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Quantifying nitrate leaching to groundwater from a corn-peanut rotation under a variety of irrigation and nutrient management practices in the Suwannee River Basin, Florida

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ABSTRACT

Nitrate leaching from agricultural fields is a significant contributor of groundwater pollution globally, threatening drinking water resources and downstream ecosystems. Quantifying nitrate leaching driven by variable climate, soils, and management practices is challenging, but it is critical for developing sustainable agricultural production systems. While irrigation and fertilizer "best management practices" (BMPs) have been widely implemented to reduce agricultural nitrate leaching, their ability to meet environmental protection goals remains uncertain. In this study, we used the Soil and Water Assessment Tool (SWAT) to simulate crop yields and nitrate leaching for corn-peanut rotations under a variety of nutrient and irrigation management practices in the Suwannee River Basin (Florida), where groundwater feeds springs that are protected by a federally mandated nutrient criteria of 0.35 mg/L Nitrate-Nitrogen (NO_3-N). Data from a field experiment of nine irrigation and nitrogen (N) management treatments were used to calibrate SWAT, with good to excellent results (Nash Sutcliffe Efficiencies from 0.72 to 0.97 for soil moisture, 0.85–0.96 for crop yield, 0.48–0.96 for crop N uptake, and 0.15–0.82 for soil nitrate). The calibrated model was then used to quantify differences in crop yields, irrigation applied and nitrate leaching among practices over a range of historical weather. Soil moisture sensor-based irrigation with 246 kg N/ha for corn and 0 kg N/ha for peanut had no statistical difference in yields compared to common practices in the region (calendar-based irrigation, fertilization of 336 kg N/ha corn and 17 kg N/ha peanut), while reducing N leaching by 40% and irrigation applied by 45% (reductions of ~70 kg N/ha/yr and ~300 mm/year, respectively). Planting a rye cover crop reduced leaching by an additional ~50 N/ha/yr for all treatments. These results show the potential for widespread adoption of nutrient and water conservation practices to achieve the reductions in NO_3-N load needed to meet environmental and regulatory goals without impacting crop yields.

1. Introduction

Agricultural intensification and extensification to meet the food demands of a growing global population has led to elevated groundwater pumping and nitrogen (N) fertilizer usage worldwide (Spalding and Exner, 1993; Vitousek et al., 1997). Synthetic and animal waste-based N fertilizers are used in most agricultural operations to enhance plant growth (Motavalli et al., 2008), but excessive application may increase the risk of nitrate loading to groundwater (Singh et al., 1995; Nolan and Ruddy, 1996; Erisman et al.,2008). The adverse effects of elevated nitrate concentrations on human health (De la Monte et al., 2009) and the environment (Mitsch et al., 1999; Bowen et al., 2007) have prompted regulators to establish limits of allowable nitrate concentration in groundwater and surface water. Meeting these criteria can be challenging since they often require widespread changes in water and nutrient management practices, and the effects of these changes can take decades to manifest in receiving waters (Vero et al., 2017; Van Meter et al., 2018). Local assessment and modeling of management practice changes that provide for agricultural sustainability while maintaining groundwater quality are thus necessary to develop informed and

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effective watershed management strategies.

Connectivity between agricultural lands and the underlying aquifer plays a significant role in the mass of nitrate leaching to groundwater (Kellman and Hillaire-Marcel, 2003). Important factors include soil drainage characteristics, depth to water table, crop type and mass of N in applied fertilizer. Nitrate concentrations are typically higher under agricultural fields with well-drained soils overlying highly permeable aquifers (Nolan, 2001). For example, high concentrations of nitrate are often found in karst aquifers, where discrete fractures and conduits can rapidly transmit large volumes of nitrate-enriched water with little attenuation (Vesper et al., 2001, Doerfliger et al., 1999). The vulnerability of karst aquifers to nutrients from agriculture has been well-documented (Boyer and Pasquarell, 1995, 1996; Panno et al., 2001, Peterson et al., 2002); however, effective management strategies to minimize the nitrate loading to karst aquifers must be developed considering local economies and hydrogeologic settings (Coxon, 2011). Development and application of robust models to support decision-making is especially important in karstic regions, where wide variation in travel times can cause lags of years to decades between practice implementation and surface water quality improvement (Meals et al., 2010; Amin et al., 2017; Fenton et al., 2017).

The karstic Upper Floridan aquifer (UFA) is one of the most productive aquifers in the world. It is the major source of public water supply and irrigation in north and central Florida (Bush and Johnston, 1988), supporting a productive agricultural economy and supplying more than 10 million people with drinking water. Large portions of the UFA are characterized by unconfined, hydraulically connected carbonate rocks with high permeability and transmissivities, which allow nutrients to leach into the aquifer and quickly travel long distances (Bush and Johnston, 1988; Arthur et al., 2007). Agriculture and silviculture are the predominant land uses in the Suwanee River Basin (SRB) that overlies the UFA in north Florida. Increases in population and changes in land use across Florida have shifted the SRB toward more intensive agriculture practices such as row crops, cow-calf operations, dairy and poultry farms (FDEP, 2012), which has resulted in increased nitrate-nitrogen (NO_3-N) concentrations in the UFA (FDACS, 2015, 2018; Harrington et al., 2010; Hochmuth et al., 2014). The region also has a high density of large freshwater springs, supplied with water from the UFA. Nitrate-N concentrations in UFA springs have increased over the last 40 years from background concentrations of $\leq$ 0.1 mg/L NO_3-N to above 5 mg/L NO_3-N in some springs (Katz, 2004; Katz et al., 1999; Heffernan et al., 2010).

In response to increasing NO_3-N concentrations and spring ecosystem degradation, a Numeric Nutrient Criteria (NNC) of 0.35 mg/L NO_3-N was set for water emanating from UFA springs (62-302.530 (47) (b), F.A.C.; FDEP, 2013). Total Maximum Daily Loads (TMDLs; EPA, US Environmental Protection Agency, 2016) required to achieve the NNC were then estimated, and Basin Management Action Plans (BMAPs) required to meet the TMDL have been established for UFA springs not meeting the NNC. Current BMAPs for the SRB estimate that synthetic fertilizer is the largest NO_3-N source to springs and specify load reductions ranging from 35% (FDEP, 2012) to 88% (FDEP, 2018) to meet the NNC. In this regulatory setting, a quantitative assessment of the effects of alternative water and nutrient management practices on crop yield, irrigation water requirements, and NO_3-N leaching is needed to determine whether adoption of agricultural BMPs can achieve the load reductions mandated to achieve the NNC. Critically, NNC have been partially or fully developed for 29 US states and territories (EPA, US Environmental Protection Agency, 2016) and are widely adopted across Europe as part of the European Water Framework Directive (Poikane et al., 2019). Across regions, developing effective nutrient mitigation approaches to meet these environmental standards while also meeting human food demand is a grand global challenge (Robertson and Swinton, 2005; Davidson et al., 2015) with agricultural water management at its core.

Agricultural BMPs have been widely proposed to reduce adverse water quality impacts both globally (Liu et al., 2017) and in the SRB (FDEP, 2012). However, determining the effectiveness of these practices for reducing N leaching and meeting regional water quality goals is an on-going challenge due to difficulties in quantifying nutrient fate and transport processes (Chaubey et al., 2010). For instance, measuring N fertilizer transformations and losses (e.g., leaching, volatilization and denitrification) is expensive, time-consuming and difficult due to variability in weather, soil properties and agricultural management practices across fields (Mulla et al., 2004). Given these challenges, computer simulation models are commonly used to leverage field observations and improve estimates of the fate and transport of water and nutrients (Xie et al., 2015). However, data-intensive model calibration and validation for the specific soil, climate and agricultural management conditions being modeled must be performed for models to be effective (Ramos and Carbonell, 1991) and trusted by stakeholders (Karki et al., 2019).

This work leverages a uniquely robust experimental dataset (Zamora et al., 2018, 2020) to provide quantitative estimates of long-term changes in crop yield, water use, and NO_3-N leaching under alternate management scenarios. This effort is part of longer-term project that is bringing together scientists, regulators, agricultural producers, and non-governmental organizations to collaboratively evaluate tradeoffs among crop production, water quality, and water quantity associated with alternative land use and land and water management strategies. The coupled SWAT-MODFLOW model (Aliyari et al., 2019; Wei et al., 2018) was selected as the platform for this analysis because complex surface-groundwater interactions in the karst watershed require explicit modeling of the groundwater system and its interaction with surface waters, which are not rigorously represented in typical agricultural watershed models such as SWAT (Arabi et al., 2008; Bieger et al., 2014; Cerro et al., 2014; Gassman et al., 2014; Francesconi et al., 2016), AGNPS (Young et al., 1989) or EPIC (Williams et al., 1989). Thus, the immediate goal of this study was to assess whether SWAT can provide reliable groundwater recharge and nutrient leaching fluxes to MODFLOW, while also producing accurate crop yields for subsequent economic-environmental tradeoff analyses. While other field-scale agricultural models (e.g., DSSAT [Jones et al., 2003]; HYDRUS 1-D [Simunek et al., 2008]; Leaching Estimation and Chemistry Model [Hutson and Wagenet, 1992]; and Root Zone Water Quality Model [RZWQM, USDA-ARS, 1992a]) may be more biophysically rigorous than SWAT, none of these models are integrated with hydrologic models that can simulate the complex watershed-scale surface water-groundwater interactions that are important in the study area.

The overall goal of this study was to use SWAT to simulate the long-term response of crop yield, crop N uptake, irrigation requirements, and NO_3-N leaching under different irrigation, N fertilization, and cover crop management practices for a corn-peanut rotation, the most common row crop rotation in the SRB (USDA 2012). Specific objectives were to: (1) calibrate SWAT using observations from a three-year irrigation and N fertilizer rate management experiment for a corn-peanut rotation conducted in Live Oak, Florida (Zamora et al., 2018, 2020); (2) evaluate the long-term effects of the experimental irrigation and fertilization treatments on annual yield, N uptake, irrigation applied, and NO_3-N leaching using calibrated parameters over a 39-year (1980–2018) historic weather record; and (3) estimate the effect of planting a rye cover crop on NO_3-N leaching, irrigation water use, and yield in corn-peanut rotations. Future studies will aggregate these practices to the watershed scale to determine the ability of changes in agricultural management practices to achieve the NO_3-N loading reductions required to meet the federally mandated NNC in the SRB. This work provides a framework for developing effective, socially acceptable strategies for achieving stringent water quality regulations while maintaining a robust agricultural economy that is transferrable to other agricultural watersheds throughout the world.

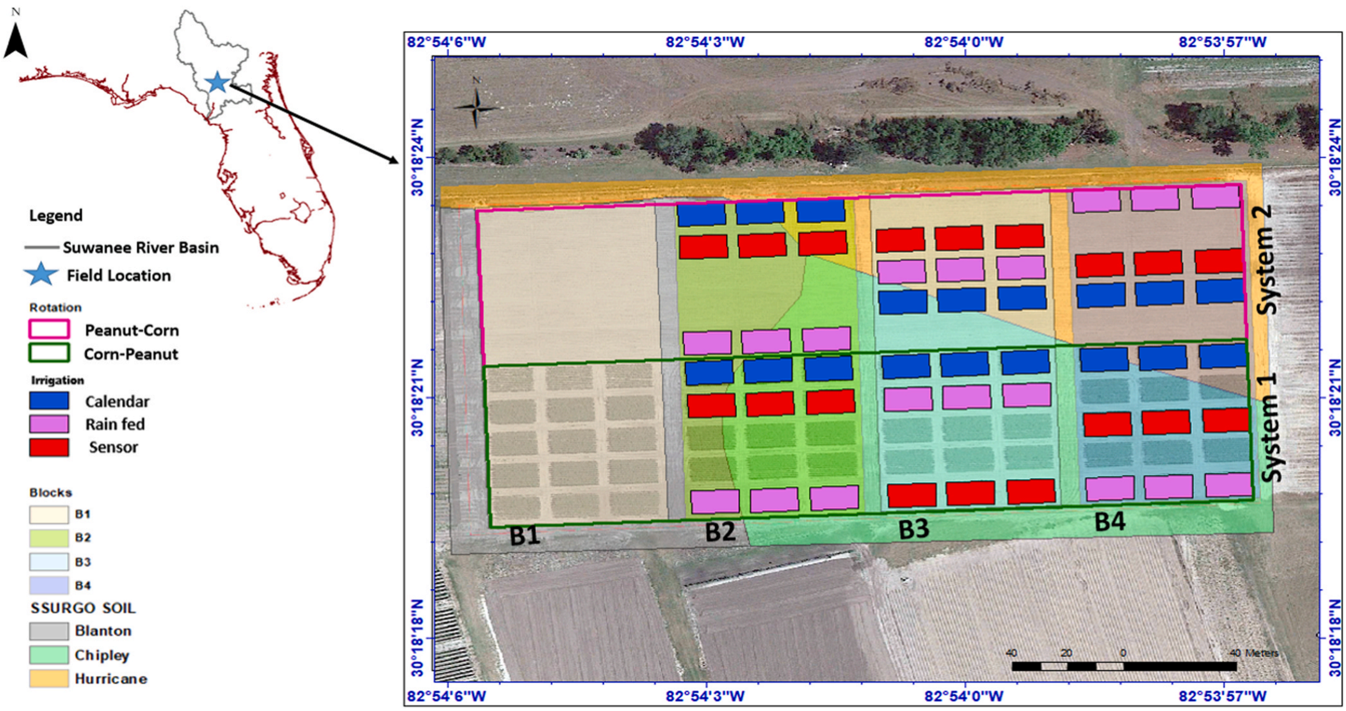

Fig. 1. Site map showing layout of the experimental site with highlighted (blue, red and purple) plots considered in this study. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Irrigation and N fertilizer treatments for the nine treatments in Systems 1&2.

Irrigation treatment	Irrigation applied (mm)			N fertilizer rate	
	2015	2016	2017[a]	Rate	(kg N/ha)
Corn					
Calendar	330	490	546	High	336
				Medium	246
				Low	157
Soil Moisture Sensors (SMS)	151	291	302	High	336
				Medium	246
				Low	157
Rain fed	15	25	48	High	336
				Medium	246
				Low	157
Peanut					
Calendar	132	555	368		
SMS	25	205	122		17[b]
Rain fed	0	30	20		

[a] In 2017, due to leaching rainfall events occurring early in the season, an additional 17 kg N/ha were applied to each corn N fertility rate.
[b] No difference in N fertilizer rate for peanut.

2. Materials and methods

2.1. Study area and experimental design

The experimental field site is located at the North Florida Research and Education Center – Suwannee Valley (NFREC-SV), near Live Oak, Florida (30.31 N, − 82.90 W, Fig. 1). The field is at an elevation of 49–50 m above mean sea level and has flat topography with an average slope of less than 0.5%. The site consists of three types of well-drained soil: Chipley, Hurricane and Blanton sand (SSURGO (Soil Survey Geographic database), NRCS 2016). Soils in the southern portion of the site are mostly Chipley, while those in the northern portion are mostly Hurricane (Fig. 1). The site was divided into two systems based on the timing of rotation. System 1 (southern portion of the site) was a corn-peanut-corn rotation planted during 2015–17, and System 2 (northern portion) was a peanut-corn-peanut rotation grown during the same period. In this manuscript results and analysis from System 1 are presented in detail; results from System 2 were very similar and are thus summarized in the body of the paper and fully documented in the Supplemental Material.

Systems 1 and 2 were divided into four blocks (i.e., replicates B1-B4), each containing fifteen 12.2 m x 6.1 m (74.4 m^2) plots (Fig. 1). Each plot received a different irrigation management strategy ($n = 5$) and N fertilizer rate ($n = 3$) resulting in 15 treatments, each with 4 replicates. In this study, the subset of these plots that had most field observations were selected to develop the model. This subset included 9 treatments (3 irrigation methods and 3 fertilizer rates; Table 1). Complete documentation of the field experiment can be found in Zamora et al. (2018).

The three irrigation methods consisted of calendar-based irrigation, soil moisture sensor-based irrigation and no irrigation (rainfed). Calendar-based irrigation for corn consisted of no irrigation for the first 30 days after planting (DAP), unless severely windy conditions caused blowing sand to burn the plants. Beginning on 31 DAP, a target amount of 25 mm/week was established that could be made up of rain or irrigation, if rain events were > 13 mm. For 40–59 DAP, a 41 mm/week target was established. One irrigation event was skipped if 13–20 mm rainfall occurred, and two irrigation events were skipped if > 20 mm of rain occurred. For 60–105 DAP a 61 mm/week irrigation target was used. One irrigation event was skipped if 13–25 mm of rain occurred the day prior to a scheduled irrigation, and two irrigation events were skipped if > 25 mm of rain occurred. Finally, around 105 DAP at full dent stage, weekly irrigation targets were reduced to 41 mm/week for one week and 20 mm/week for another week until finally irrigation was terminated at 115 DAP. Individual irrigation events were 13 mm.

A similar calendar-based irrigation schedule was applied during the peanut growing season. This consisted of no irrigation from 0 to 30 DAP; from 31 to 44 DAP 25 mm/week was applied unless rainfall provided target irrigation amount; from 45 to 64 DAP 38 mm/week was applied, however if rainfall between 13 and 19 mm occurred one irrigation event was skipped and if rainfall > 19 mm occurred two events were skipped.

Finally, from 65 to 135 DAP 51 mm/week was applied, one irrigation event was skipped if 13–25 mm of rain occurred, and two irrigation events were skipped if > 25 mm of rain occurred. Individual irrigation events were 10 mm.

For the soil moisture sensor (SMS)-based irrigation scheduling, the volumetric soil water content (VWC) was monitored continuously using sensors. Irrigation was triggered when the maximum allowable depletion (MAD) was 50% of the difference between field capacity (FC) and permanent wilting point (PWP). The irrigation volume required to refill the active root depth to field capacity was estimated according to guidelines proposed by Zotarelli et al. (2013). Active root depth was varied throughout the season based on root development.

The three N fertilizer treatments consisted of high, medium and low application rates (336, 246 and 157 kg N/ha for corn, respectively). The high fertilizer application rate of 336 kg N/ha for corn and 17 kg N/ha peanut, is a common grower practice in the region (Zamora et al., 2018). The medium rate closely follows the University of Florida Institute for Food and Agricultural Sciences (UF-IFAS) recommendations (235 kg N /ha for irrigated corn and 0 kg/ha for peanut; Hochmuth et al., 1992; Mylavarapu et al., 2015). The low N represents the minimum N required to establish the corn crop in the low water holding capacity, low organic matter and low cation exchange capacity sandy soils at the field site. For corn an extra application of up to 17 kg N /ha was made within the first four weeks after planting if 76–100 mm of rainfall occurred in a week (FDACS, 2015). The fertilizer composition and application schedule is presented in Table S1.

2.2. Data collection and processing

Table S2 summarizes the type, location and frequency of data collected from each plot. Soil moisture content was obtained from Sentek drill and drop capacitance probes (Sentek Pty Ltd 2003) installed in three replicates (blocks 2, 3 and 4) in each of the nine treatments (Fig. 1). Each probe consists of nine sensors placed every 100 mm interval up to 900 mm. Probes recorded data every 30 min, which were averaged to daily values of soil moisture storage for comparison with SWAT daily output. The Sentek probes were calibrated at the factory. After installation at the field site the Sentek soil moisture measurements were checked against observed volumetric water content (estimated using gravimetric water content measured from soil cores within the same replicate and bulk density measured at the field site) to verify the factory calibration and establish their reliability for use in model calibration and validation. Soil Nitrate-N was collected from all plots at four depths (0–150, 150–300, 300–600 and 600–900 mm) throughout the rotation. Aboveground biomass and nitrogen uptake were collected at key growth stages from all plots under SMS-based irrigation. Detailed information about the data collection procedures is provided in Zamora et al. (2018). Soil properties measured at the site are summarized in Table S3.

2.3. Model description

SWAT is a semi-distributed, continuous, process-based watershed-scale model used to evaluate the impact of different land management practices on surface and subsurface water quality and quantity, sediment, and agricultural yields (Arnold et al., 1998; Neitsch et al., 2004; Gassman et al., 2014). For spatial representation, SWAT delineates a watershed into hydrological response units (HRUs), which are homogenous regions with similar slope, land use and soil type (Neitsch et al., 2011; Winchell et al., 2013). HRUs can be used for field or plot-level estimation of nitrate leaching, crop yield, evapotranspiration and other management practice assessments (Neitsch et al., 2004; Anand et al., 2007; Gitau et al., 2008; Sinnathamby et al., 2017; Moloney et al., 2015; Cibin et al., 2015; Karki et al., 2019).

SWAT has two infiltration schemes: The Curve Number (CN) method at daily intervals and the Green-Ampt method when hourly precipitation data are available; CN-based infiltration was used in this study. SWAT simulates the movement of infiltrated flow between soil layers using a storage routing (tipping bucket) method, which allows downward movement or percolation of saturated flow when field capacity of a soil layer is exceeded and the underlying layer is not saturated (Arnold et al., 2012; Mapfumo et al., 2004). Soil moisture distribution below field capacity is governed by plant water uptake and soil water evaporation through two parameters, the soil evaporation compensation coefficient (ESCO) and the plant uptake compensation factor (EPCO), respectively (Vazquez-Amabile and Engel, 2005; Neitsch et al., 2011). The crop growth algorithm in SWAT is based on the Environmental Impact Policy Climate (EPIC) crop growth model (Williams et al., 1989; Neitsch et al., 2004). SWAT calculates the potential growth of the plant for each day as a function of solar radiation and leaf area index (LAI). Actual growth and LAI are dependent on stress factors including water, temperature and nutrient stress. SWAT computes the accumulation of heat units until the crop attains maturity, after which crop growth ceases (Nair et al., 2011).

2.4. Model setup

In this study, SWAT (version 2012/Rev664) was applied at the plot scale for the calibration and validation of soil and crop parameters following the approaches of Anand et al. (2007), Maski et al. (2008), Marek et al. (2016, 2017) and Chen et al. (2017). The experimental area (Fig. 1) was auto delineated into one basin with three HRUs (one per irrigation treatment) using the USGS 30 m DEM (Digital Elevation Map), USDA NRCS SSURGO soil map and USDA NASS Cropland Data Layer (CDL). These HRUs were converted to plots of equal size (74.4 m^2) by adjusting the area in the sub basin input file and the fraction of area of HRU in the HRU input file (Marek et al., 2016; Moloney et al., 2015; Karki et al., 2019). Each HRU was provided with information regarding management practices conducted in the experimental study period (e.g., planting date, irrigation and fertilizer schedules and harvest date). The default SSURGO soil data of soil bulk density, soil texture and organic carbon (%) were replaced with field measurements (Zamora et al., 2018) for each HRU (Table S3). The total root zone depth in each HRU was set to 900 mm, with four layers (0–150 mm, 150–300 mm, 300–600 mm, and 600–900 mm) for consistency with measured soil nitrate depth resolution.

The source of irrigation water at the experimental site is the Upper Floridian Aquifer, which is approximately 3 m below land surface (USGS, 1983), with no interaction with the root zone. Surface runoff was never observed during the experiment at this well-drained site (Zamora et al., 2018). Thus, the irrigation source was set to an unlimited source outside of the field scale model domain. SWAT daily weather data (i.e., rainfall, temperature, solar radiation, relative humidity, and wind speed) required for the Penman–Monteith evapotranspiration module were obtained from the Live Oak Florida Automated Weather Network (FAWN) located at the experimental site (30.305 lat, − 82.898 long, https://fawn.ifas.ufl.edu/). Missing data were filled using the SWAT weather generator (Neitsch et al., 2011).

2.5. Calibration methodology

Crop growth simulation depends on both crop biophysical processes as well as soil moisture dynamics, so model calibration and validation followed an integrated approach to predict both processes reasonably (Wang et al., 2016; Sinnathamby et al., 2017; Yang et al., 2017). The data used for calibration versus validation is summarized in Table 3. The calibration procedure is detailed below.

Soil moisture was the first variable to be calibrated with default SWAT crop parameters. The Sequential Uncertainty Fitting (SUFI-2) algorithm in SWAT Calibration and Uncertainty Procedures (SWAT-CUP 2012) was used to calibrate and validate the model and the Nash–Sutcliffe model efficiency (NSE) was chosen as the objective function (Abbaspour et al., 2018). The SUFI-2 algorithm has been extensively used in the calibration of the SWAT model due to its easy implementation, high flexibility in selecting parameters and the range for calibration, and the reduced number of model runs needed to achieve good prediction (Yang et al., 2008; Malago et al., 2015). For this study, the methodology recommended in the SWAT-CUP user manual (Abbaspour, 2013) and several SWAT-CUP calibration papers (Yang et al., 2008; Abbaspour et al., 2015, 2018; Kamali et al., 2017) were followed.

The initial range of soil parameters were selected based on literature values (Arnold et al., 2012) and prior experiments conducted on similar soils in the region (Zotarelli et al., 2007; Prasad et al., 2015; Prasad and Hochmuth, 2016). Sensitivity analysis was carried out within SWAT-CUP to determine sensitive parameters to be included in the calibration. Sentek soil moisture sensor data was used to calibrate total soil moisture storage in the entire root zone (900 mm) at the daily scale during the cropping season because currently SWAT-CUP has no provision to calibrate the soil moisture storage for individual soil layers. SWAT provides a simulated soil moisture only for the whole soil column (output file) which is utilized by SWAT-CUP for the auto-calibration process.

Soil and hydrological parameters were calibrated using daily soil moisture storage (total soil moisture from 0 to 900 mm) averaged across replicates for each high N irrigation treatment (i.e., Calendar, SMS and Rain fed) from 2015 to 2017 (Fig. 1), after a three-year warm up period to stabilize the initial hydrological condition. The three high N irrigation treatments were selected for calibration to account for spatial variability in soil properties across a variety of moisture regimes under the assumption of plant growth under no N stress. The calibrated soil parameters were then validated for each irrigation treatment in the medium and low N fertilizer treatments. The three calibrated HRUs with the high N management schedule were replaced with the medium and the low N fertilizer schedule for validation.

After best-fit soil and hydrological parameters were identified, crop parameters were calibrated using the above ground biomass data averaged across replicates of the SMS high N treatments (note that biomass was measured at key growth stages only for SMS treatments (Table S2)). Sensitivity analysis of seasonal biomass growth to SWAT crop parameters was conducted to determine the most sensitive parameters, after which the sensitive parameters were adjusted to reproduce the observed trend of crop growth in the high N fertilizer SMS treatment. Calibrated parameter values were validated using data from the low- and medium-N fertility SMS treatments. The calibrated soil moisture parameters were further verified by re-simulating with the final crop parameters.

Field-measured harvest indices (i.e., average fraction of final biomass removed from the field across the treatment replicates) for the SMS and Calendar High N treatments were used to estimate yield for both corn and peanut, assuming yields were optimum (without any water and nutrient stress (Neitsch et al., 2004) for those treatments. The default SWAT nitrogen uptake parameters, PLTNFR-1 (N uptake at emergence), PLTNFR-2 (N uptake at 50% maturity), and PLTNFR-3 (N uptake at full maturity), and default Nitrogen transformation parameters were used in all simulations. The adequacy of these parameters in simulating the N balance for the experiment was assessed by comparing measured and predicted N uptake by the crop and NO_3-N soil concentrations soil over time for each treatment. System 1 calibrated crop parameters were also validated using system 2 data.

For all comparisons, statistical indices such as Nash Sutcliffe efficiency (NSE), Root Mean Squared Error (RMSE) and percent bias (PBIAS) were used. NSE and RMSE were estimated accounting for replicate measurement variability (Harmel and Smith, 2007; Harmel et al., 2010) using the software "FITVAL" (https://abe.ufl.edu/faculty/carpena/software/FITEVAL) developed by Ritter and Muñoz-Carpena (2013). These modified statistical indices are denoted here as NSE_M, and $RMSE_M$. PBIAS was estimated without measurement variability (Moriasi et al., 2012). The performance indices were judged based on the criteria of satisfactory ($NSE_M > 0.50$) to very good ($NSE_M > 0.75$) set by Moriasi et al. (2007, 2012).

2.6. Development of long-term scenarios

In order to estimate irrigation requirements, nitrate leaching and crop yield over the wider range of historical weather conditions, the corn-peanut rotation was simulated for the nine experimental treatments using 39 years of North American Land Data Assimilation System (NLDAS) historical weather data (1980–2018), using 1980 and 1981 as warmup period). In addition, scenarios were developed to estimate the potential reduction in nitrate leaching if a rye winter cover crop were planted instead of letting the land remain fallow between two subsequent crops. SWAT default parameters of rye crop was used for long term scenario. While many studies have shown that winter cover crops have benefits such as preventing soil erosion, improving long term soil quality and enhancing carbon sequestration (Basche et al., 2016; Kaspar and Singer, 2011; Moore et al., 2014), the impact of cover crops on reducing nitrate leaching has not been fully established (Martinez-Feria et al., 2016; Dabney et al., 2010; Thorup-Kristensen and Dresboll, 2010).

A calendar irrigation schedule was developed from the historic rainfall data following an approach suggested by University of Florida Extension Specialists (Table S4). Sensor-based irrigation was simulated with the SWAT auto irrigation option based on plant water demand, which triggers irrigation when the ratio of actual transpiration to potential transpiration becomes less than the user-defined threshold (Arnold et al., 2013). After multiple simulation trials and comparison with the experimental soil moisture scheduling irrigation amounts, and recommendations from stakeholders, a 0.65 threshold was used for both corn and peanut with an irrigation application of 13 mm/day for corn and 10 mm/day for peanut.

Table 2
Irrigation and N fertilizer management schedule used to perform long-term simulations using historical weather data (1980–2018).

	Baseline scenario[a]		Cover crop scenario[b]
	Corn	Peanut	Rye
Planting	20 March	12 May	01 October
Harvest	05 August	27 September	Chemically kill cover crop one month before planting corn and peanut[c]
Irrigation	Calendar Irrigation Schedule (Table S4)	Calendar Irrigation Schedule (Table S4)	None
	SWAT Auto irrigation (12.7 mm per event)	SWAT Auto irrigation (10.16 mm per event)	
	Rain fed (No irrigation)	Rain fed (No irrigation)	
Fertilizer	N Fertilization rates (low, med, high) schedule (Table S1 and 1)	None	None

[a] Baseline includes a fallow period between cropping seasons (i.e. corn-fallow-peanut-fallow).
[b] Cover crop scenario includes rye instead of fallow periods between cropping seasons (i.e. corn-rye-peanut-rye).
[c] Harvest and kill option 8 in SWAT, 100% biomass incorporated as residue.

Table 3
Summary of parameters used for calibration versus validation.

Observation	Calibration data	Validation data
Soil moisture	Calendar Irrigation – High N, 2015–2017. SMS Irrigation – High N, 2015–2017. Rain fed – High N, 2015–2017.	Calendar Irrigation – Med & Low N, 2015–2017.SMS Irrigation – Med & Low N, 2015–2017.Rainfed – Med & Low N, 2015–2017.
Biomass dynamics	SMS Irrigation – High N, 2015–2017.	SMS Irrigation – Med & Low N, 2015–2017.
Final biomass	SMS Irrigation – High N, 2015–2017.	Calendar Irrigation – High, Med & Low N, 2015–2017. SMS Irrigation – Med & Low N, 2015–2017.Rainfed – High, Med & Low N, 2015–2017.
Final yield	Calendar Irrigation – High N, 2015–2017. SMS Irrigation – High N, 2015–2017. Rain fed – High N, 2015–2017.	Calendar Irrigation – Med & Low N, 2015–2017.SMS Irrigation – Med & Low N, 2015–2017.Rainfed – Med & Low N, 2015–2017.
Crop N uptake	None (default parameters used)	Calendar Irrigation – High, Med & Low N, 2015–2017. SMS Irrigation – High, Med & Low N, 2015–2017.Rainfed – High, Med & Low N, 2015–2017.
Soil N	None (default parameters used)	Calendar Irrigation – High, Med & Low N, 2015–2017. SMS Irrigation – High, Med & Low N, 2015–2017.Rainfed – High, Med & Low N, 2015–2017.

Split application of the three N fertilizer rates used in the field experiment (Table 1, S1) were applied using ammonium nitrate fertilizer as it is a common source of N fertilizer in the region. For simplicity, fixed planting and harvesting dates were adopted throughout the simulation period (Table 2). Based on local practices and communication with Extension Specialists, a rye cover crop planting and herbicide application schedule was incorporated into the simulations. The agricultural management schedule for the corn and peanut rotation with and without the cover crop is presented in Table 2.

3. Results and discussion

3.1. Model calibration and validation

Table 4 presents final calibrated values, ranges, and p-values to indicate the sensitivity of parameters ($p < 0.05$ indicates a sensitive parameter). Available water content (AWC), Soil Evaporation Compensation Factor (ESCO) and Plant Uptake Compensation Factor (EPCO) were the most sensitive soil and hydrological parameters. Notably, saturated hydraulic conductivity and curve number were not sensitive parameters. Best-fit parameters were similar, though not identical, between systems (Table 4).

Total heat units required to reach maturity (HEAT_UNITS) (in this experiment maturity for corn was 135 days after planting) and biomass-to-energy ratio (BIO_E) were the sensitive crop parameters, which is in accordance with previous studies (Abbaspour et al., 2015; Almeida et al., 2017; Faramarzi et al., 2009; Kiniry et al., 2002, 2008). Maximum potential leaf area index (BLAI) for corn and peanut were assigned to be 3 and 4 respectively, as specified in the SWAT database (Kiniry et al., 2002; Almeida et al., 2017). The final ranges of BIO_E for corn and peanut were close to ranges included in the SWAT manual (BIO_E corn: 39–45 and BIO_E peanut: 20–25). The calibrated HEAT_UNITS value for peanut (1800) was close to that for Georgia green peanut variety (1900) estimated from previous experiments (Bennett et al., 1993; Kiniry et al., 2005). The optimal harvest index parameter (HVSTI) was set to the measured harvest index (the average quantity of biomass removed from field as yield) for the SMS and Calendar High N treatments, which was 0.60 for corn and 0.55 for peanut. The minimum harvest index parameter (WSYF) was kept at the default value of 0.3 for both corn and peanut.

3.1.1. Soil moisture storage

Fig. 2 shows modeled and observed soil moisture storage for the three treatments used for calibration (SMS, Calendar and Rain fed irrigation, all under high N fertilization). The range of the observed measurements represents the spatial variability of soil moisture across replicates for each treatment. Soil moisture validation for the remaining six treatments (SMS, Calendar and Rain fed irrigation under medium and low N fertilization) for System 1 are shown in Figs. S1 and S2. Plots of modeled versus observed soil moisture for System 2 are presented in Figs. S6–S8.

Overall, soil moisture predictions showed satisfactory to very good fits ($0.67 < NSE_M < 0.97$) in both calibration and validation treatments for both systems (Table 5). However, observed soil moisture peaks during high rainfall events were under-predicted in System 1 Calendar and SMS treatments across all fertilization rates. These results indicate that, although SWAT was able to capture general patterns of soil moisture variation across the three growing seasons for both systems, soil water drained too rapidly when soil moisture was above field capacity. Discrepancies between simulated and observed soil moisture, particularly during high rainfall events, due to simplified runoff and percolation process in SWAT were also reported by Rajib et al. (2016), Yang et al. (2017), and Zhang et al. (2017). SWAT has a simplified approach for estimating soil moisture percolation that assumes soil water above field capacity in a particular layer percolates to the next layer at a rate governed by the saturated hydraulic conductivity (Neitsch et al., 2011).

Table 4
Calibrated soil, hydrological and crop parameters including p-values for sensitivity and uncertainty range.

Water balance parameters	Definition	System 1 Final range	System 1 Used value	System 1 p-value	System 2 Final range	System 2 Used value	System 2 p-value
r_CN2.mgt	SCS Curve Number	−0.04–0.137	−0.03(40*)	0.18	−0.17–0.13	−0.06(40*)	0.34
v_ESCO.hru	Soil evaporation compensation factor	0.49–0.60	0.52	5.29×10^{-07}	0.68–0.86	0.71	0.0003
v_EPCO.hru	Plant uptake compensation factor	0.15–0.26	0.21	0.01	0.15–0.26	0.16	9.04×10^{-41}
v_GW_DELAY.gw	Groundwater delay, days	2–10	8.35	0.8	2–10	7.9	0.45
v_SOL_AWC(1).sol	Soil available water storage capacity	0.07–0.12	0.09	7.08×10^{-9}	0.06–0.12	0.09	2.21×10^{-43}
v_SOL_AWC(2).sol		0.07–0.13	0.08	9.37×10^{-60}	0.030–0.10	0.05	5.13×10^{-83}
v_SOL_AWC(3).sol		0.07–0.10	0.08	7.65×10^{-14}	0.10–0.15	0.12	4.19×10^{-29}
v_SOL_AWC(4).sol		0.13–0.16	0.16	2.20×10^{-34}	0.14–0.16	0.15	8.9×10^{-20}
r_SOL_K(1).sol	Saturated hydraulic conductivity (mm/h)	0.010–0.028	0.017(204*)	0.8	0.02–0.03	0.022	0.41
r_SOL_K(2).sol		−0.002–0.014	0.005(205*)	0.59	0.008–0.013	0.010	0.29
r_SOL_K(3).sol		0.007–0.024	0.021(202*)	0.7	0.027–0.037	0.034	0.29
r_SOL_K(4).sol		−0.014–0.008	0.007(198*)	0.78	−0.12–0.026	−0.047	0.59
		Crop parameters (corn)			Crop parameters (peanut)		
BIO_E.plant.dat	Biomass/energy	39–48	46	6.9×10^{-7}	20–35	26	2.18×10^{-5}
HEAT_UNITS.mgt	Total heat units for plant to mature	2000–2500	2400	0.03	1700–2500	1800	2.63×10^{-23}
HVSTI	Harvest Index for optimal growing condition		60[1]			55[1]	

r = relative changes in parameter values.
v = absolute changes in parameter values.
1, 2, 3 and 4 denote the four soil layers 0–150, 150–300, 300–600 and 600–900 mm.
* Absolute value used in the model.
[1] Manual adjustment based on experiment and suggestion from stakeholders.

Due to this SWAT model structure and its high sensitivity to available water content and low sensitivity to hydraulic conductivity (Table 4), the calibrated soil parameters were unable to reproduce some of the transient soil moisture peaks measured by the Sentek probes during large (particularly multi-day) rainfall events (Fig. 2). However, manually increasing available water content and lowering hydraulic conductivity of the soil from the calibrated parameters to try to match the peaks resulted in long periods of time where the soil moisture remained much higher than the observations, deteriorating the overall model fit statistics significantly. In the sandy soils at the experimental site (and throughout much of the SRB region), the transient high soil moisture drains back to field capacity more slowly than SWAT predicts, but typically within a few days, causing this excess water (and any nitrate it contains) to eventually leach past the root zone. The fact that nitrogen uptake and biomass accumulation by the crop as well as soil nitrate storage were adequately predicted by the model (see following sections) provides some reassurance that the transient inaccuracies around large-rainfall events do not affect the seasonal water and nitrogen mass balances.

With the calibrated Soil Conservation Service Curve Number (SCS-CN), the total overland runoff volume generated for the highest runoff generating treatment (calendar based irrigation with high N) was 0.77% of applied water (precipitation plus irrigation), compared to 54% for ET and 46% for percolation below the root zone, generally in conformance with the observation of no surface runoff at the field site. The small amount of runoff generated by SWAT occurred during large events such as Hurricane Irma in September 2017.

3.1.2. Crop biomass and yield

Crop growth dynamics for corn and peanut were very well predicted ($NSE_M > 0.95$) for the SMS irrigation treatments across both calibrated (high-N) and validated (medium- and low-N) fertilizer rates in System 1 (Table 6, Fig. 3). Validation results for yield for all treatments in System 1 (Fig. 4) were generally consistent with measured values (all $NSE_M > 0.75$); however, in 2017 the model over-predicted both total aboveground biomass and yield for rainfed corn under all fertilization rates. This may indicate that water stress is under-predicted by the SWAT crop parameters that were calibrated using SMS-high N treatments. Validation results for crop growth dynamics for System 2 also showed very good results for 2015 peanut and 2016 corn ($0.86 < NSE_M < 0.99$; Table 6, Fig. S9), but total aboveground biomass and yields were not well predicted for any peanut treatments in 2017 (Fig. S10). Low observed peanut biomass and yield in 2017 were associated with crop loss caused by Hurricane Irma that hit the region in September 2017. These effects were not captured in SWAT simulations that were calibrated under limited stress conditions (Mitteslet et al., 2015).

3.1.3. Crop nitrogen uptake

Modeled N uptake dynamics followed the observed trends well for System 1 SMS treatments using default nitrogen uptake parameters (Fig. 5 and Table 7). While observed total nitrogen uptake had high variability within treatments (last column Fig. 4), System 1 total N uptake predictions reproduced mean observed values quite well (NSE_M 0.48–0.96, PBIAS − 0.1 to 9.7%; Fig. 4). Note that although there was no difference in N applied to the System 1 peanut treatments in 2016 both the observed and simulated peanut nitrogen uptake in 2016 were influenced by different irrigation treatments.

Modeled N uptake dynamics followed well the observed trends for System 2 SMS treatments in 2015 and 2016, but N uptake for peanut was significantly overpredicted in 2017. This was a result of overprediction of biomass and yield since SWAT was not able to correctly predict the crop loss that occurred as a result of Hurricane Irma in 2017 (Fig. S11 and Table 7). For System 2, total N uptake for corn was adequately predicted (NSE_M 0.63, PBAIS − 8.8%); however, for peanut (N fixation plus N uptake from soil) was slightly underpredicted in 2015 (NSE_M

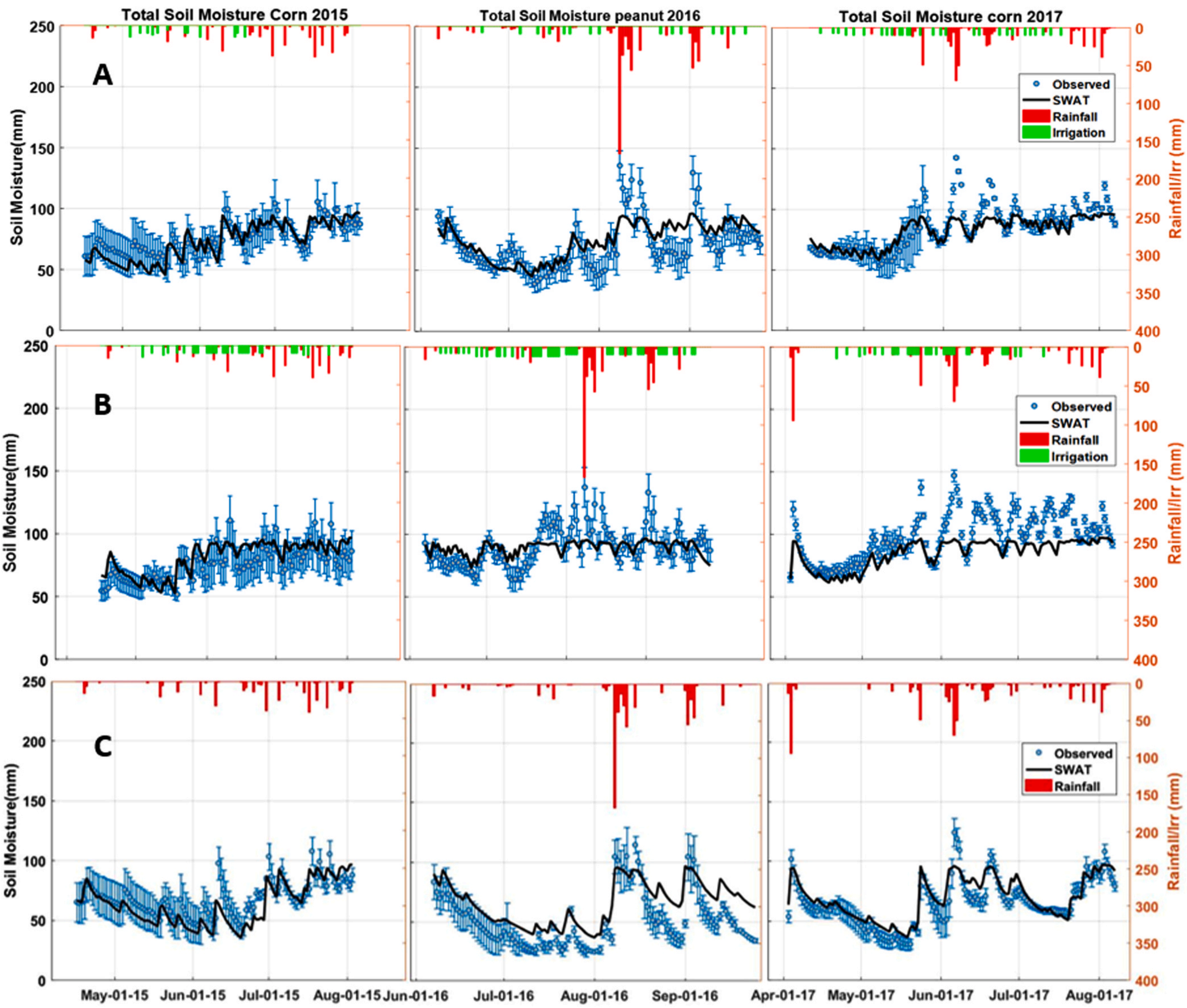

Fig. 2. Observed and simulated total soil moisture (mm) in root zone (900 mm) during corn-peanut-corn growing seasons for calibrated SMS-High (A), Calendar-High (B) and Rain fed-High (C) for System 1. Vertical bars correspond to the standard deviation of measured data.

Table 5
Goodness-of-fit indicators (NSE_M, PBIAS (%) and $RMSE_M$ (mm)) for calibration and validation of total soil moisture.

	System 1				System 2		
	Calibration				Calibration		
	NSE_M	PBIAS (%)	$RMSE_M$		NSE_M	PBIAS (%)	$RMSE_M$
SMS-High	0.88	−0.9	6.37	SMS-High	0.94	7	3.64
Calendar-High	0.72	3.4	9.63	Calendar-High	0.84	0.8	5.86
Rain fed-High	0.82	−7.7	8.76	Rain fed-High	0.92	5.3	4.71
Validation				Validation			
SMS-Medium	0.82	−1	9.62	SMS-Medium	0.86	3.5	7.16
Calendar-Medium	0.67	−1.7	12.43	Calendar-Medium	0.96	2.2	3.43
Rain fed-Medium	0.82	−12	8.15	Rain fed-Medium	0.93	−1.8	6.33
SMS-Low	0.69	−1.8	12.83	SMS-Low	0.77	5.6	7.87
Calendar-Low	0.76	−0.9	9.39	Calendar-Low	0.89	1.6	5.58
Rain fed-Low	0.83	−16.1	8.49	Rain fed-Low	0.97	−0.2	4.73

− 9.23, PBIAS 25%) and overpredicted in 2017 (NSE_M − 11.44, PBIAS − 89.7%) (Fig. S12).

Overall, SWAT predictions of final biomass, N uptake and yield for both systems agreed with the Zamora et al. (2018, 2020) experimental results in which the calendar-based and SMS irrigation management practices produced statistically higher final biomass, N uptake and yield than the rainfed practices. Zamora et al. (2018) found no statistically significant differences in final corn biomass across N rates, but

Table 6
Modified goodness-of-fit indicators for biomass trend with measurement uncertainty.

	System 1 Biomass trend									
	Treatments	Corn 2015			Peanut 2016			Corn 2017		
		NSE_M	PBIAS (%)	$RMSE_M$ (kg/ha)	NSE_M	PBIAS (%)	$RMSE_M$ (kg/ha)	NSE_M	PBIAS (%)	$RMSE_M$ (kg/ha)
Calibration	SMS-High	0.99	14.1	820	0.99	−5.4	182	0.99	−4.2	733
Validation	SMS-Medium	0.99	17.2	709	0.99	−10.8	321	0.97	−4	1440
	SMS-Low	0.99	11	472	0.99	−10.7	391	0.99	8.3	599
	System 2 Biomass trend									
	Treatments	Peanut 2015			Corn 2016			Peanut 2017		
	SMS-High	0.99	8.8	157	0.86	−35	3544	−1.34	−74.9	3884
Validation	SMS-Medium	0.96	5.3	1109	0.91	−31	2802	0.17	−60.6	3230
	SMS-Low	0.99	6.3	0	0.93	−10.5	2362	−0.34	−69.4	3696

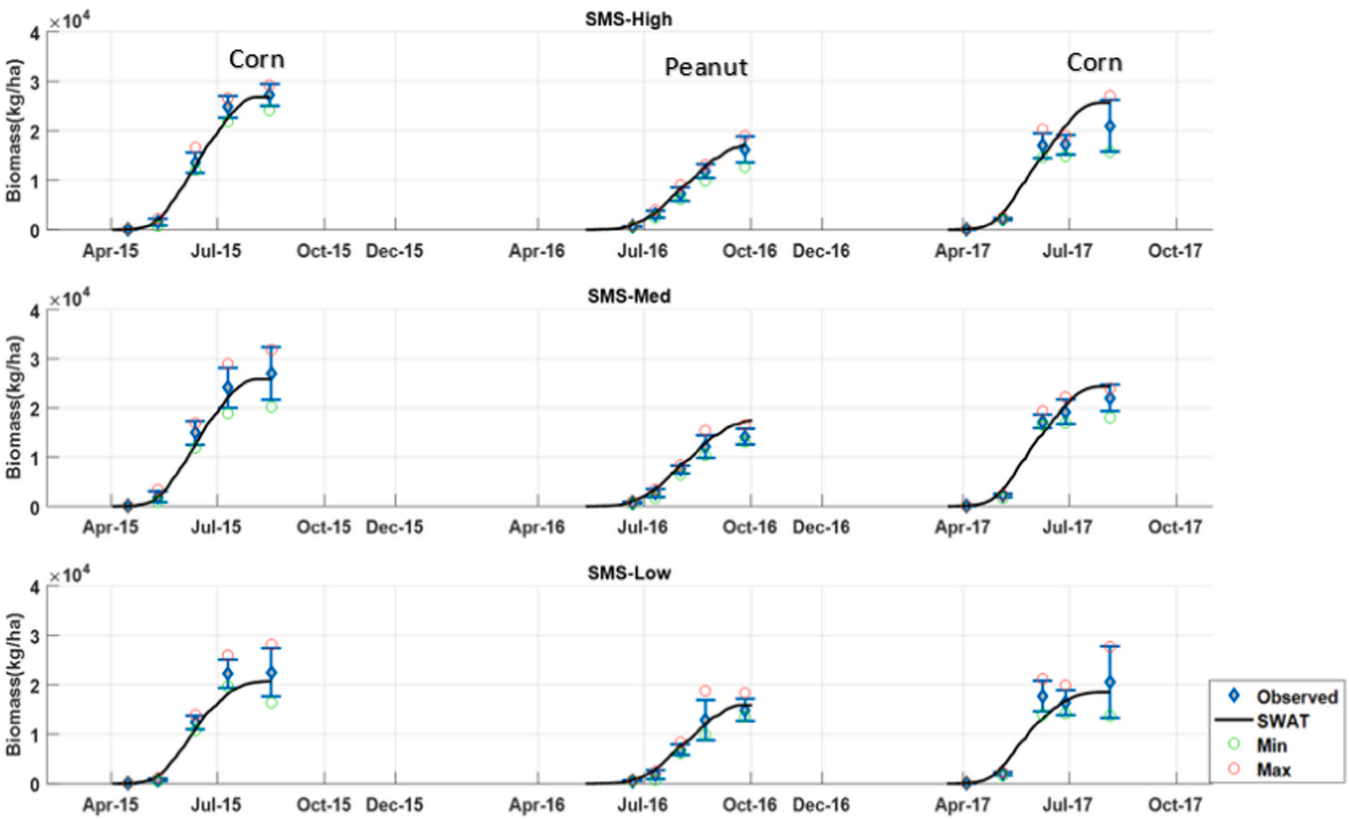

Fig. 3. Simulated (lines) vs observed (dots) aboveground biomass dynamics for calibrated SMS-High (a) and validated SMS-Medium (b) and SMS-Low (c) for System 1 (corn 2015-peanut 2016-corn 2017). The experimental variation shown is the minimum and maximum of the field measurements (error bars).

differences in total N uptake were found between the low and the high N rates. SWAT predicted both lower biomass and N uptake for the low N fertilizer rate.

3.1.4. Soil nitrate-N

Time series of System 1 simulated and measured soil nitrate-N in the entire root zone (0–900 mm) for Calendar, SMS and Rainfed irrigation with high N treatments are shown in Fig. 6. The remainder of the System 1 treatments are shown in Figs. S3 and S4, and similar results for System 2 are shown in Figs. S13–S15. For both systems, soil nitrate-N simulated using default soil nitrate parameters followed the trend of the observed data with NSE_M values ranging from 0.55 (satisfactory) to 0.95 (very good) for all treatments except the rainfed high fertilizer treatment. The Rainfed high fertilizer treatment over-predicted soil nitrate-N for both Systems, primarily during the fallow season following corn production (NSE_M 0.16 and 0.25, respectively; Table 8). As mentioned earlier, SWAT overestimated the corn biomass and N uptake for the rainfed case, most likely because the SWAT corn parameters used for calibration had no water or N stress (i.e., SMS-high treatment). Since 40% of the corn biomass is left on the field to mineralize, the erroneously high corn N uptake may have led to the erroneously high soil N in the fallow periods due to mineralization of plant residues after harvest.

3.2. Nitrate-N leaching

Based on satisfactory to very good prediction of simulated crop N uptake and soil nitrate-N storage (the only measured components of N balance in this study), simulated nitrate-N leaching was compared across treatments for the corn-peanut-corn rotation including the fallow periods between cropping seasons (System 1, Fig. 7). As expected, the high N fertilizer practice (336 kg N/ha) caused more nitrate-N leaching to groundwater than the medium and low fertilizer practices (246 and 157 kg N/ha) in all irrigation management systems. Similarly, the medium N rate caused more nitrate leaching to groundwater than the low fertilization practice. Somewhat surprisingly, more nitrate leaching occurred during the fallow periods between crops than during the crop growing seasons across treatments.

Within the high N fertilizer practice, calendar irrigation caused more

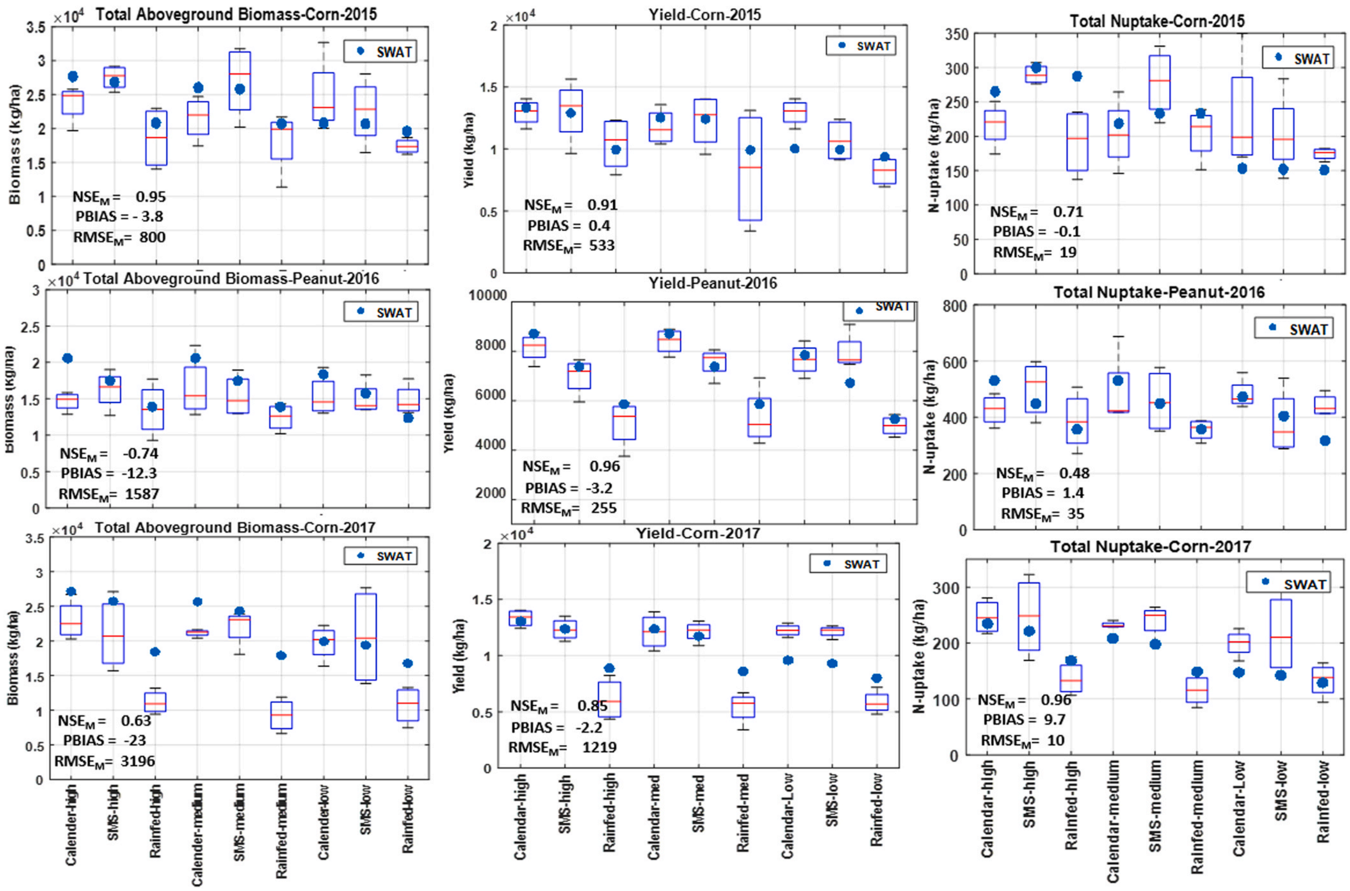

Fig. 4. Simulated (dots) vs observed (boxplots) aboveground biomass, yield and N uptake for corn 2015-peanut 2016-corn 2017 for System 1. Model performance statistics evaluated were NSE$_M$, PBIAS (%) and RMSE$_M$ (kg/ha).

nitrate leaching to ground water than SMS and rainfed practices during the 2015 corn growing season (Fig. 7). However, the highest nitrate leaching occurred during the 2015–16 fallow period after the 2015 rainfed-high corn. Across all treatments the corn and peanut biomass left in the field after harvest (40% and 45%, respectively) caused nitrate-N leaching ranging from 15 to 70 kg N/ha and from 10 to 20 kg N /ha during the 2015–16 and 2016–17 fallow periods, respectively. Compared to 2015, corn grown in 2017 exhibited more leaching due to extreme weather conditions and the extra 17 kg/ha of N fertilizer that was added to compensate the loss of N due to leaching rain. Results show a ~40% (70 kg N/ha) reduction in nitrate leaching for the SMS-medium fertilizer treatment compared to the calendar irrigation and high N fertilizer practices that are common in the region.

3.3. *Long term simulation results*

3.3.1. *Crop yield*

The long-term simulations (1980–2018) showed no significant difference in average crop yields for the high and medium N fertilizer treatments when using Calendar or SMS irrigation scheduling methods. The rainfed and low fertility treatments showed statistically lower average yields (Fig. 8). These results are consistent with the field experiment results reported by Zamora et al. (2018). The incorporation of rye as a cover crop did not show any statistical significant effect on average corn yield for the high and medium N treatments. However, the Calendar and SMS low fertility corn treatments showed an average of 12% and 9% increase in corn yield following cover crops, respectively. For these low fertilizer treatments, the incorporation and mineralization of cover crop biomass provided additional nutrients beneficial for corn production (Krueger et al., 2011). Similar field results were reported by Zotarelli et al. (2009) where at lowest supplemental N rates, cover crops added benefits to sweet corn yields in Florida, USA. No statistically significant effects of cover crops on average peanut yields were observed. The wide variation in predicted rainfed corn and peanut yields across all N fertility rates represents variations in water stress due to variations in annual rainfall.

3.3.2. *Nitrate-N leaching*

Fig. 9 shows long term leaching simulated over the crop rotation including fallow and cover crops between growing seasons (corn – fallow/cover crop – peanut – fallow/cover crop). As expected, high N fertilization rates resulted in more nitrate-N leaching than medium fertilization rates, which in turn resulted in greater leaching than low fertilization rates. Long-term simulations showed that SMS irrigation resulted in statistically significant less leaching than calendar irrigation across all fertilization rates. Furthermore, introducing cover crops during the fallow periods reduced nitrate-N leaching by a statistically significant average of approximately 50 kg N/ha across all treatments. The calendar-based irrigation with high fertilizer and no cover crop practice resulted in ~65% more leaching (~120 kg N/ ha) in comparison to the SMS-based irrigation with medium fertilizer and cover crop practice. Moreover, the extra 100 kg/ha fertilizer and 45% more irrigation water applied by this common practice did not provide any statistically difference in average corn or peanut yields (Fig. 8). Long-term irrigation applied by the Calendar treatment averaged 506 and 309 mm during corn and peanut, respectively, whereas the SMS treatment (using auto-irrigation) applied an average of 290 and 160 mm, respectively. Thus, average irrigation reductions of 43% and 48% were achieved by using a sensor-based instead of calendar-based irrigation scheduling method in corn and peanut production, respectively.

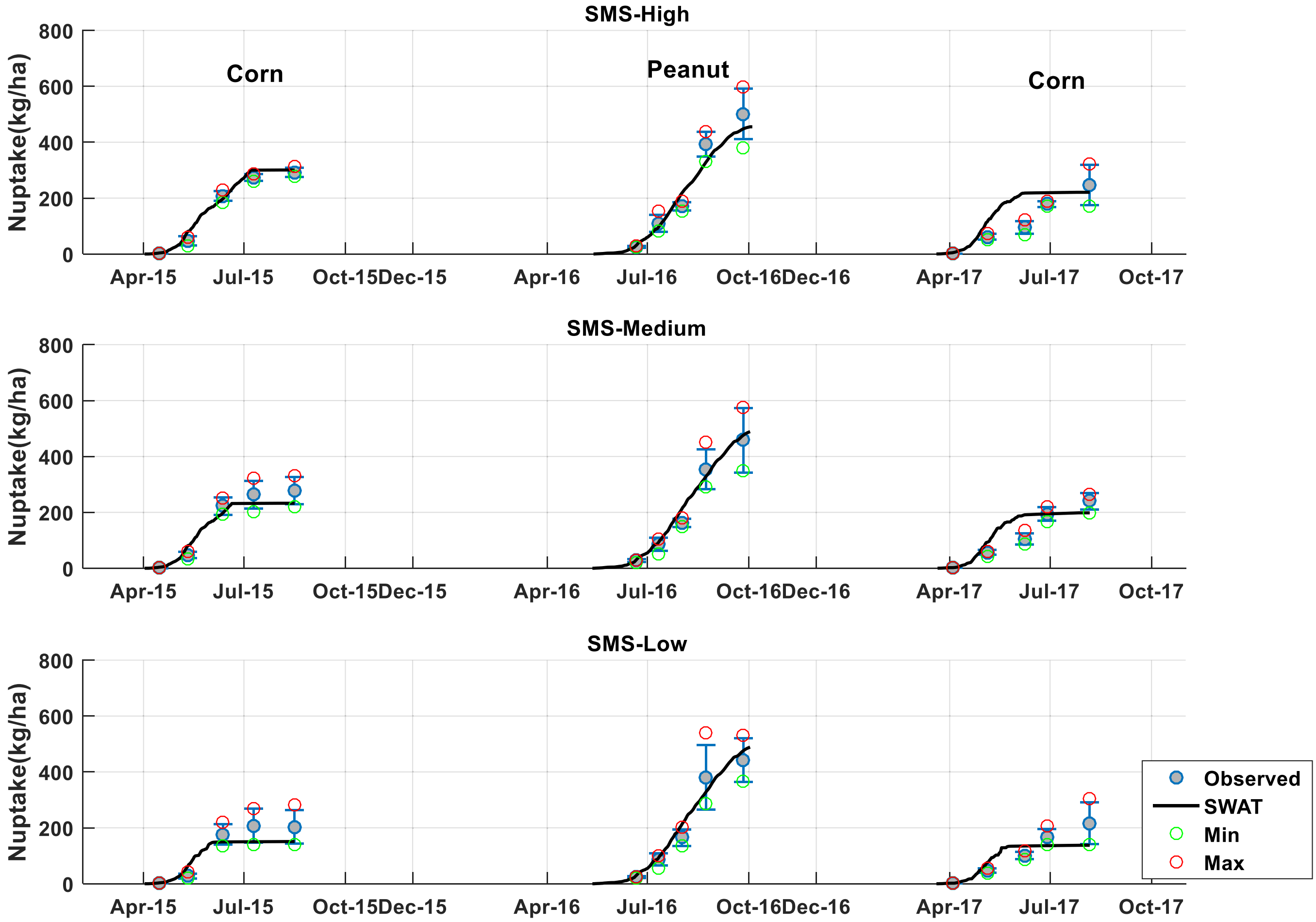

Fig. 5. Simulated (line) vs observed (dots) N uptake during crop growing seasons for SMS-high, medium and low in System 1.

Table 7
Modified goodness-of-fit indicators for total aboveground N uptake trend with measurement uncertainty. PBIAS is in %.

	System 1 Nitrogen Uptake trend								
Treatments	Corn 2015			Peanut 2016			Corn 2017		
	NSE_M	PBIAS	$RMSE_M$ (kg/ha)	NSE_M	PBIAS	$RMSE_M$ (kg/ha)	NSE_M	PBIAS	$RMSE_M$ (kg/ha)
SMS-High	0.99	−5	7	0.99	8.3	8	0.56	−42	58
SMS-Medium	0.99	3.1	11	0.99	−4.7	14	0.89	−13.6	29
SMS-Low	0.99	15.6	8	0.99	−3.8	4	0.97	8.7	12
	System 2 Nitrogen Uptake trend								
Treatments	Peanut 2015			Corn 2016			Peanut 2017		
SMS-High	0.97	17	25	0.74	−36.3	53	0.77	−41.4	43
SMS-Medium	0.95	17.8	39	0.97	−2.1	18	0.95	−12.5	20
SMS-Low	0.99	8.9	7	0.76	24.1	47	0.88	−17.1	29

Further analysis of N leaching patterns showed that on average the calendar-based irrigation with high N fertilizer practice resulted in an average of ~100 kg N/ha leaching within the corn growing season followed by an average of ~50 kg N/ha during the subsequent fallow season. In contrast, the rainfed – high N fertilizer practice resulted in an average of ~34 kg N/ha leaching during the corn season and an average of ~100 kg N/ha leaching during the subsequent fallow period (Fig. S5). For the rainfed corn, the fertilizer not taken up by the crop during the growing season along with the N mineralization from corn residue resulted in more leaching during the fallow period than either the calendar or SMS irrigation practices. Nitrogen leaching from peanut residue (average of ~ 50 kg/ha across all management practices) was significantly reduced (~80%) by planting rye as a cover crop compared to leaving the fields fallow between cropping seasons (Fig. S5).

4. Conclusions

Providing quantitative support for the efficacy and economic feasibility of agricultural best management practices is becoming more and more critical as communities around the globe seek to balance agricultural production and environmental protection. Coupling robust field experiments of specific management practices with modeling approaches that allow inference to be drawn at larger spatiotemporal scales is particularly useful for exploring tradeoffs among alternative future scenarios and comparing results to regulatory requirements and the preferences of diverse stakeholders. In this study, it is shown that SWAT successfully estimated soil moisture, crop biomass, yield, crop N uptake and soil nitrate for corn-peanut rotations grown using a variety of irrigation and N fertilizer management practices in the Suwannee River Basin, Florida. Leveraging robust field measurements from a 3-year field

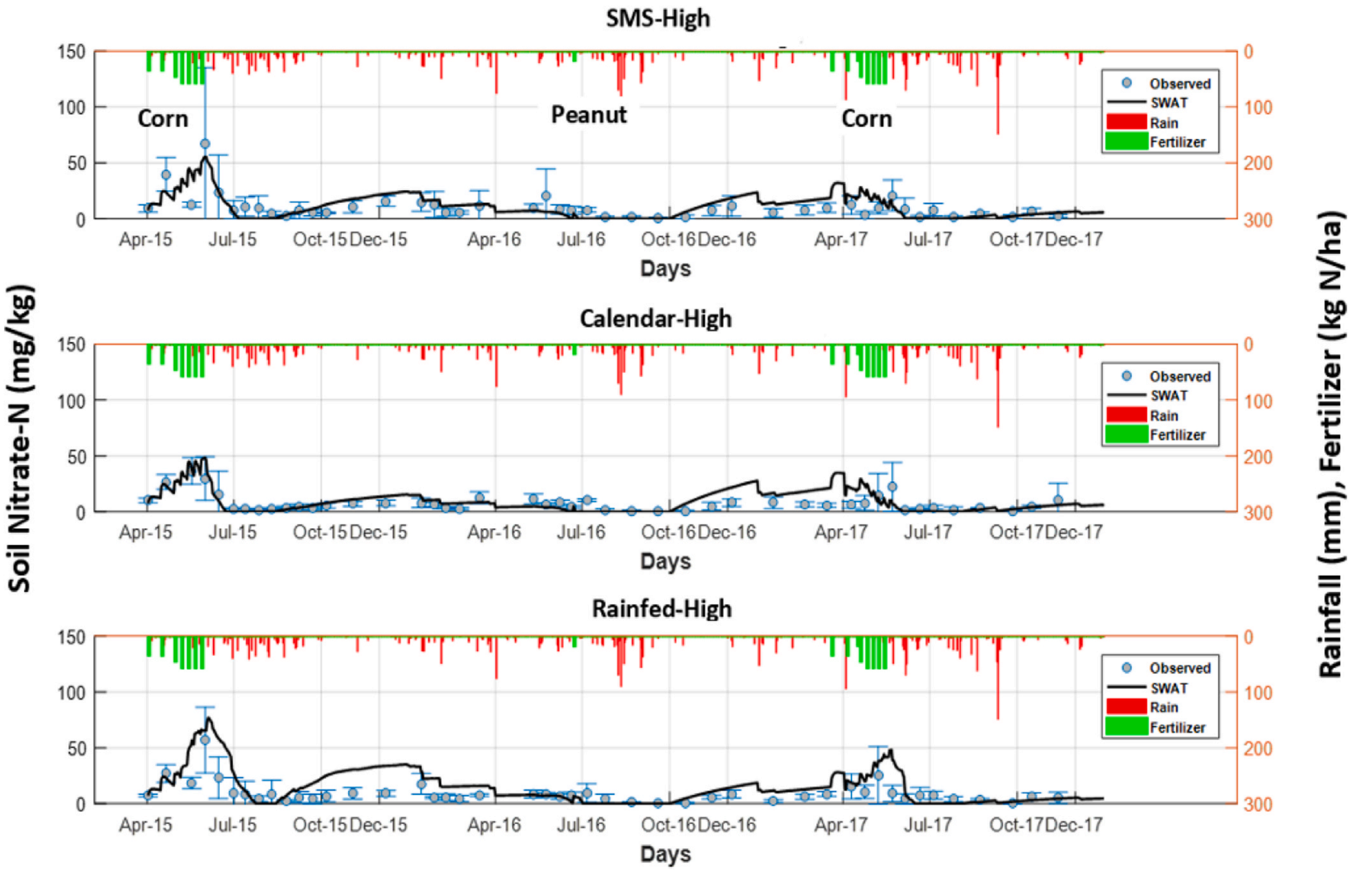

Fig. 6. Observed (dots) vs simulated (lines) soil nitrate-N in root zone (0–900 mm) for SMS, Calendar and Rainfed-High treatments for System 1. Red and green bars denote daily rainfall and fertilizer applications. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 8
Modified goodness-of-fit indicators for simulated soil nitrate-N for both systems.

	System 1			System 2		
	NSE_M	PBIAS (%)	$RMSE_M$ (mg/kg)	NSE_M	PBIAS (%)	$RMSE_M$ (mg/kg)
SMS-High	0.81	−6.1	4.8	0.58	−6.4	9.46
Calendar-High	0.70	−16.7	4.2	0.80	−11.7	4.40
Rainfed-High	0.16	−66.8	8.45	0.25	−18.4	12.73
SMS-Medium	0.64	9.8	2.83	0.93	14	2.24
Calendar-Medium	0.74	20.6	3.33	0.90	17.9	3.30
Rain fed-Medium	0.76	−5.3	3.52	0.75	−1.9	6.56
SMS-Low	0.55	35.6	2.79	0.79	37.9	4.51
Calendar-Low	0.61	43.4	4.05	0.86	36.2	2.67
Rain fed-Low	0.65	43.1	3.22	0.84	26.1	4.08

study (Zamora et al., 2018, 2020) allowed us to predict likely long-term changes in crop yields, water use, and N leaching over a range of historical conditions. By expanding experimental results beyond the temporal limits of specific field seasons, these model results provide more widely applicable guidance for reductions in nutrient loads that can be expected from BMP implementation.

Specifically, we found that improving irrigation scheduling practices, reducing N fertilization rates and planting a cover crop during fallow periods has the potential to reduce NO_3-N leaching by ~65% over current commonly used corn-peanut rotation practices. Notably, this is within the 35–88% reduction in NO_3-N load that is estimated to be needed to achieve the NNC in SRB spring ecosystems (FDEP, 2012, 2018). Furthermore, our results indicate that these load reductions can be achieved without adversely affecting crop yield. This suggests that an

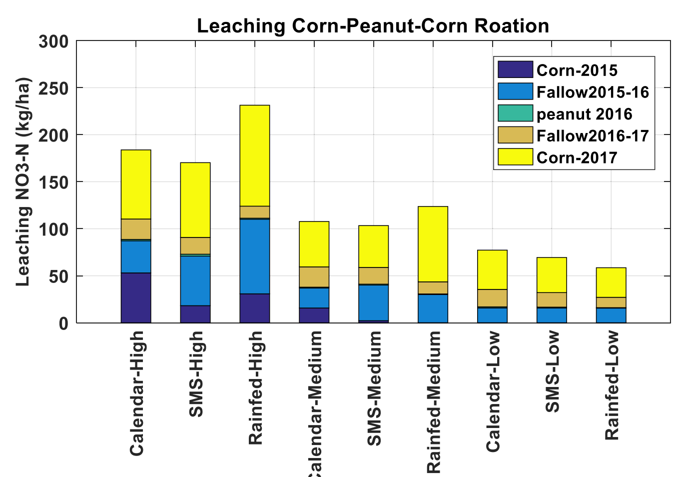

Fig. 7. Simulated nitrate-N leaching during complete crop rotation for System 1 (corn 2015-peanut 2016-corn 2017) including intercropping bare fallow periods (2015–16 and 2016–17). In staggerd bar graph nitrate-N leaching corresponds to corn 2015 (bottom) to corn 2017 (top).

incentive program that cost-shares equipment purchases and protects producers from the risk of yield reductions may be an effective way to overcome barriers to the widespread adoption of SMS irrigation scheduling, reduced N fertilization rates and cover cropping practices in the region. Building from these results, we are currently engaging stakeholders to develop alternative land use-land management scenarios at

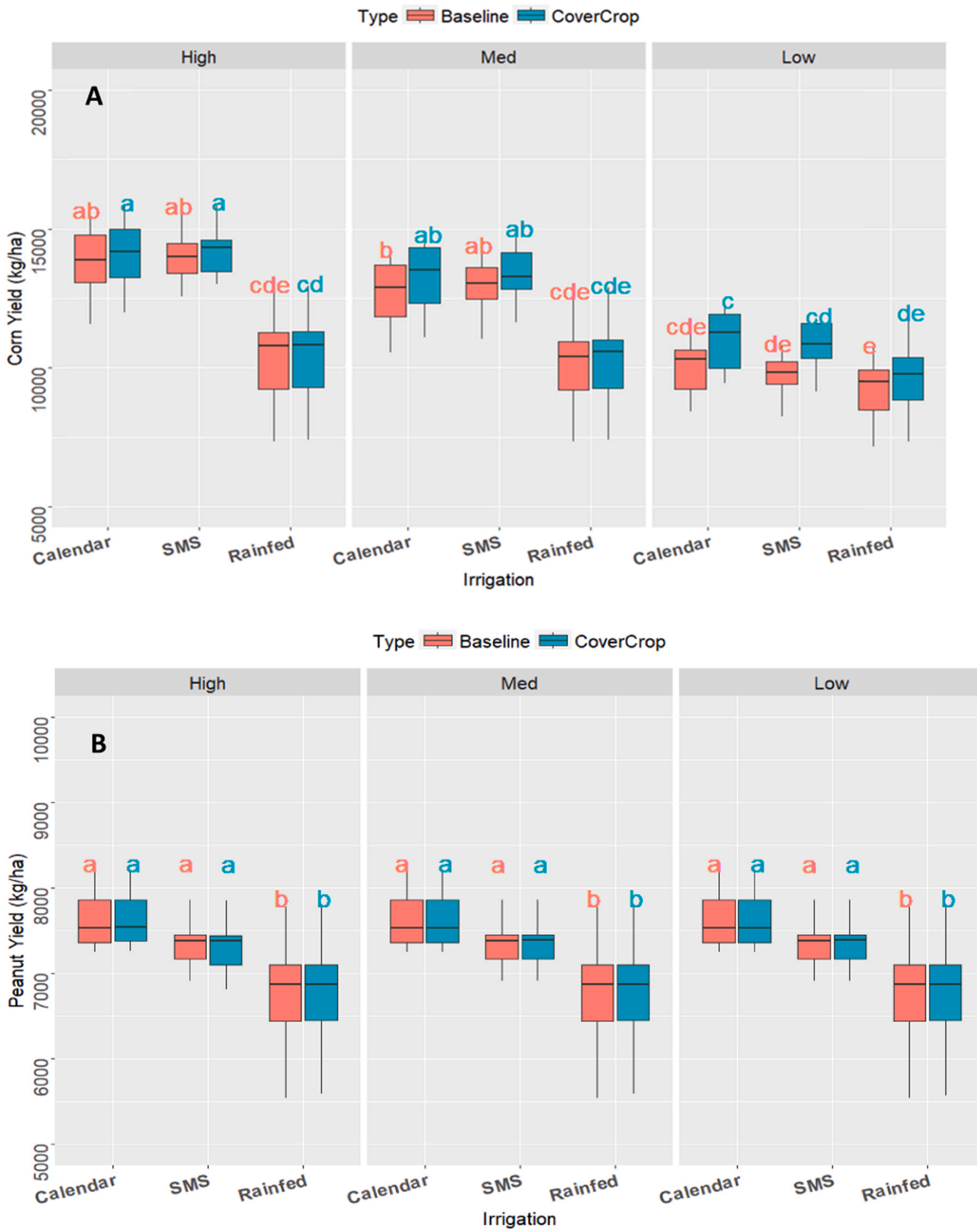

Fig. 8. Long-term corn (A) and peanut (B) yield simulations with fallow (baseline) and with rye cover crop between cropping seasons across irrigation treatments (Calendar, SMS and Rain fed) and N fertility rates (low, medium and high). Different letters indicate significant difference at α = 0.05 level. Boxplots for each irrigation treatment corrspond to baseline (left) and covercrop (right).

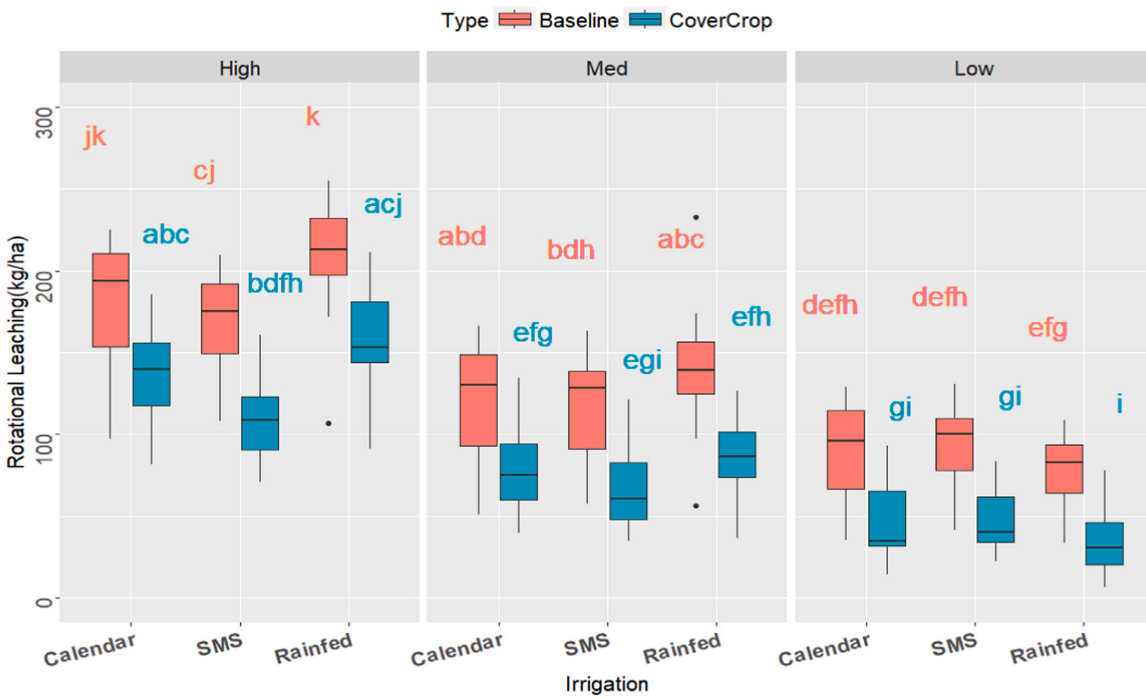

Fig. 9. Long-term simulated N leaching over the crop rotation with fallow and rye cover crop between cropping seasons (corn-fallow/rye-peanut-fallow/rye). Different letters indicate significant difference at α = 0.05 level. Boxplots for each irrigation treatment corrspond to baseline (left) and covercrop (right).

the watershed scale. These scenarios will be used to drive a SWAT-MODLOW model to evaluate tradeoffs among the regional agricultural economy, surface water and groundwater quantity, and stream/aquifer water quality, and to determine whether improved management practices alone can achieve the NNC. Overall, the results of this study and our ongoing efforts provide a transferable framework for developing effective and economically feasible strategies for meeting water quality regulations while maintaining agricultural landscapes and livelihoods.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. None

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Data availability

The experimental data and models used in this study will be uploaded to the Consortium of Universities for the Advancement of Hydrologic Science Inc. (CUAHSI) Hydroshare repository and made publicly available upon acceptance of the manuscript.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2020.106634.

References

Abbaspour, K.C., 2013. SWAT-CUP 2012. SWAT Calibration and Uncertainty Program-A User Manual.
Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. J. Hydrol. 524, 733–752.
Abbaspour, K.C., Vaghefi, S., Srinivasan, R., 2018. A guideline for successful calibration and uncertainty analysis for soil and water assessment: a review of papers from the 2016 International SWAT Conference. Water 10 (10), 6. https://doi.org/10.3390/w10010006.
Aliyari, F., Bailey, T.R., Tasdighi, A., Dozier, A., Arabi, M., Zeiler, K., 2019. Coupled SWAT-MODFLOW model for large-scale mixed agro-urban river basins. Environ. Model. Softw. 115, 200–210.
Almeida, E.R., Favarin, L.J., Otto, R., Pierozan, C., Oliveira, C., Tezotto, T., Lago, C.B., 2017. Effects of nitrogen fertilization on yield components in a corn-palisade grass intercropping system. AJCS 11 (03), 352–359. https://doi.org/10.21475/ajcs.17.11.03.
Amin, M.M., Veith, T.L., Collick, A.S., Karsten, H.D., Buda, A.R., 2017. Simulating hydrological and nonpoint source pollution processes in a karst watershed: a variable source area hydrology model evaluation. Agric. Water Manag. 180, 212–223.
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. JAWRA J. Am. Water Resour. Assoc. 43 (4), 899–910.
Arabi, M., Frankenberger, J.R., Engel, B., Arnold, J.G., 2008. Representation of agricultural management practices with SWAT. Hydrol. Process. 22, 3042–3055.
Arnold, J.G., Kiniry, J.R., Srinivasan, R., Williams, J.R., Haney, E.B., Neitsch, S.L., 2013. SWAT 2012 Input/Output Documentation. Texas Water Resources Institute.
Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., 2012. SWAT: Model use, calibration, and validation. Transactions of the ASABE 55 (4), 1491–1508.
Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams R., J., 1998. Large area hydrologic modeling and assessment part I: model development. J. Am. Water Resour. Assoc. 34 (1), 73–89. https://doi.org/10.1111/j.1752-1688, 1998. tb05961.x.
Arthur, J.D., Wood, A.R., Baker, A.E., Cichon, J.R., Raines, G.L., 2007. Development and implementation of a bayesian-based aquifer vulnerability assessment in Florida. Nat. Resour. Res. 16 (2), 93–107.
Basche, A., Kaspar, T., Archontoulis, A., Jaynes, D., Thomas, J., Sauer, T., Parklin, T., 2016. Soil water improvements with the long-term use of a winter rye cover crop. Agric. Water Manag. 172, 40–50.
Bennett, J.M., Sinclair, T.R., Ma, Li, Boote, K.J., 1993. Single leaf carbon exchange and canopy radiation use efficiency of four peanut cultivars. Peanut Sci. 20, 1–5.
Bieger, K., Hörmann, G., Fohrer, N., 2014. Simulation of streamflow and sediment with the Soil and Water Assessment Tool model in a data scarce catchment in the Three Gorges Region, China. J. Environ. Qual. 43, 37–45.
Boyer, D.G., Pasquarell, G.C., 1995. Nitrate concentrations in karst springs in an extensively grazed area 1. JAWRA J. Am. Water Resour. Assoc. 31 (4), 729–736.

Boyer, D.G., Pasquarell, G.C., 1996. Agricultural land use effects on nitrate concentrations in a mature karst aquifer 1. JAWRA J. Am. Water Resour. Assoc. 32 (3), 565–573.
Bowen, J.L., Kroeger, K.D., Tomasky, G., Pabich, W.J., Cole, M.L., Carmichael, R.H., Valiela, I., 2007. A review of land-sea coupling by groundwater discharge of nitrogen to New England estuaries: mechanisms and effects. Appl. Geochem. 22, 175–191.
Bush, P.W., Johnston, R.H., 1988. Ground-Water Hydraulics, Regional Flow, and Ground-Water Development of the Floridan Aquifer System in Florida and in Parts of Georgia, South Carolina, and Alabama. U.S. Government Printing Office, Washington, D.C.
Cerro, I., Antigüedad, I., Srinavasan, R., Sauvage, S., Volk, M., Sanchez-Perez, J.M., 2014b. Simulating land management options to reduce nitrate pollution in an agricultural watershed dominated by an alluvial aquifer. J. Environ. Qual. 43 (1), 67–74. https://doi.org/10.2134/jeq2011.0393.
Cibin, R., Chaubey, I., Helmers, M., Sudheer, K.P., White, M., Arnold, J.G., 2015. Improved Physical Representation of Vegetative Filter Strip in SWAT.
Chaubey, I., Chiang, L., Gitau, M.W., Mohamed, S., 2010. Effectiveness of best management practices in improving water quality in a pasture-dominated watershed. J. Soil Water Conserv. 65 (6), 424–437.
Chen, Y., Marek, W.G., 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 9 (9), 509. https://doi.org/10.3390/w9070509.
Coxon, C., 2011. Agriculture and karst. Karst Management. Springer, Dordrecht, pp. 103–138.
Dabney, S.M., Delgado, J.A., Meisinger, J.J., Schomberg, H.H., Liebig, M.A., Kaspar, T., et al., 2010. Using cover crops and cropping systems for nitrogen management. In: Delgado, J.A., Follet, R.F. (Eds.), Advances in Nitrogen Management for Water Quality. Soil and Water Conservation Society, Ankeny, IA, pp. 230–281.
Davidson, E.A., Suddick, E.C., Rice, C.W., Prokopy, L.S., 2015. More food, low pollution (Mo Fo Lo Po): a grand challenge for the 21st century. J. Environ. Qual. 44 (2), 305–311.
De la Monte, S.M., Neusner, A., Chu, J., Lawton, M., 2009. Epidemiological trends strongly suggest exposures as etiologic agents in the pathogenesis of sporadic Alzheimer's disease, Diabetes Mellitus, and Non-Alcoholic Steatohepatitis. J. Alzheimers Dis. 17, 519–529.
Doerfliger, N., Jeannin, P.Y., Zwahlen, F., 1999. Water vulnerability assessment in karst environments: a new method of defining protection areas using a multi-attribute approach and GIS tools (EPIK method). Environ. Geol. 39 (2), 165–176, 1999.
EPA, US Environmental Protection Agency, 2016. Ground water and drinking water: table of regulated drinking water contaminants. <⟨https://www.epa.gov/ground-water-and-drinking-water/table-regulated-drinking-water-contaminants#Inorganic⟩>. (Accessed 20 March 2016).
Erisman, J.W., Sutton, M.A., Galloway, J., Klimont, Z., Winiwarter, W., 2008. How a century of ammonia synthesis changed the world. Nat. Geosci. 1, 636–639.
Faramarzi, M., Abbaspour, K.C., Schulin, R., Yang, H., 2009. Modeling blue and green water availability in Iran. Hydrol. Process. 23 (3), 486–501.
FDACS, 2018. Status of Implementation of Agricultural Nonpoint Source Best Management Practices. Report to the Governor, the President of the Senate, and the Speaker of the House Pursuant to s. 403.0675(2), Florida Statutes.
FDACS, 2015. Water Quality/Quantity Best Management Practices for Florida Vegetable and Agronomic Crops, 2015th ed. Florida Department of Agriculture and Consumer Services, Tallahassee, Florida.
FDEP, 2013. Surface Water Quality Standards. Florida Administrative Code, 62-302(62-302), 530–531.
FDEP, 2012. BASIN MANAGEMENT ACTION PLAN for the Implementation of Total Daily Maximum Loads for Nutrients Adopted by the Florida Department of Environmental Protection in the Santa Fe River Basin.
FDEP, 2018. BASIN MANAGEMENT ACTION PLAN for the Environmental Assessment andRestoration Water Quality Restoration Program Florida Department ofEnvironmental Protection in the Santa Fe River Basin. floridadep.gov 2018.
Fenton, O., Mellander, P.E., Daly, K., Wall, D.P., Jahangir, M.M.R., Jordan, P., Hennessey, D., Huebsch, M., Blum, P., Vero, S., Richards, K.G., 2017. Integrated assessment of agricultural nutrient pressures and legacies in karst landscapes. Agric. Ecosyst. Environ. 239, 246–256.
Francesconi, W., Srinivasan, R., Pérez-Miñana, E., Willcock, S.P., Quintero, M., 2016. Using the Soil and Water Assessment Tool (SWAT) to model ecosystem services: a systematic review. J. Hydrol. 535, 625–636. https://doi.org/10.1016/j.jhydrol.2016.01.034.
Gitau, M.W., Gburek, W.J., Bishop, P.L., 2008. Use of the swat model to quantify water quality effects of agricultural BMPs at the farm-scale level. Am. Soc. Agric. Biol. Eng. 51 (6), 1925–1936.
Gassman, P.W., Sadeghi, A.M., Srinivasan, R., 2014. Applications of the SWAT Model Special Section: overview and insights. J. Environ. Qual. 43, 1–8.
Harmel, R.D., Smith, P.K., 2007. Consideration of measurement uncertainty in the evaluation of goodness-of-fit in hydrologic and water quality modeling. J. Hydrol. 337, 326–336.
Harmel, R.D., Smith, P.K., Migliaccio, K.W., 2010. Modifying goodness-of-fit indicators to incorporate both measurement and model uncertainty in model calibration and validation. Trans. ASABE 53, 55–63.
Harrington, D., Maddox, G., Hicks, R., 2010. Florida Springs Initiative Monitoring Network Report and Recognized Sources of Nitrate. Florida Department of Environmental Protection, Tallahassee, Florida.
Heffernan, J.B., Cohen, M.J., Frazer, T.K., Thomas, R.G., Rayfield, T.J., Gulley, J., Martin, J.B., Delfino, J.J., Graham, W.D., 2010. Hydrologic and biotic influences on nitrate removal in a subtropical spring-fed river. Limnol. Oceanogr. 55 (1), 249–263.
Hochmuth, G.J., Hanlon, E.A., Hochmuth, B.C., 1992. Responses of pepper, muskmelon, watermelon, and sweet corn to P and K fertilization at Live Oak, Fla. Suwannee Valley REC Research Report 92-28.
Hochmuth, G., Mylavarapu, R., Hanlon, E., 2014. The four Rs of fertilizer management. Soil and Water Science Department, UF-IFAS Extension, SL411, 1–4.
Hutson, J., Wagenet, R., 1992. LEACHM (Leaching Estimation and Chemistry Model): A Process-Based Model of Water and Solute Movement, Transformations, Plant Uptake and Chemical Reactions in the Unsaturated Zone, Version 3.0, Department of Soil, Crop and Atmospheric Sciences, Cornell University, Ithaca.
Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18 (3), 235–265.
Kamali, B., Abbaspour, K.C., Yang, H., 2017. Assessing the uncertainty of multiple input datasets in the prediction of water resource components. Water 9, 709. https://doi.org/10.3390/w9090709.
Karki, R., Srivastava, P., Bosch, D.D., Kalin, L., Lamba, J., Strickland, T.C., 2019. Multi-variable sensitivity analysis, calibration, and validation of a field-scale swat model: building stakeholder trust in hydrologic/water quality modeling.trans(asabe).
Kaspar, T.C., Singer, J.W., 2011. The Use of Cover Crops to Manage Soil. Publications from USDA-ARS / UNL Faculty. 1382. ⟨http://digitalcommons.unl.edu/usdaarsfacpub/1382⟩.
Katz, B.G., 2004. Sources of nitrate contamination and age of water in large Karstic springs of Florida. Environ. Geol. 46 (6–7), 689–706.
Katz, B.G., Hornsby, H.D., Bohlke, J.F., Mokray, M.F., 1999. Sources and Chronology of Nitrate Contamination in Spring Waters, Suwannee River Basin, Florida, Report 99-4252 Ed., U.S. Geological Survey, Tallahassee, Florida.
Kellman, L.M., Hillaire-Marcel, C., 2003. Evaluation of nitrogen isotopes as indicators of nitrate contamination sources in an agricultural watershed. Agric. Ecosyst. Environ. 95 (1), 87–102.
Kiniry, J.R., Arnold, J.G., Xie, Y., 2002. Application of models with different spatial scales. In: Lajpat, R.A., Ma, L., Howell, T.A. (Eds.), Agricultural System Models in Field Research and Technology Transfer. CRC Press, Boca Raton. https://doi.org/10.1201/9781420032413.ch10.
Kiniry, J.R., Simpson, C.E., Schubert, A.M., Reed, J.D., 2005. Peanut leaf area index, light interception, radiation use efficiency, and harvest index at three sites in Texas. Field Crops Res. 91, 297–306.
Kiniry, J.R., Macdonald, J.D., Armen, R., Watson, B., prepas, E.E., 2008. Plant growth simulation for landscape-scale hydrological modelling. Hydrol. Sci. J. 53 (5), 1030–1042. October 2008.
Krueger, E.S., Ochsner, T.E., Porter, P.M., Baker, J.M., 2011. Winter rye cover crop management influences on soil water, soil nitrate, and corn development. Agron. J. 103, 316–323 (2011).
Liu, Y., Engel, B.A., Flanagan, D.C., Gitau, M.W., McMillan, S.K., Chaubey, I., 2017. A review on effectiveness of best management practices in improving hydrology and water quality: needs and opportunities. Sci. Total Environ. 601, 580–593.
Malagò, A., Pagliero, L., Bouraoui, F., Franchini, M., 2015. Comparing calibrated parameter sets of the SWAT model for the Scandinavian and Iberian peninsulas. Hydrol. Sci. J. https://doi.org/10.1080/02626667.2014.978332.
Mapfumo, E., Chanasyk, D.S., Willms, W.D., 2004. Simulating daily soil water under foothills fescue grazing with the soil and water assessment tool model (Alberta, Canada). Hydrol. Process. 18, 2787–2800.
Marek, G.W., Gowda, P.H., Evett, S.R., Baumhardt, R.L., Brauer, D.K., Howell, T.A., Srinivasan, R., 2016. Calibration and validation of the SWAT model for predicting daily ET over irrigated crops in the Texas High Plains using lysimetric data. Trans. ASABE 59 (2), 611–622.
Marek, G.W., Gowda, P.H., Marek, T.H., Porter, D.O., Baumhardt, R.L., Brauner, D.K., 2017. Modelling long-term water use of irrigated cropping rotations in the Texas High Plains using SWAT. Irrig. Sci. 35 (2), 111–123.
Martinez-Feria, R.A., Dietzel, R., Liebman, M., Helmers J., M., Archontoulis V., S., 2016. Rye cover crop effects on maize: a system-level analysis. Field Crops Res. 196, 145–159.
Maski, D., Mankin, K.R., Janssen, K.A., Tuppad, P., Pierzynski, G.M., 2008. Modeling runoff and sediment yields from combined in-field crop practices using the Soil and Water Assessment Tool. J. Soil Water Conserv. 63 (4), 193–203.
Meals, D.W., Dressing, S.A., Davenport, T.E., 2010. Lag time in water quality response to best management practices: a review. J. Environ. Qual. 39 (1), 85–96.
Mitteslet R., A., Storm E., D., Stoecker, A.L., 2015. Using SWAT to simulate crop yields and salinity levels in the North Fork River Basin, USA. Int. J. Agric. Biol. Eng. 8 (3), 110–124.
Mitsch, W.J., Day Jr., J.W., Gilliam, J.W., Groffman, P.M., Hey, D.L., Randall, G.W., Wang, N., 1999. Reducing nutrient loads, especially nitrate-nitrogen, to surface water, groundwater, and the Gulf of Mexico, Topic 5 Report for the integrated assessment on hypoxia in the Gulf of Mexico, NOAA Coastal Ocean Program Decision Analysis Series No.19, NOAA Coastal Ocean Program, Silver Spring, MD.
Moore, E.B., Wiedenhoeft, M.H., Kaspar, T.C., Cambardella, C.A., 2014. Rye cover crop effects on soil quality in no-till corn silage–soybean cropping systems. Soil Sci. Soc. Am. J. 78, 968–976.
Moloney, C., Cibin, R., Chaubey, I., 2015. Using a Single HRU SWAT Model to Examine and Improve Representation of Field-Scale Processes.
Moriasi, D.N., Arnold, G.J., Van Liew, W.M., Bingner, L.R., Harmel, D.R., Veith, L.T., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.
Moriasi, D.N., Gitau, M.W., Pai, N., Daggupati, P., 2012. Hydrologic and water quality models: performance measures and evaluation criteria. Trans. ASABE 58 (6), 1763–1785.

Motavalli, P.P., Goyne, K.W., Udawatta, R.P., 2008. Environmental impacts of enhanced-efficiency nitrogen fertilizers. Crop Manag. 7 (1), 1–15.
Mulla, D.J., Kitchen, N., David, M., 2004. Evaluating the effectiveness of agricultural management practices at reducing nutrient losses to surface waters.
Mylavarapu, R., Wright, D., Kidder, G., 2015. UF-IFAS Standardized Fertilization Recommendations for Agronomic Crops. Soil and Water Science Department, UF-IFAS Extension, (SL129), 10/1/2015-8.
Nair, S.S., King, K.W., Witter, J.D., Sohngen, B.L., Fausey, N.R., 2011. Importance of crop yield in calibrating watershed water quality simulation models. J. Am. Water Res. Assoc. 47 (6), 1285–1297.
Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Srinivasan, R., Williams, J.R., 2004. Soil and Water Assessment Tool Input/Output File Documentation version 2005. Grassland, Soil and Water Research Laboratory, USDA-ARS andBlackland Research and Extension Center, Texas A&M University, Temple, Texas.
Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R. 2011. Soil and Water Assessment Tool theoretical documentation: Version 2009. USDA– ARS, Grassland, Soil and Water Research Laboratory, Temple, TX; and Blackland Research and Extension Center, Texas AgriLife Research, Temple, TX. Texas Water Resources Institute Technical Rep. 406, Texas A&M University System, College Station, TX. ⟨http://swatmodel.tamu⟩. Edu/documentation/. (Accessed 8 December 2012).
Nolan, B.T., 2001. Relating nitrogen sources and aquifer susceptibility to nitrate in shallow ground waters of the United States. Groundwater 39 (2), 290–299.
Nolan, B.T., Ruddy, B.C., 1996. Nitrate in Ground Waters of the United States-Assessing the Risk; U.S. Geological Survey: Reston, VA, 1996; Fact Sheet FS-092-96.
Panno, S.V., Hackley, K.C., Hwang, H.H., Kelly, W.R., 2001. Determination of the sources of nitrate contamination in karst springs using isotopic and chemical indicators. Chem. Geol. 179 (1–4), 113–128.
Peterson, E.W., Davis, R.K., Brahana, J.V., Orndorff, H.A., 2002. Movement of nitrate through regolith covered karst terrane, northwest Arkansas. J. Hydrol. 256 (1–2), 35–47.
Poikane, S., Kelly, M.G., Herrero, F.S., Pitt, J.A., Jarvie, H.P., Claussen, U., Leujak, W., Solheim, A.L., Teixeira, H., Phillips, G., 2019. Nutrient criteria for surface waters under the European Water Framework Directive: current state-of-the-art, challenges and future outlook. Sci. Total Environ. 695, 133888.
Prasad, R., Hochmuth, G.J., Boote, K.J., 2015. Estimation of nitrogen pools in irrigated potato production on sandy soil using the Model SUBSTOR. PLoS One 10 (1), e0117891. https://doi.org/10.1371/journal.pone.0117891.
Prasad, R., Hochmuth, G.J., 2016. Environmental nitrogen losses from commercial crop production systems in the Suwannee River Basin of Florida. PLoS One 11 (12), e0167558. https://doi.org/10.1371/journal.pone.0167558.
Rajib, M.A., Merwade, V., Yu, Z., 2016. Multi-objective calibration of a hydrologic model using spatially 680 distributed remotely sensed/in-situ soil moisture. J. Hydrol. 536, 192–207.
Ramos, C., Carbonell, E.A., 1991. Nitrate leaching and soil moisture prediction with the LEACHM model. Fertil. Res. 27, 171–180.
Ritter, A., Muñoz-Carpena, R., 2013. Predictive ability of hydrological models: objective assessment of goodness-of-fit with statistical significance. J. Hydrol. 480 (1), 33–45. https://doi.org/10.1016/j.jhydrol.2012.12.004.
Robertson, G.P., Swinton, S.M., 2005. Reconciling agricultural productivity and environmental integrity: a grand challenge for agriculture. Front. Ecol. Environ. 3 (1), 38–46.
Simunek, J., van Genuchten, M.T., Šejna, M., 2008. Development and applications of the HYDRUS and STANMOD software packages and related codes. Vadose Zone J. 7, 587–600.
Singh, B., Singh, Y., Sekhon, G.S., 1995. Fertilizer-N use efficiency and nitrate pollution of groundwater in developing countries. J. Contam. Hydrol. 20, 167–184.
Sinnathamby, S., Douglas, K.R., Craige, C., 2017. Field-scale calibration of crop-yield parameters in the Soil and Water Assessment Tool (SWAT). Agric. Water Manag. 180, 61–69.
Spalding, R.F., Exner, M.E., 1993. Occurrence of nitrate in groundwater—a review. J. Environ. Qual. 22 (3), 392–402.
Thorup-Kristensen, K., Dresboll, D.B., 2010. Incorporation time of nitrogen catch crops influences the N effect for the succeeding crop. Soil Use Manag. 26, 27–35.
U.S. GEOLOGICAL SURVEY Water-Resources Investigations Report, 1983. 83-4075; Water Resources of the Santa Fe River Basin, Florida.
USDA-ARS, 1992a. Root zone water quality model version 1.0. Technical Documentation. GPSR Technical Report No. 2. USDA-ARS Great Plains Systems Research Unit. Ft. Collins, CO., 1992.
Van Meter, K., Cappellen, V.P., Nandita, B., Basu, B.N., 2018. Legacy nitrogen may prevent achievement of water quality goals in the Gulf of Mexico. Science 360, 427–430.
Vazquez-Amabile, G.G., Engel, B.A., 2005. Use of SWAT to compute groundwater table depth and streamflow in the Muscatatuck River watershed. Trans. ASAE 48 (3), 991–1003.
Vero, E.S., Basu, B.N., Van meter, K., Richards, G.K., Mellander, P., 2017. Review: the environmental status and implications of the nitrate timelag in Europe and North America. Hydrogeol. J.
Vesper, D.J., Loop, C.M., White, W.B., 2001. Contaminant transport in karst aquifers. Theor. Appl. Karstol. 13 (14), 101–111.
Vitousek, P.M., Aber, J.D., Howarth, R.W., Likens, G.E., Matson, P.A., Schindler, D.W., Schlesinger, W.H., Tilman, D.G., 1997. Human alteration of the global nitrogen cycle: sources and consequences. Ecol. Appl. 7, 737–750.
Wang, R., Bowling C., L., Cherkauer A., K., 2016. Estimation of the effects of climate variability on crop yield in the Midwest USA. Agric. For. Meteorol. 216, 141–156.
Wei, X., Bailey, T.R., Records, M.R., Wible, C.T., Arabi, M., 2019. Comprehensive simulation of nitrate transport in coupled surface-subsurface hydrologic systems using the linked SWAT-MODFLOW-RT3Dmodel. Environ. Model. Softw. 122, 104242 https://doi.org/10.1016/j.envsoft.2018.06.012.
Winchell, M., Srinivasan, R., Diluzio, M., Arnold, J., 2013. ArcSwat Interface for SWAT 2012: User's Guide. Blackland Research Center, Texas Agri Life Research.
Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth model. Trans. Am. Soc. Agric. Eng. 32 (2), 497–511.
Xie, H., Chen, L., Shen, Z., 2015. Assessment of agricultural best management practices using models: current issues and future perspectives. Water 7 (3), 1088–1108.
Yang, J., Abbaspour, K.C., Reichert, P., 2008. Comparing uncertainty analysis techniques for a SWAT application to Chaohe Basin in China. Journal of Hydrology 358 (1–2), 1–23.
Yang, Q., Zhang, X., Abraha, M., Del Grosso, S., Robertson, G.P., Chen, J., 2017. Enhancing the soil and water assessment tool model for simulating N2O emissions of three agricultural systems. Ecosyst. Health Sustain. 3 (2), e01259.
Young, A.R., Onstad, A.C., Bosch, D.D., Anderson, P.W., 1989. AGNPS: a nonpoint-source pollution model for evaluating agricultural watersheds. J. Soil Water Conserv. 44 (2), 168–173.
Zamora, M., Dukes, M., Rowland, D., Hensley, D., Graham, W., Hochmuth, B., 2018. Evaluation of water use, water quality and crop yield impacts of corn and peanut irrigation and nutrient BMPs in the spring sheds of Suwannee River Water Management District. Project Final Report FDACS Contract No. 21894.
Zamora-Re, M.I., Dukes, M.D., Hensley, D., Rowland, D., Graham, W.D., 2020. The effect of irrigation strategies and nitrogen fertilizer rates on maize growth and grain yield. Irrig. Sci. 38, 461–478.
Zotarelli, L., Scholberg, J.M., Dukes, M.D., Carpena M., R., 2007. Monitoring of nitrate leaching in sandy soils: comparison of three methods. J. Environ. Qual. 36, 953–962.
Zotarelli, L., Avila, L., Scholberg, J.M.S., Alves, B.J.R., 2009. Benefits of vetch and rye cover crops to sweet corn under no-tillage. Agron. J. 101, 252–260.
Zotarelli, L., Rens, C. Barrett, Cantliffe, D.J., Dukes, M.D., Clark, M., Lands, S., 2013. Subsurface Drip Irrigation (SDI) for Enhanced Water Distribution: SDI—Seepage Hybrid System. HS1217. University of Florida Institute of Food and Agricultural Sciences, Gainesville. ⟨http://edis.ifas.ufl.edu/hs1217⟩.
Zhang, Y., Hou, J., Gu, J., Huang, C., Li, X., 2017. SWAT-based hydrological data assimilation system (SWAT-HDAS): description and case application to river basin-scale hydrological predictions. J. Adv. Model. Earth Syst. 9, 2863–2882.