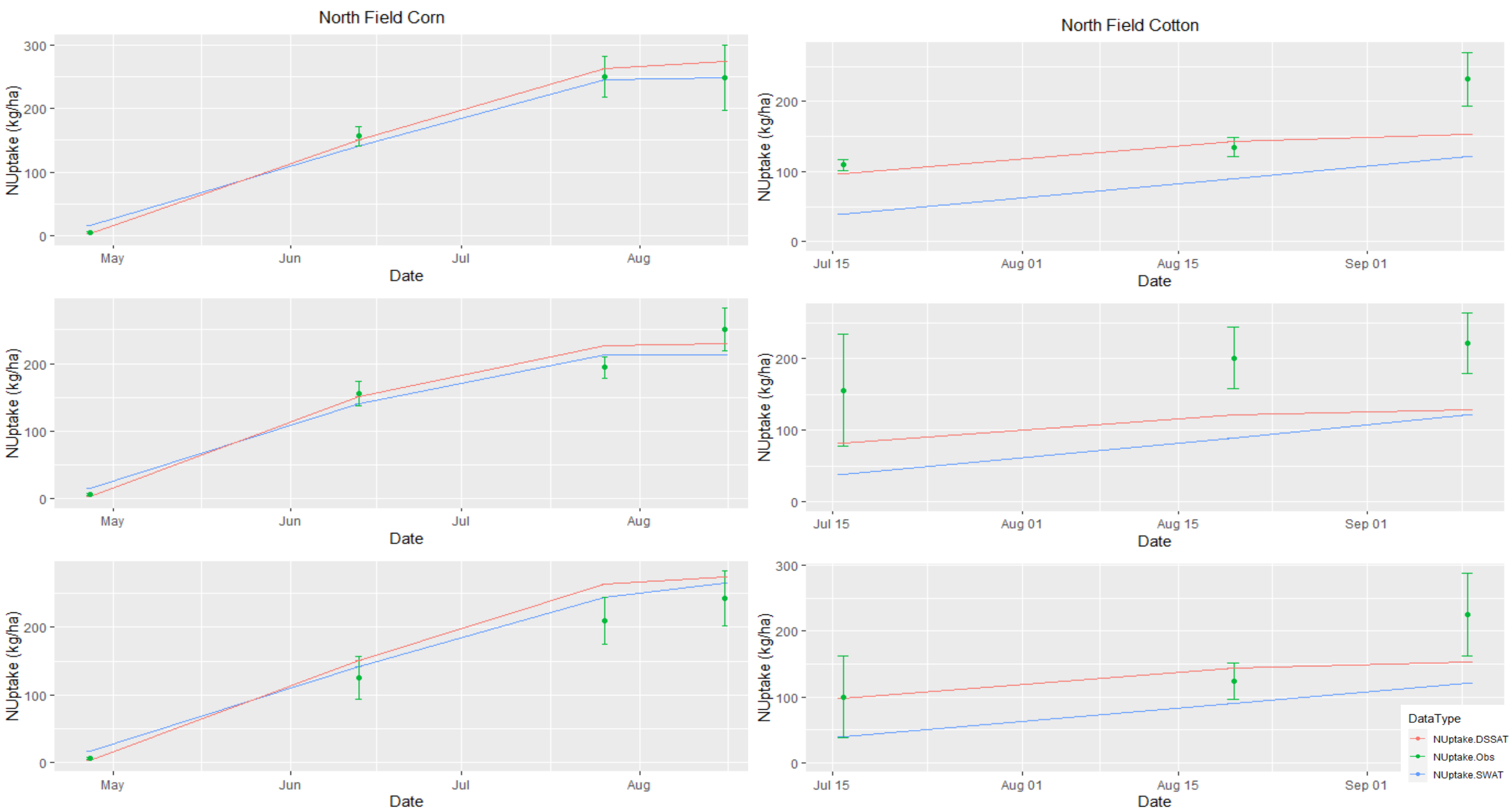

Figure 2-9. Observed plant nitrogen values plotted against simulated plant nitrogen uptake values for corn (left) and cotton (right) in the north field for treatments 1 (top), 4 (middle), and 7 (bottom)

Table 2-19. Adjusted soil parameters for soil moisture calibration in south field

Parameter	Soil Layer	Adj	Initial Parameter	Calibrated Parameter
SOL_AWC	ALL	v	0.01 to 0.2	0.17
SOL_K	ALL	v	50 to 70	70

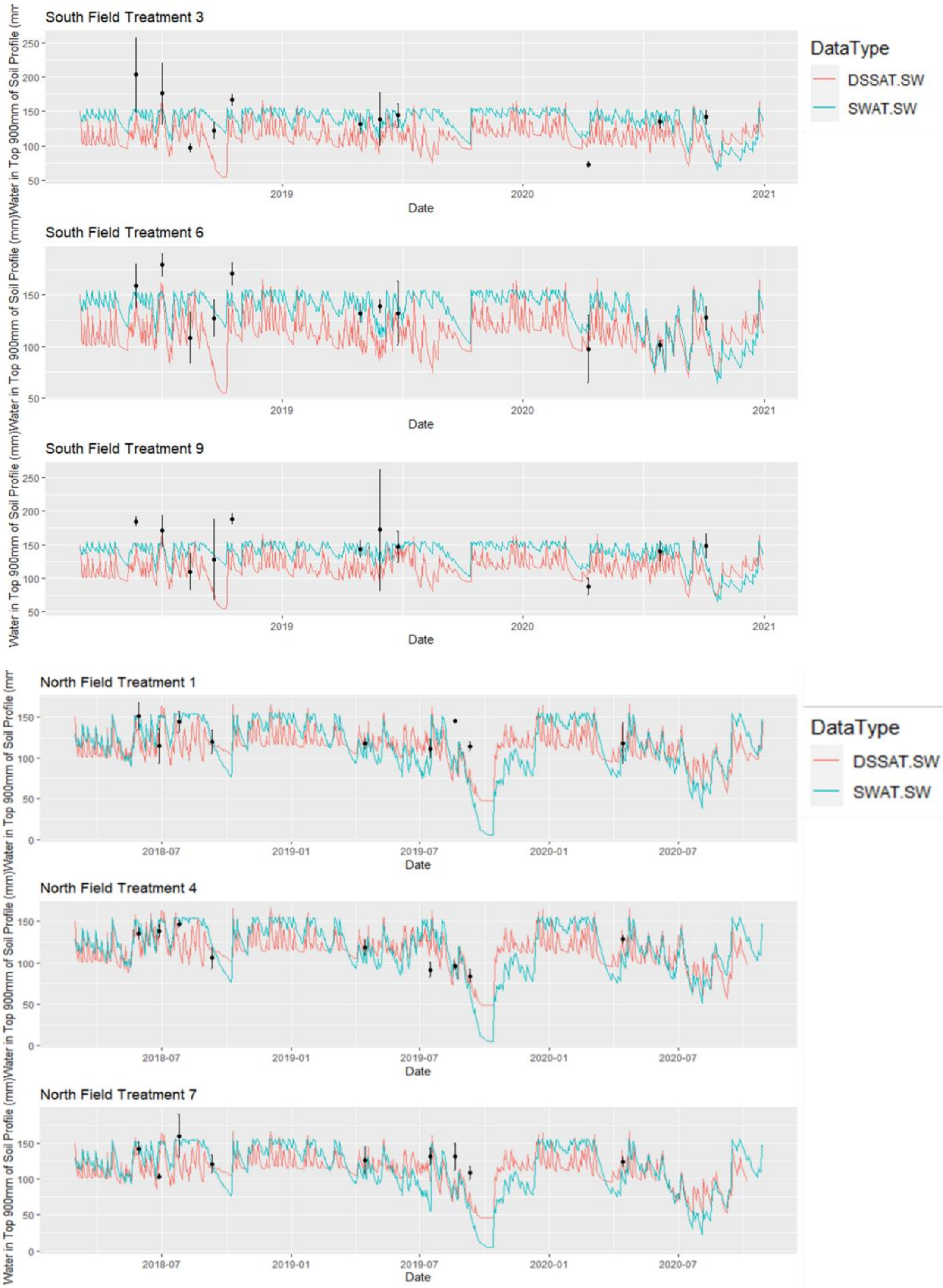

Figure 2-10. Plot of observed soil moisture values compared to simulated soil moisture values. South field (top) was used for SWAT calibration while north (bottom) was used for validation.

Table 2-20. nRMSE values for soil moisture

	South Field		North Field		Middle Field	
Treatment	SWAT (calibration)	DSSAT	SWAT (validation)	DSSAT	SWAT (validation)	DSSAT
1	22.29	27.41	21.39	18.71	19.03	18.33
2	22.29	24.51	18.45	19.70	21.42	21.51
3	26.07	26.02	19.09	19.62	22.78	19.60
4	29.55	22.13	17.74	12.97	25.72	18.51
5	24.96	22.49	8.80	14.09	31.77	25.39
6	19.09	22.02	9.97	12.16	17.16	23.10
7	27.22	27.17	30.16	20.13	26.28	20.60
8	23.49	21.56	23.83	27.04	23.54	25.79
9	22.25	26.56	16.53	16.04	19.07	17.29
Average	24.13	24.43	18.44	17.83	22.98	21.13

Table 2-21. PBIAS for soil moisture

Soil Water	South Field		North Field		Middle Field	
Treatment	SWAT (calibration)	DSSAT	SWAT (validation)	DSSAT	SWAT (validation)	DSSAT
1	0.50%	-13.50%	-8.30%	-6.40%	10.40%	-13.70%
2	2.70%	-11.50%	-5.40%	-11%	10.70%	-12%
3	3.10%	-12.20%	-8.30%	-13.90%	12.70%	-9.60%
4	19.60%	1.80%	4.30%	2.90%	16%	-9.30%
5	5.90%	-8.30%	-7%	-12%	14.50%	-10.90%
6	1.90%	-12.10%	-0.20%	-5.90%	3.80%	-17.50%
7	1.90%	-13.10%	-14.10%	-10.70%	17.50%	-5.20%
8	10.60%	-6%	7.70%	-0.20%	8%	-13.40%
9	-2.20%	-17.10%	1.70%	-5.30%	12.10%	-9.30%
Average	4.89%	-10.22%	-3.29%	-6.94%	11.74%	-11.21%

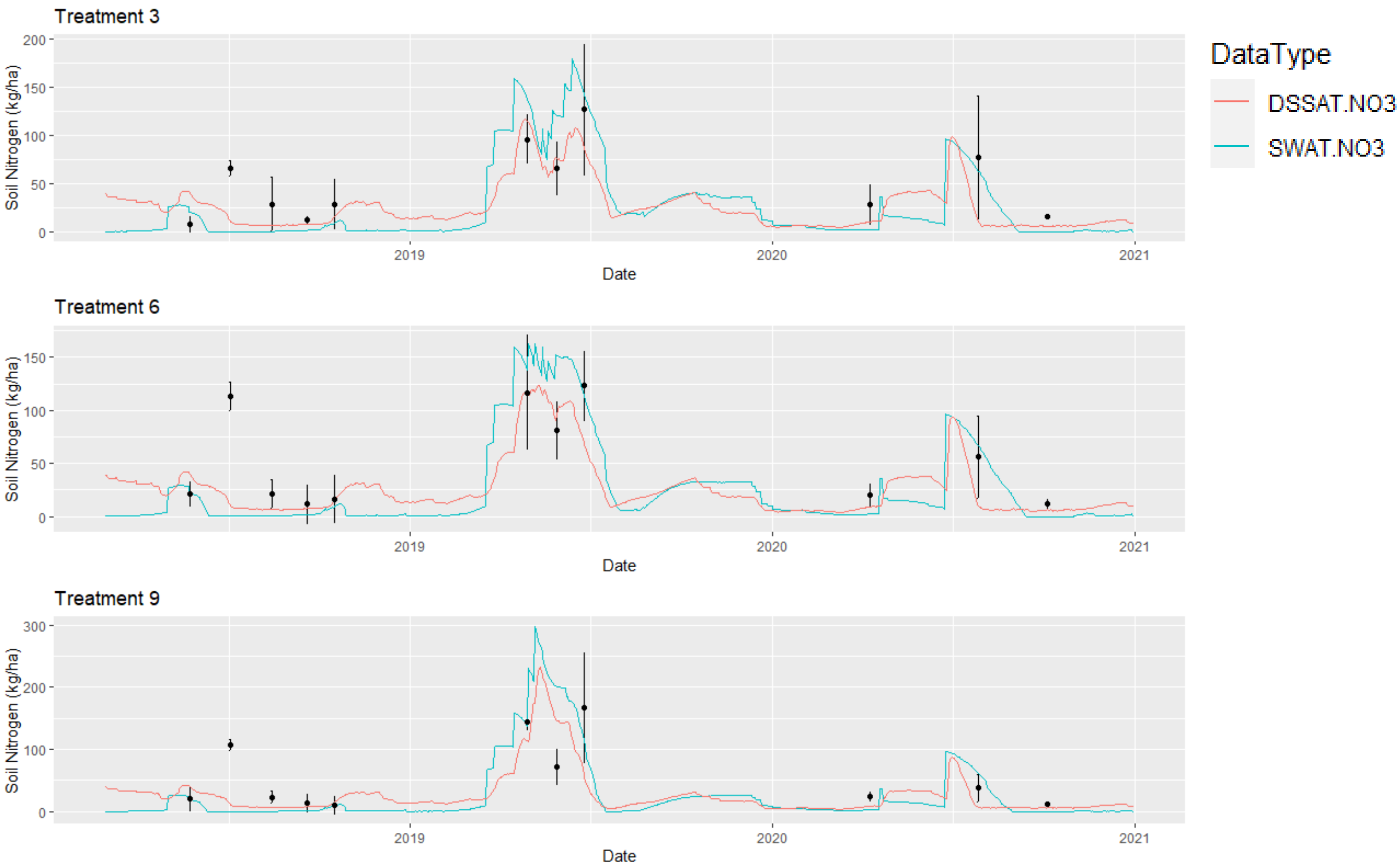

Figure 2-11. Observed soil nitrogen values plotted against simulated values for treatments 3, 6, and 9 in the south field.

Table 2-22. nRMSE values for soil nitrogen

nRMSE	South Field		North Field		Middle Field	
Treatment	SWAT	DSSAT	SWAT	DSSAT	SWAT	DSSAT
1	111.60	111.41	132.00	91.30	119.75	97.15
2	119.35	120.67	72.23	66.46	91.73	98.24
3	65.86	65.45	56.19	46.32	124.34	107.43
4	108.18	97.35	171.91	122.29	151.04	135.00
5	94.74	91.20	87.49	65.57	155.38	125.22
6	77.84	72.03	63.33	50.84	132.95	113.91
7	127.46	104.31	106.24	77.06	121.07	86.96
8	112.95	105.51	95.27	68.45	79.68	92.16
9	95.67	91.72	60.80	65.75	94.26	101.51
Average	101.52	95.52	93.94	72.67	118.91	106.40

Table 2-23. PBIAS values for soil nitrogen

PBIAS	South Field		North Field		Middle Field	
Treatment	SWAT	DSSAT	SWAT	DSSAT	SWAT	DSSAT
1	-55.5%	-58.8%	46.1%	5.5%	-74.3%	-51.4%
2	-78.9%	-71.2%	-21.2%	-8.7%	-59%	-43.3%
3	-9.7%	-30.3%	-42.6%	-24.4%	-80.4%	-54.5%
4	-56.8%	-59.7%	92.5%	27.2%	-85.4%	-66.7%
5	-70.2%	-61.9%	-3.4%	-34.3%	-81.4%	-50.1%
6	-14.8%	-35.3%	-15.9%	-11.6%	-77.4%	-47%
7	-59.8%	-56.4%	55.2%	-2.4%	-66.4%	-21.5%
8	-77.7%	-67.9%	29.2%	-18.1%	-46.5%	-31.7%
9	-13.9%	-33.7%	1.5%	16.4%	-52.5%	-47%
Average	-48.59%	-52.80%	15.71%	-5.60%	-69.26%	-45.91%

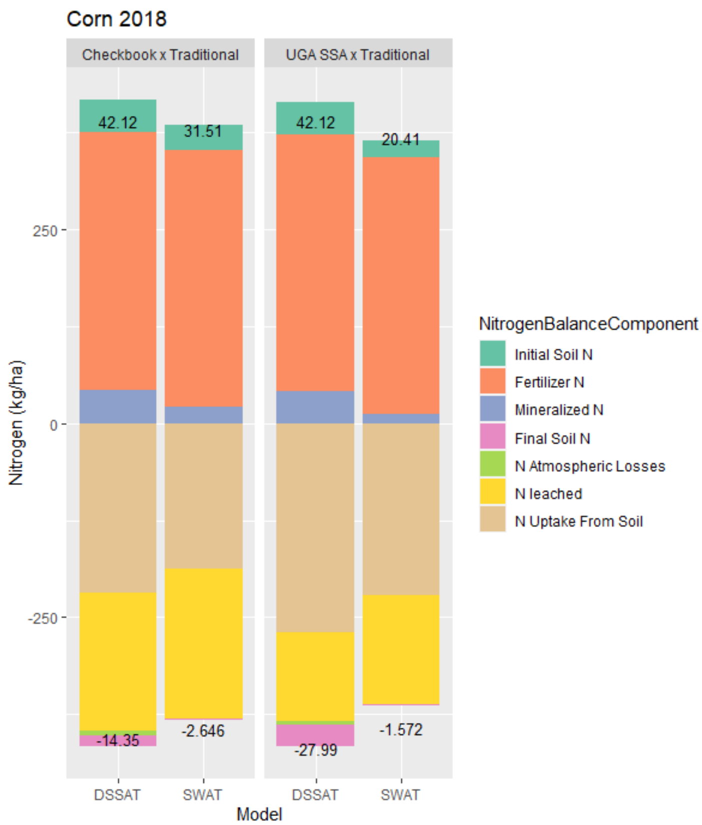

Figure 2-12. Nitrogen balance during the 2018 corn season

Table 2-24. Nitrogen balance during the 2018 corn season

Corn	DSSAT	SWAT	DSSAT	SWAT
Nitrogen Balance Component	Checkbook x Traditional	Checkbook x Traditional	UGA SSA X Traditional	UGA SSA X Traditional
Initial Soil N	42.12	31.51	42.12	20.41
Fertilizer N	332	331.052	332	331.052
Net Mineralized N	43.72	20.792	41.76	12.656
N leached	177.65	192.31	114.58	141.87
N Uptake from Soil	218.81	188.4	268.93	220.67
N Atmospheric Losses	7.03	0	4.38	0
Final Soil N	14.35	2.646	27.99	1.572

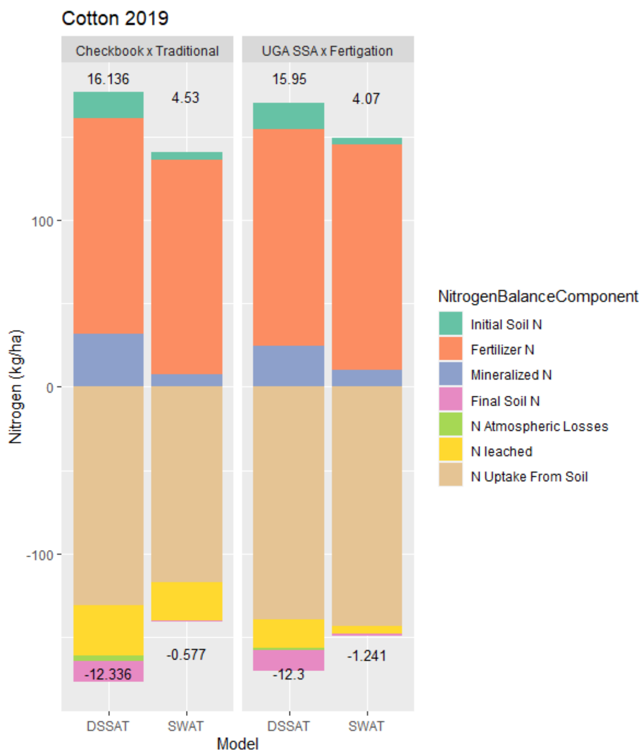

Figure 2-13. Nitrogen balance for cotton 2019 season

Table 2-25. Nitrogen balance during the 2019 cotton season

Cotton Nitrogen Balance Component	DSSAT Checkbook x Traditional	SWAT Checkbook x Traditional	DSSAT UGA SSA x Fertigation	SWAT UGA SSA x Fertigation
Initial Soil N	16.136	4.53	15.95	4.07
Fertilizer N	129	128.63	130	130.63
Net Mineralized N	31.94	7.547	24.35	9.886
N leached	29.89	22.53	16.79	4.74
N Uptake from Soil	131.26	117.598	139.81	143.605
N Atmospheric Losses	3.59	0	1.4	0
Final Soil N	12.336	0.507	12.3	1.241

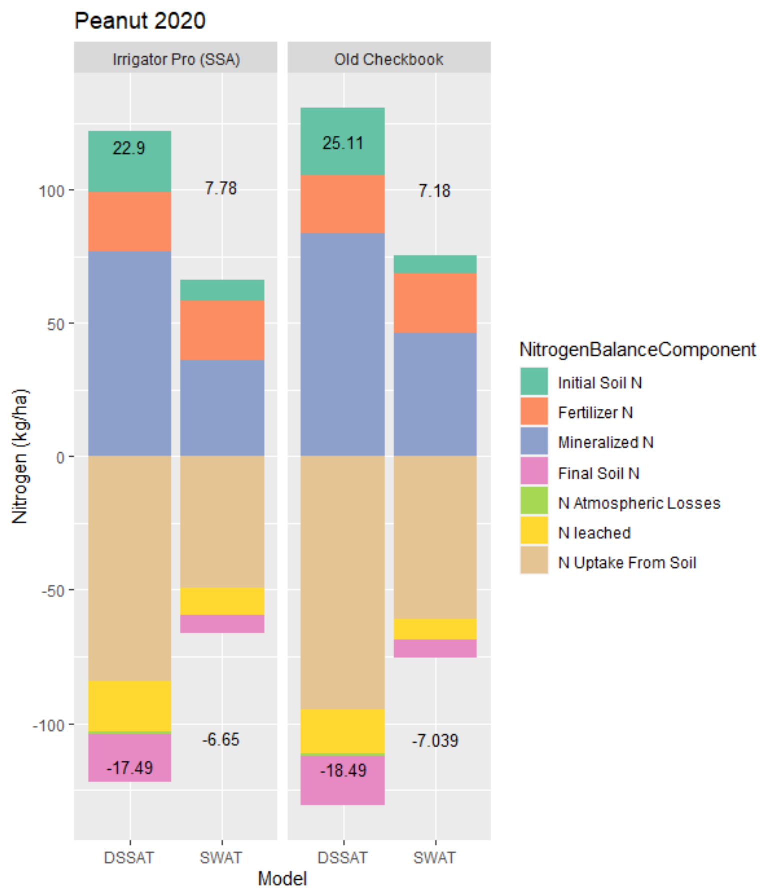

Figure 2-14. Nitrogen balance for peanut 2020 season

Table 2-26. Nitrogen balance during the 2020 peanut season

Peanut	DSSAT	SWAT	DSSAT	SWAT
Nitrogen Balance Component	Old Checkbook	Old Checkbook	Irrigator Pro (SSA)	Irrigator Pro (SSA)
Initial Soil N	25.11	7.18	22.9	7.78
Fertilizer N	22	22	22	22
Net Mineralized N	83.69	46.37	76.93	36.285
N leached	16.45	7.511	19.06	10.305
N Uptake from Soil	94.77	61	84.27	49.11
N Atmospheric Losses	1.09	0	1.01	0
Final Soil N	18.49	7.039	17.49	6.649

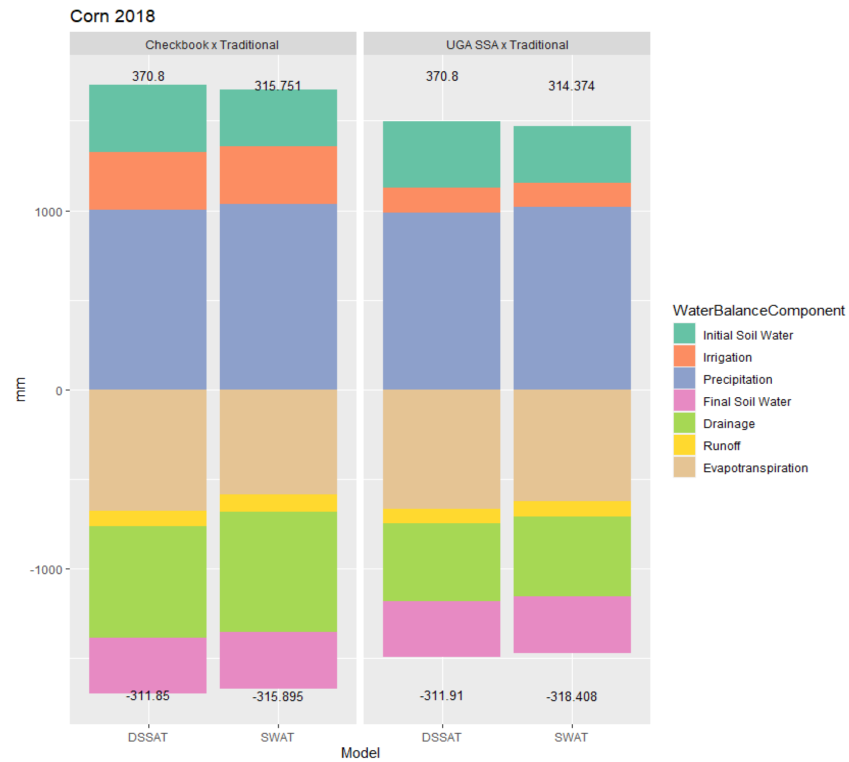

Figure 2-15. Water balance for corn 2018 season

Table 2-27. Water balance for corn 2018 season

Corn Water Balance Component (mm)	DSSAT Checkbook x Traditional	SWAT Checkbook x Traditional	DSSAT UGA SSA X Traditional	SWAT Checkbook x Traditional
Initial Soil Water	370.8	315.751	370.8	314.374
Irrigation	326.3	325.12	135.3	134.62
Precipitation	1001.5	1033.7	989.1	1021.3
Drainage	622.31	673.24	435.78	444.783
Runoff	89.62	98.87	83.6	89.384
Evapotranspiration	674.81	586	663.92	620.781
Final Soil Water	311.85	315.895	311.91	318.408

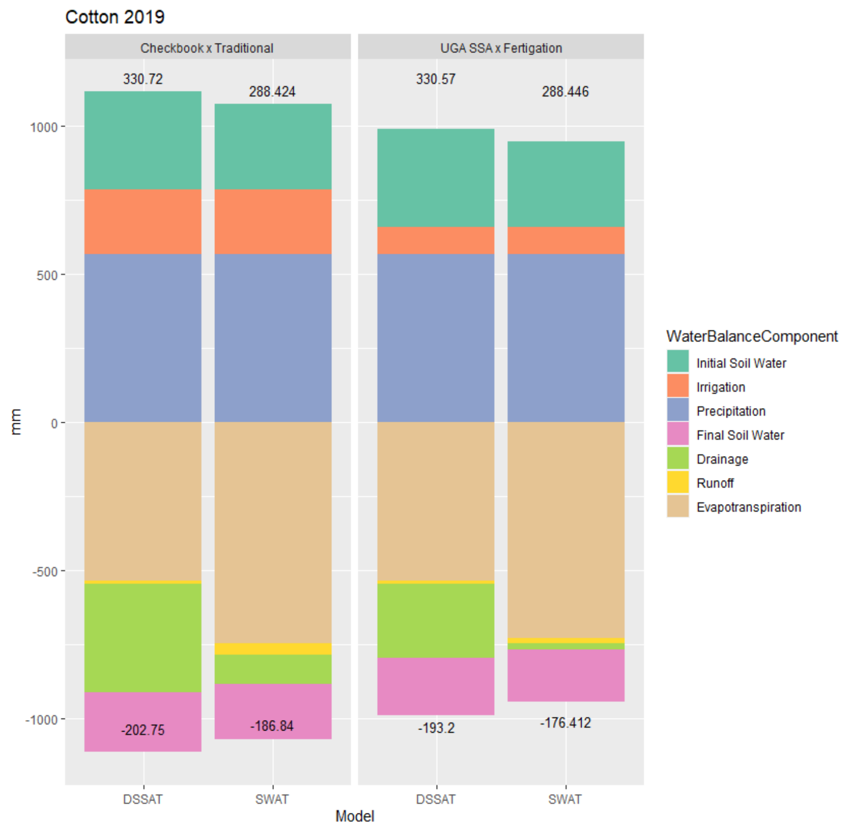

Figure 2-16. Water balance for cotton 2019 season

Table 2-28. Water balance for cotton 2019 season

Cotton Water Balance Component (mm)	DSSAT Checkbook x Traditional	SWAT Checkbook x Traditional	DSSAT UGA SSA x Fertigation	SWAT UGA SSA x Fertigation
Initial Soil Water	330.72	288.424	330.57	288.446
Irrigation	218.4	219.2	92.7	92.71
Precipitation	565	565	565	565
Drainage	363.55	98.005	249.6	21.212
Runoff	10.54	38.433	10.3	18.005
Evapotranspiration	537.27	747.377	535.17	729.681
Final Soil Water	202.75	186.84	193.2	176.412

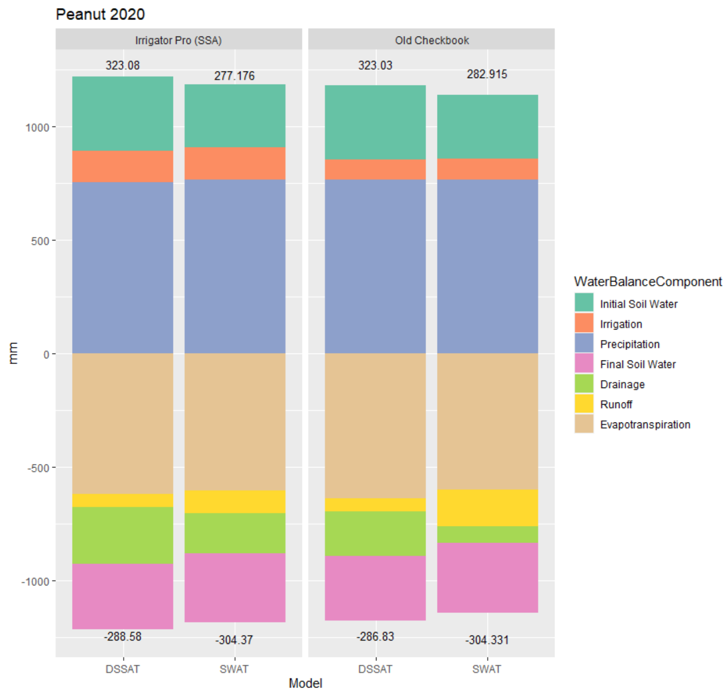

Figure 2-17. Water balance for peanut 2020 season

Table 2-29. Water balance for peanut 2020 season

Peanut	DSSAT	SWAT	DSSAT	SWAT
Water Balance Component (mm)	Old Checkbook	Old Checkbook	Irrigator Pro (SSA)	Irrigator Pro (SSA)
Initial Soil Water	323.03	282.915	323.08	277.176
Irrigation	90	89.92	140	139.7
Precipitation	764.7	766	753	766
Drainage	195.97	76.534	249.96	176.525
Runoff	57.76	161.363	56.42	101.094
Evapotranspiration	637.1	594.9	620.27	603.271
Final Soil Water	286.83	304.331	288.58	304.37

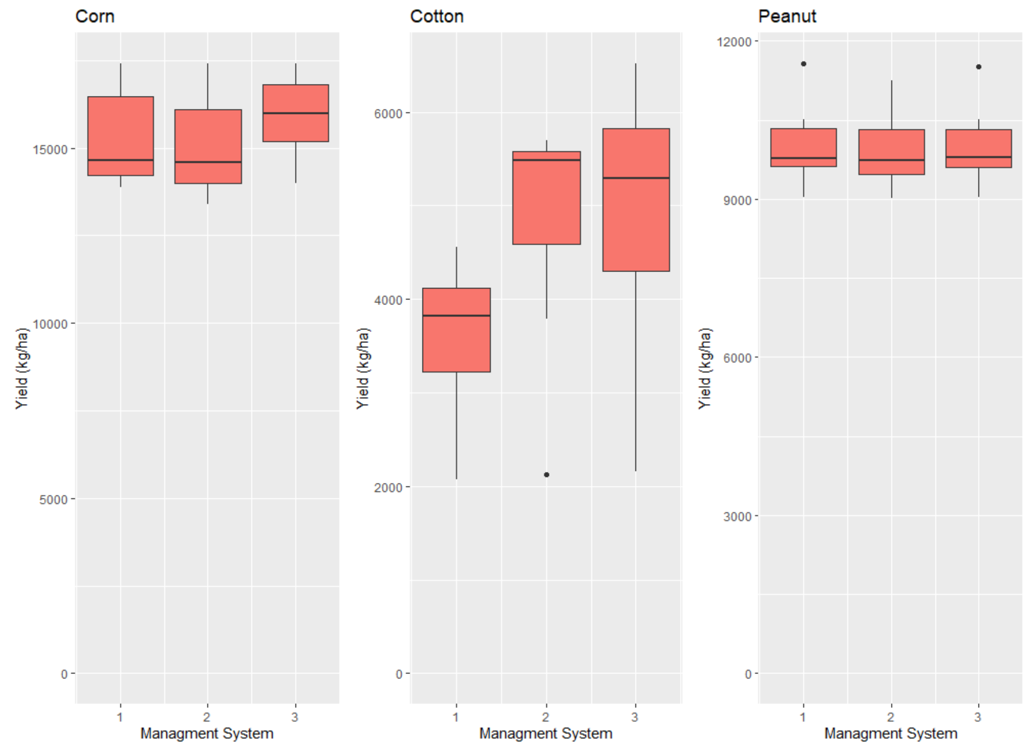

Figure 2-18. Simulated annual corn, cotton, and peanut yields for the three management levels. The same color indicates that the means are not significantly different.

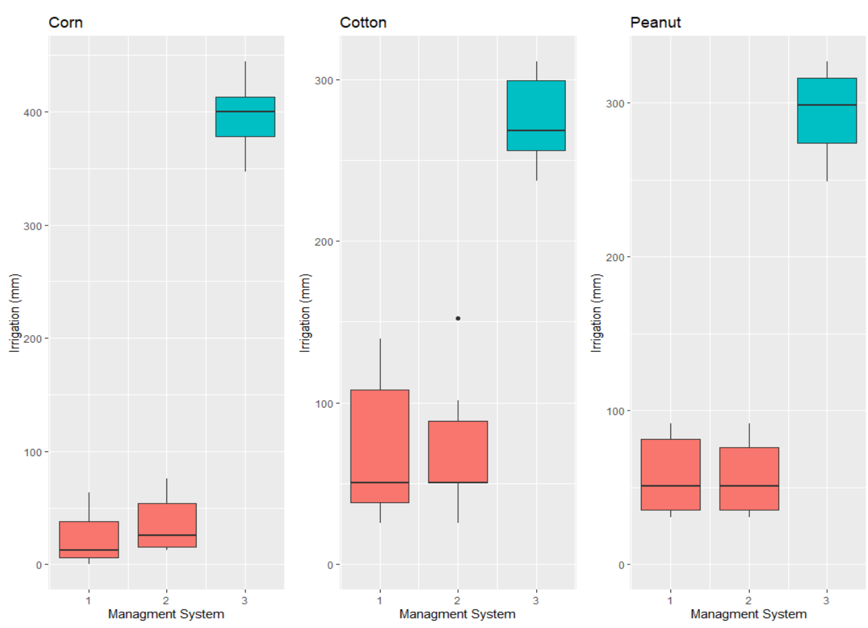

Figure 2-19. Simulated annual water use for corn, cotton, and peanut for the three management levels. The same color indicates that the means are not significantly different.

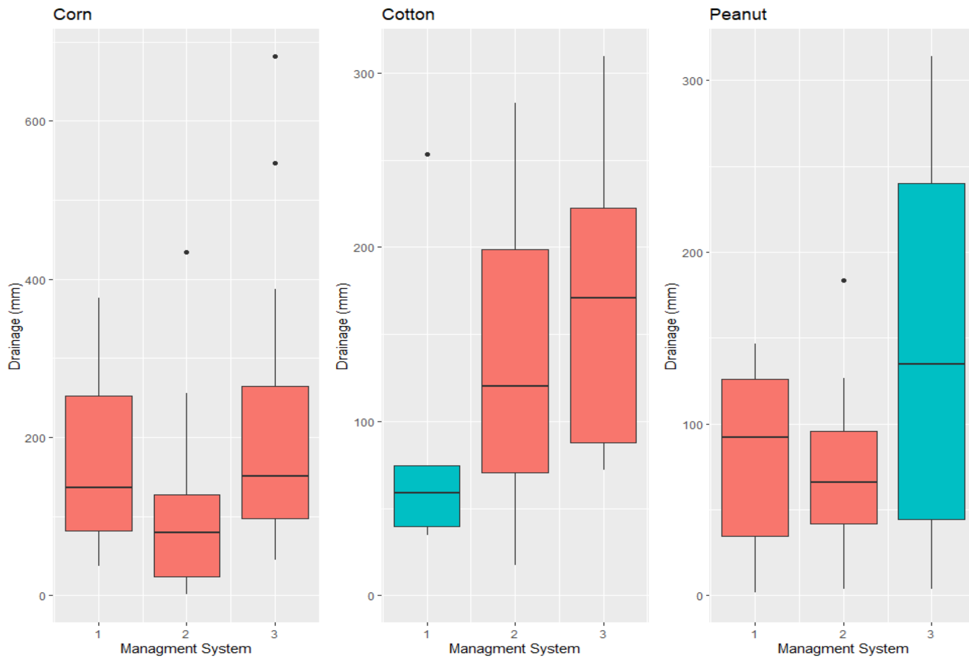

Figure 2-20. Simulated annual drainage for corn, cotton, and peanut for the three management levels. The same color indicates that the means are not significantly different.

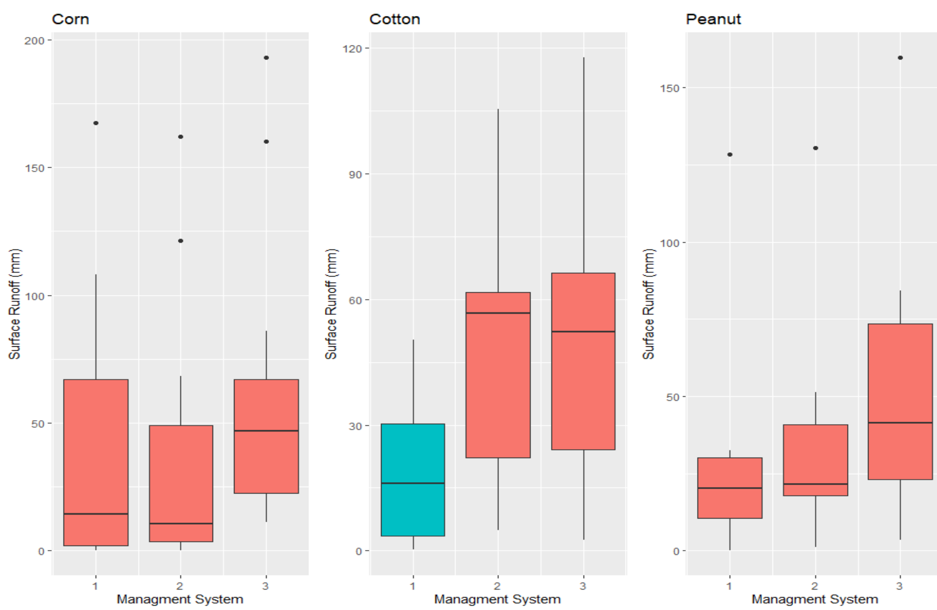

Figure 2-21. Simulated annual surface runoff for corn, cotton, and peanut for the three management levels. The same color indicates that the means are not significantly different.

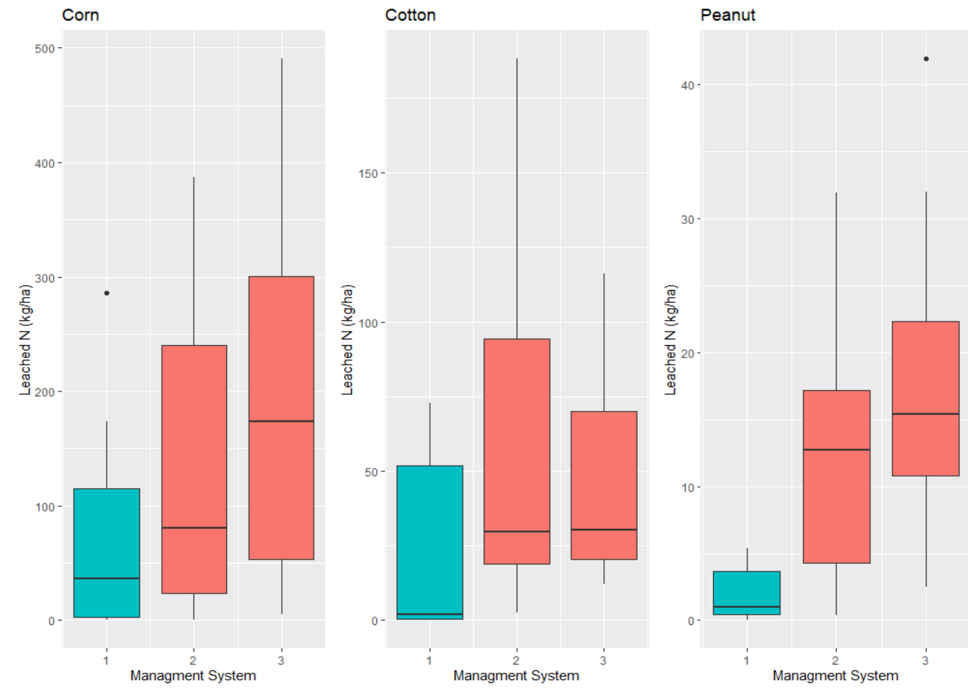

Figure 2-22. Simulated annual leached nitrogen for corn, cotton, and peanut for the three management levels. The same color indicates that the means are not significantly different.

CHAPTER 3
SUMMARY AND CONCLUSIONS

Effects of BMPs and Model Performance

For all crops, all nine experimental treatments led to yields that were not statistically significant over all years, according to a one-way ANOVA with post-hoc Tuke test at 95% confidence interval. The use of SMS decreased applied irrigation by 51-57% across the three crops. Fertigation in corn used 17% less nitrogen, while fertigation in cotton used the same amount of nitrogen, with no differences in yield. Implementation of SMS irrigation decreased applied irrigation while maintaining yields. The N balance revealed that use of SMS irrigation decreased leached N, which would be beneficial for the health of the Floridan aquifer and the ecosystems it supplies water to.

This study showed that both SWAT and DSSAT can adequately simulate yield and soil moisture, while showing less accuracy in simulations of biomass, soil nitrogen, and nitrogen uptake at the field scale. Calibration of crop parameters and soil parameters was critical in SWAT's simulation of yield and soil moisture, while adjustment of crop parameters based off previous studies was sufficient in DSSAT's simulation of yield.

Both DSSAT and SWAT simulated corn and peanut yields with good fit, while simulations of cotton yield showed moderate fit for both models. Both models show good simulation of final season biomass for corn and cotton and moderate simulation of final N uptake in corn, but underpredicted total N uptake in cotton. Soil moisture predictions showed moderate fit for both models; however, DSSAT tended to underpredict soil moisture while SWAT tended to overpredict soil moisture. Soil N yielded poor nRMSE values, but generally followed observed temporal trends in both models.

The use of these crop simulation models allowed for estimation of soil drainage and nitrogen leaching which are difficult to measure in the field. N balances and water balances constructed from simulation results illustrated differences among water and nitrogen transport processes between the models and across treatments. Use of SMS in corn and cotton reduced the amount of applied irrigation which resulted in a decrease in leached N as well as drainage and surface runoff, while maintaining similar yields to the checkbook method. However, use of SMS did not have the same effect in peanut, and instead slightly increased irrigation, drainage, and leached N, while again maintaining similar yields.

Management Scenarios

Long-term SWAT simulations were used to evaluate alternative nutrient and water management systems for irrigation water use, crop yield, drainage, runoff, and nitrogen leaching. at the field scale over a 20-year historic weather record. Modeled results of these management systems showed that implementation of MS1 which includes SMS irrigation system, a rye cover crop, and strip-tillage is the most water efficient option which minimizes nitrate leaching with no statistical difference in yield for corn, cotton, or peanut. Evaluation of SWAT's performance in simulating the results of field experiments, particularly in comparison to a more well accepted crop growth model such as DSSAT, is important for increasing scientist and stakeholder trust in the model, and its future use at the watershed scale for evaluating impacts of land use change and BMP adoption on receiving water quality and quantity and the regional economy.

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BIOGRAPHICAL SKETCH

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