Evaluating Nitrogen Management for Corn Production with Supplemental Irrigation on Sandy Soils of the Southeastern Coastal Plain Region of the U.S.

C. D. D. Sohoulande, L. Ma, A. A. Szogi, G. C. Sigua, K. C. Stone, R. W. Malone

Highlights

- This study addressed the inclusion of field-scale soil variability in nitrogen (N) management for corn production.
- RZWQM2 was calibrated for corn yield and N dynamics on four sandy soil series under supplemental irrigation.
- Multi-year simulations of corn production under high and low N application rates were analyzed.
- Results showed room to reduce N use and N leaching without affecting corn production on Coastal Plain sandy soils.

Abstract. *Nitrogen (N) fertilization contributes significantly to maintain high yields in corn (*Zea mays *L.) production. In the Southeastern Coastal Plain of the U.S. where soils are sandy with poor water and nutrient holding capacity, a fraction of the N applied to corn fields is often leached from the root zone and becomes unavailable to plants. As these soils belong to various taxonomic classes, research has shown significant corn yield differences among soil series. However, few studies have focused on integrating field-scale soil variability, N leaching, and corn production. To address this knowledge gap, this study used the Root Zone Water Quality Model (RZWQM2) to simulate different N management scenarios in corn production for four sandy soil series under supplemental irrigation. The calibrated model was used to simulate nine consecutive years of corn production under four N management scenarios, including two high rates of N application (rate A = 224 kg N ha^{-1} with 25 kg N ha^{-1} at preplant; rate A′ = 224 kg N ha^{-1} without preplant N), and two low rates of N application (rate B = 157 kg N ha^{-1} with 25 kg N ha^{-1} at preplant; rate B′ = 157 kg N ha^{-1} without preplant N). Simulation results showed that without preplant N application, N leaching was reduced by up to 17% with no significant impact on corn yield, depending on the soil series. Hence, consideration of field-scale soil variability could help improve N management by reducing N use and N leaching without impacting corn production.*

Keywords. *Corn yield components, Growing season, Modeling, Nitrogen dynamics, RZWQM2, Soil variability.*

The intensive use of nitrogen (N) fertilizers is essential in modern agriculture to reach high crop production and feed the increasing world population. Each year, more than 5 million tonnes of N fertilizers are used in corn (*Zea mays* L.) production across the U.S. (Ribaudo et al., 2011). Such intensive use of N fertilizers has become a growing concern because N losses from farmlands have been linked to cases of surface and groundwater contamination (Swaney et al., 2018). Hence, it is an imperative to develop N management strategies that limit N losses while maintaining high corn yields. Particularly, in the Southeastern U.S. Coastal Plain, N management for corn production is a major challenge because of the sandy textures, low nutrient content, and low water holding capacity of the soils in this region. To sustain high grain yields in the Southeastern U.S. Coastal Plain sandy soils, farmers apply N fertilizers to corn fields at sufficiently high rates to ensure yields with maximum economic return for the N fertilizer used (Morris et al., 2018). For instance, in South Carolina, N recommendations for corn production are based on yield goals (Clemson, 2019). These recommendations are split applications, which include an early preplant application of N as starter fertilizer followed by additional N applications during the growing season (Spackman et al., 2019; Clemson, 2019). This split application of N fertilizer aims to synchronize N supply with corn N uptake during the growing season (Spackman et al., 2019). However, precise prediction of the

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quantity of N required by corn has been challenging because of the effects of precipitation, supplemental irrigation, temperature, and soil properties on the N cycle (Sigua et al., 2017; Stone et al., 2016). Therefore, improved N recommendations are critical for sustainable corn production and abatement of N losses to the environment in the Southeastern U.S. Coastal Plain region.

To improve N management in corn production, thorough understanding is needed of the N dynamics in the soil-water-plant-atmosphere continuum. This can be achieved with either field experiments or simulation models. Unlike field experiments, simulations have the advantages of being time and cost effective. At the field scale, system models such as the Root Zone Water Quality Model (RZWQM2) have been widely used to assess N management in crop production (Ma et al., 2012). For instance, Malone et al. (2019) used RZWQM2 to assess the effect of corn stover harvest on N dynamics and corn production in central Iowa. Likewise, Sun et al. (2018) used RZWQM2 to assess the long-term effects of irrigation and fertilizer management on corn yield and nitrate leaching in China. In general, RZWQM2 has performed reasonably well for corn and nutrient simulations for various soils and environmental conditions (Xu et al., 2020; Ma et al., 2012). Soils in the Southeastern U.S. Coastal Plain belong to various taxonomic classes, and it is common to identify different soil series at the field scale. Research has shown significant corn yield differences among different soil series subjected to the same N management (Sigua et al., 2017; Stone et al., 2016). However, few studies have focused on the inclusion of field-scale soil variability on N leaching and corn yield. As a result, current crop nutrient management practices in the Southeastern Coastal Plain region do not sufficiently emphasize the diversity of sandy soils series at the field scale. In view of this shortcoming, it is paramount to elucidate the potential contribution of a field-scale soil variability on nutrient management. This could help improve management practices aiming to reduce nitrogen losses while maintaining high grain yields. Hence, this study uses RZWQM2 to elucidate multi-year N dynamics on different sandy soils under corn production.

MATERIALS AND METHODS

EXPERIMENTAL DATA

The experimental data were obtained from a site in Florence County, South Carolina (34.245° N, -79.807° W). The site consists of a 6 ha crop field with an average slope of 1.7% and is managed by the USDA Agriculture Research Service (ARS) at Florence, South Carolina. The crop field is encompassed by the Southern Coastal Plain's land resource area (LRA) (USDA-NRCS, 2006). The Southern Coastal Plain's LRA essentially includes highly weathered soils with sandy textures, highly variable water holding capacities, and low organic matter contents. Crop yields are largely affected not only by fertilizer management but also by the large physical and chemical variability of the soils in the Southern Coastal Plain's LRA. A soil survey of the 6 ha crop field at 15 m × 15 m spatial resolution helped identify different soil series. Although all the soils have sandy textures, they belong to various taxonomic classes, and they differ in term of slope, layer thickness, and the presence and depth of a clay layer in the profile (Karlen et al., 1990). Table 1 presents details of the taxonomic classes and some chemical properties of four of these soil series, including Bonneau soil (BnA), Norfolk soil (NkA), Dunbar soil (Dn), and Noboco soil (NcA), which were used for this study. The differences among the soil series suggest potential differences in N dynamics at the field scale. The climate in the Southern Coastal Plain's LRA is humid with annual precipitation above 1100 mm (Sohoulande et al., 2019). This allows farmers to grow seasonal crops such as corn, cotton, soybean, peanut, and tobacco regardless of the poor water holding capacity of the soil. To maintain high crop yields, substantial amounts of N are seasonally applied to these soils at recommended rates based on Clemson University's Agricultural Service Laboratory (Clemson, 2019). However, this practice may not guarantee efficient N management because the soil series variability implies variable patterns in N dynamics at the field scale.

In the Southeastern Coastal Plain, studies have recommended supplemental irrigation for corn yield stability, as the region often experiences precipitation deficits during the

Table 1. Description of the four soils used in RZWQM2 modeling.

Symbol	Soil Series and Texture	Classification[a]	C (g kg^{-1})	N (g kg^{-1})	pH	CEC[b]
BnA	Bonneau loamy fine sand	Loamy, siliceous, subactive, thermic Arenic Paleudults	6.03 ±0.28	0.34 ±0.11	5.47 ±0.12	1 - 4
NkA	Norfolk loamy fine sand, moderately thick surface, deep water table	Fine-loamy, kaolinitic, thermic Typic Kandiudults	3.92 ±1.29	0.34 ±0.14	6.29 ±0.17	1 - 4
Dn	Dunbar loamy fine sand	Fine, kaolinitic, thermic Aeric Paleaquults	10.43 ±1.90	0.58 ±0.16	5.82 ±0.17	2 - 7
NcA	Noboco loamy fine sand, thick surface	Fine-loamy, siliceous, subactive, thermic Oxyaquic Paleudults	5.39 ±0.60	0.39 ±0.06	6.19 ±0.11	4 - 10

[a] According to USDA soil taxonomy (https://soilseries.sc.egov.usda.gov).
[b] CEC = cation exchange capacity (cmol/kg).

Table 2. Physical and hydraulics properties of the top 0.3 m of the four soils.

Soil Series	Texture	Sand (%)	Silt (%)	Clay (%)	Bulk Density (g cm^{-3})	K_{sat} (cm h^{-1})	Field Capacity[a] (m^3 m^{-3})	Wilting Point[a] (m^3 m^{-3})	Saturation[a] (m^3 m^{-3})
Bonneau (BnA)	Sandy loam	71.0	19.0	10.0	1.53	9.48	0.121	0.045	0.277
Norfolk (NkA)	Loamy sand	80.7	16.7	2.6	1.55	3.57	0.137	0.056	0.260
Dunbar (Dn)	Fine sandy loam	60.4	20.7	16.9	1.59	3.01	0.169	0.073	0.295
Noboco (NcA)	Sandy loam	75.5	18.0	8.5	1.62	5.36	0.145	0.055	0.261

[a] Values for field capacity, wilting point, and saturation were reported by Stone et al. (2019).

growing season (Sohoulande et al., 2019; Stone et al., 2016). During 2013 and 2014, corn was grown on the site under supplemental irrigation, and data on N management, soil moisture, soil nutrient content, and yield components (grain, biomass, grain N, and biomass N) were collected during the growing seasons. From the collected data, Sigua et al. (2017) reported significant differences in water nitrate movement among the four soil series (BnA, NkA, Dn, and NcA). Likewise, Stone et al. (2016) analyzed the related corn yields and reported significant differences depending on the soil series. Although the results of these studies suggested the role of the field-scale soil variability in corn N and water use efficiency, more details on N movement in the soil-water-plant-atmosphere continuum are needed to better quantify the effects of N movement on N use efficiency.

In this study, the 2013 and 2014 corn season data, including yield components, management practices, and soil physical and chemical data, were used in RZWQM2 modeling. Details of the data and the measurement procedures were reported by Sigua et al. (2017) and Stone et al. (2016). Additional measurements of saturated hydraulic conductivity and bulk density were conducted. Table 2 presents a summary of the physical properties of the four soil series. The management practices considered in the modeling included two high rates of N application (rates A and A′) and two low rates of N application (rates B and B′). These rates are variants of traditional corn fertilization practices in South Carolina, which are based on the yield goal system recommended by Clemson University's Agricultural Service Laboratory (Clemson, 2019). Rate A consists of 224 kg N ha^{-1} during crop growth with 25 kg N ha^{-1} at preplant, while rate A′ differs from rate A by excluding the preplant fertilization. Likewise, rate B consists of 157 kg N ha^{-1} during crop growth with 25 kg N ha^{-1} at preplant, while rate B′ does not include the preplant fertilization. The details of these management inputs are reported in table 3.

In addition to the experimental data, weather data were also used in RZWQM2. The weather data included daily precipitation, maximum and minimum temperatures, relative humidity, wind speed, and solar radiation and were collected at an on-site station managed by the USDA-ARS Coastal Plain Soil, Water, and Plant Research Center at Florence, South Carolina (34° 14′ 43.99″ N, 79° 48′ 35.86″ W). Due to data availability, daily weather records for the period 2010 to 2018 were used in this study. Any missing weather data were filled in using Florence Regional Airport weather station data retrieved from the NOAA database. Based on the daily weather data and the experimental field data, each of the soil series (BnA, NkA, Dn, NcA) were modeled independently in RZWQM2.

Table 3. Inputs for RZWQM2 assessments. Four management practices were used in RZWQM2 modeling: rate A (224 kg N ha^{-1} during crop growth with 25 kg N ha^{-1} at preplant), rate A′ (224 kg N ha^{-1} during crop growth, no preplant), rate B (157 kg N ha^{-1} during crop growth with 25 kg N ha^{-1} at preplant), and rate B′ (157 kg N ha^{-1} during crop growth, no preplant). Management for A and A′ was the same as implemented during the 2014 experiment. Management for B and B′ was the same as implemented during the 2013 experiment.

Input	Description	High N Rates A	High N Rates A′	Low N Rates B	Low N Rates B′
Corn variety	Dekalb 66-97	-	-	x	x
	DKC66-97	x	x	-	-
Tillage (subsoiler)	30 cm depth	x	x	x	x
Planting					
Dates	April 4	-	-	-	-
	April 9	-	-	-	-
Density	79,000 seeds ha^{-1}	x	x	x	x
Depth	4 cm	x	x	x	x
Row spacing	76 cm	x	x	x	x
Fertilization					
Preplant broadcast	April 2	-	-	x	-
(25 kg N ha^{-1})	March 28	x	-	-	-
Fertigation 1	May 19	x	x	-	-
(90 kg N ha^{-1})	May 25	-	-	x	x
Fertigation 2	June 4	x	x	-	-
(67 kg N ha^{-1})	June 17	-	-	x	x
Fertigation 3	June 9	x	x	-	-
(67 kg N ha^{-1})					
Irrigation					
Type	Pivot/sprinkler	x	x	x	x
Depth	30 cm	x	x	x	x
Rate	12.5 mm	x	x	x	x
Depletion trigger	50% available soil water	x	x	x	x
Harvest date	September 11	x	x	-	-
	September 16	-	-	x	x

Modeling Approach

Primarily developed as a water quality research tool, RZWQM2 has been extensively used to address nutrient and crop management issues at the field scale (Ma et al., 2006). Various algorithms are incorporated into RZWQM2 to simulate biophysical processes controlling the fate of N in the soil profile. Examples of these algorithms include the Green-Ampt equation for estimating infiltration rates in the soil matrix, the extended Shuttleworth-Wallace model for describing evapotranspiration, and the C:N module for estimating the decay of plant residues, soil humus, and microbial pools. Details of the RZWQM2 algorithms were reported by Ahuja et al. (2000). The model also imbeds plant growth modules from the Decision Support System for Agrotechnology Transfer (DSSAT) crop model (Ma et al., 2006). This enables RZWQM2 to reasonably address N management at field scale (Saseendran et al., 2007). Likewise, the model is often used to evaluate plant N uptake and yield components for major crops such as corn (Malone et al., 2019). However, RZWQM2 has not been used as a research tool to examine the role of field-scale soil variability on crop yield and nitrogen dynamics in the root zone. That aspect is addressed in this study, which focuses on sandy soils of the Southeastern U.S. Coastal Plain.

Available experimental data for two consecutive corn growing seasons (2013 and 2014) were used to calibrate RZWQM2 for simulating corn yield components (i.e., biomass, grain, grain N, and biomass N), as well as nitrogen in the soil profile. RZWQM2 includes DSSAT's CERES-Maize, which is used worldwide to model corn crops under various soil, management, and climate conditions. Due to the robustness of CERES-Maize, corn modeling studies have prioritized the calibration stage to cope with limited field data availability (López-Cedrón et al., 2008). Such an approach is suitable if the modeled corn varieties are not new and field data are limited. Hence, the modeling approach used here was carried out with reference to the robustness of CERES-Maize. The model was evaluated using four performance indicators, including the percentage bias (Pbias), root mean square error (RMSE), ratio of RMSE and observed standard deviation (RSR), and coefficient of determination (R^2) (Moriasi et al., 2015). The performance indicators were estimated for the yields in two years (2013 and 2014) on the four soil series. Hence, the number of observations used in the model evaluation was n = 8. For a given yield variable (e.g., grain yield or grain N content) with x designating the experimental observations and y designating the RZWQM2 simulations, Pbias, RMSE, RSR, and R^2 are calculated with equations 1 through 4:

$$\text{Pbias (\%)} = \frac{\sum_{i=1}^{n}(x_i - y_i)}{\sum_{i=1}^{n} x_i} \times 100 \tag{1}$$

$$\text{RMSE} = \frac{\left[\sum_{i=1}^{n}(x_i - y_i)^2\right]^{0.5}}{n} \tag{2}$$

$$\text{RSR} = \frac{\left[\sum_{i=1}^{n}(x_i - y_i)^2\right]^{0.5}}{\left[\sum_{i=1}^{n}(x_i - \bar{y})^2\right]^{0.5}} \tag{3}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}\right]^2 \tag{4}$$

where n = 8 is the sample size, x_i and y_i are the observed and simulated values, respectively, of a given yield variable ($1 \le i \le n$), and $\bar{y}$ is the mean value of the simulated yield variable.

The crop parameters for RZWQM2 were optimized for corn yield components using the parameter estimation module PEST (Malone et al., 2010). Table 4 presents the corn cultivar parameters used in the model. For the individual soil series (BnA, NkA, Dn, NcA), the measured soil properties (table 2) were input to RZWQM2, and the calibrated model was used to simulate nine consecutive years of corn production (2010 to 2018). The simulations used historic records of daily weather data at the experimental site and each of the four N applications rates described in table 3 (rates A, A′, B, and B′). In addition to yields, N stress during the growing season was also simulated for each soil series and N treatment. RZWQM2 estimates plant N stress using the nitrogen factor (NFAC) (Ma et al., 2006; Godwin and Singh, 1998). Plant N stress is estimated relatively to the daily N demand at the plant growth stage (S) and the actual plant N uptake. Hence, NFAC is defined based on the critical, minimum, and actual plant N concentrations (TCNP, TMNC, and TANC, respectively). Equations 5, 6, and 7 were used for estimating NFAC as well as TCNP and TMNC, which are functions of the plant growth stage ($0 \le S \le 7$):

$$\text{NFAC} = 1.0 - \frac{\text{TCNP} - \text{TANC}}{\text{TCNP} - \text{TMNC}} \tag{5}$$

$$\text{TCNP} = \frac{e^{1.52 - 0.16S}}{100} \tag{6}$$

$$\begin{cases} \text{TMNC} = \dfrac{1.25 - 0.20S}{100} & \text{when } S < 4.0 \\ \text{TMNC} = 0.0045 & \text{when } S \ge 4.0 \end{cases} \tag{7}$$

On a given day during the plant growth period, NFCA = 1.0 indicates no stress, while NFCA = 0 indicates maximum stress. RZWQM2 simulations of plant N stress were performed for the nine consecutive growing seasons (2010 to 2018). The non-parametric Wilcoxon signed-rank test (W-test) (Woolson, 2007; Wilcoxon et al., 1970) was used to evaluate the statistical differences between the central tendencies (i.e., medians) of the simulations with rates A, A′, B, and B′. The non-parametric W-test was used due to the limited sample size (i.e., 9) and the need to pair annual values in response to the interannual variability of the input weather data (Woolson, 2007). The outcomes of these RZWQM2 simulation analyses are discussed considering the field-scale soil variability.

Results and Discussion

RZWQM2 Simulated Yield Component

Figure 1 presents the linear fit between the experimental and RZWQM2-simulated biomass, biomass N content, grain yield, and grain N content. Each of the four graphs (figs. 1a to 1d) show an overall acceptable linear fit between the experimental data and RZWQM2 simulations. Table 5 summarizes the values of the model performance indicators. For each of the yield components, the values of the performance indicators (Pbias, RMSE, RSR, R^2) are concordant, indicating rea-

Table 4. Corn cultivar parameters used in RZWQM2 for U.S. Coastal Plain sandy soils.

Parameter	Default Range	Value Used
P1: Thermal time from seeding emergence to juvenile phase (°C days above 8°C)	100 - 450	374
P2: Delay in development for each hour that daylength is greater than 12.5 h (d h^{-1})	0.01 - 1	0.44
P5: Thermal time from silking to physiological maturity (°C days above 8°C base temperature)	500 - 1000	965
G2: Maximum possible number of kernels per plant	440 - 1500	1126
G3: Kernel filling rate during linear grain filling stage and under optimum conditions (mg d^{-1})	5 - 16	6.87
PHINT: Phylochron; the interval in °C days between leaf tip appearance	38 - 55	38.17
Maximum plant height at maturity (cm)	-	244.6
Plant biomass at half of maximum height (g $plant^{-1}$)	-	43.07

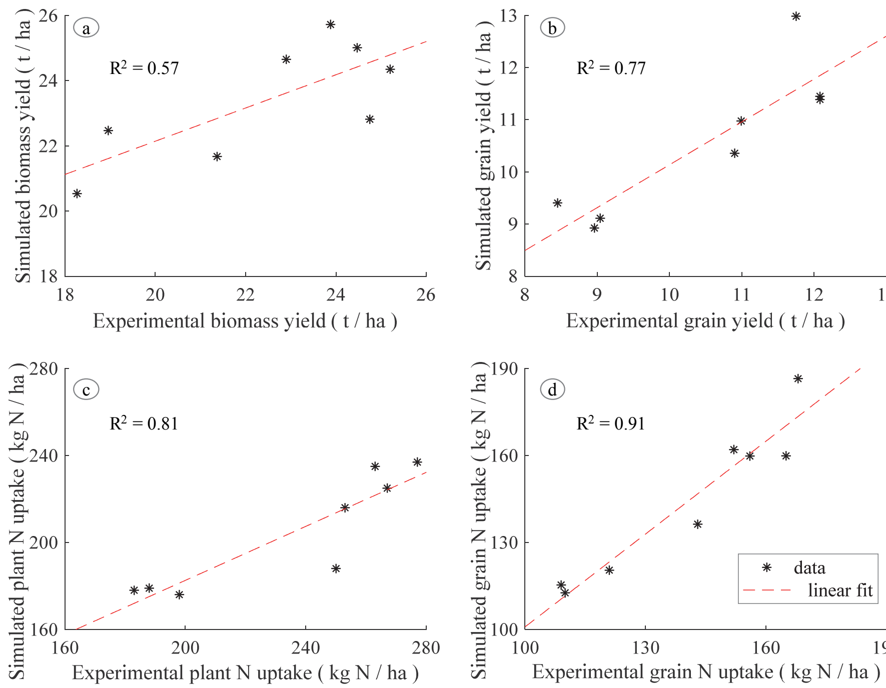

Figure 1. RZWQM2 simulation of corn yield and nitrogen uptake with experimental data. Each plot includes data for all four soil series.

Table 5. RZWQM2 performance indicators for simulating corn yield components and N uptake in sandy soils.

Indicator	Biomass Yield	Grain Yield	Biomass N	Grain N
Pbias	-4.12%	-0.40%	13.16%	-2.53%
RMSE	0.67 t ha^{-1}	0.24 t ha^{-1}	12.57 kg ha^{-1}	3.02 kg ha^{-1}
RSR	0.71	0.48	0.75	0.37
R^2	0.57	0.77	0.81	0.91

sonable model simulations. Particularly, for plant N uptake, grain yield, and grain N uptake, the ranges of R^2 ($0.77 \leq R^2 \leq 0.91$) and Pbias (-2.53% ≤ Pbias ≤ 13.16%) reflect the ability of RZWQM2 to capture and closely reproduce corn yield and N dynamics regardless of the sandy soil series. These results are relevant because they indicate an acceptable calibration of the model, which was subsequently used to simulate different N management scenarios for each of the soil series (BnA, NkA, Dn, NcA) under supplemental irrigation.

To ensure adequate calibration of RZWQM2, Ma et al. (2012) highlighted the importance of making sure that all model output values are reasonable under the simulated conditions. This implies the need to evaluate N budget components such as N denitrification and N mineralization. However, these N budget components are not often measured in field experiments due to resource and time limitations. In such circumstances, the use of literature data is recommended to check how reasonably RZWQM2 represents N dynamics (Gillette et al., 2018; Malone et al., 2017). Indeed, the value of a process-based water quality model is in filling gaps by estimating components of the soil-water-plant continuum (Malone et al., 2004; Oreskes et al., 1994). In this study, the RZWQM2 simulations showed a seasonal N denitrification of 0.11 kg N ha^{-1}. Such a low N denitrification value is reasonable for sandy soils, as their hydraulic properties (i.e., quickly drained) restrain water from puddling, which is a condition for denitrification. Regarding N mineralization, RZWQM2 simulated an average N mineralization of 69 kg N ha^{-1} during the crop season. This value aligns with previous studies, which reported N mineralization within the range of 22 to 100 kg N ha^{-1} (Alva et al., 2002; Stanford, 1973). For instance, Alva et al. (2002) quantified N mineralized from corn residues in the top 30 cm depth of sandy soils under irrigation and reported a cumulative amount of 75.7 kg N ha^{-1} from May to September. The RZWQM2 simulation of N dynamics is therefore consistent with the literature. This implies an adequate RZWQM2 calibration for corn production under supplemental irrigation on the Coastal Plain's sandy soils.

Nitrogen Dynamics Estimated with RZWQM2

From a quantitative prospect, N addition (i.e., the quantity of plant-assimilable N in the soil), plant N uptake, and N leaching are the three main components of the N budget simulated by RZWQM2 under the studied conditions (i.e., soils, weather, and management). N addition represents the pooled N in the soil, including preplant N fertilizer, N fertigation, N in rainwater, and N released by residue and dead roots. For each of the four soil series, the estimated daily values of N addition, N leaching, and plant N uptake during the 2013 and 2014 corn growing seasons are shown in figure 2. The three N component curves show comparable trends for the four soil series during 2013 and 2014. The year 2013 corresponds to a low rate of N application (i.e., rate B = 157 kg N ha^{-1} with 25 kg N ha^{-1} preplant application), while 2014 corresponds to a high rate of N application (i.e., rate A = 224 kg N ha^{-1} with 25 kg N ha^{-1} preplant application). Rates A and B imply different levels of N availability, justifying the interannual discrepancies between 2013 and 2014. However, analysis of the N leaching curves shows in most cases a peak in N loss via leaching at the beginning of the growing season, while the plant N uptake is below the N addition. Table 6 summarizes

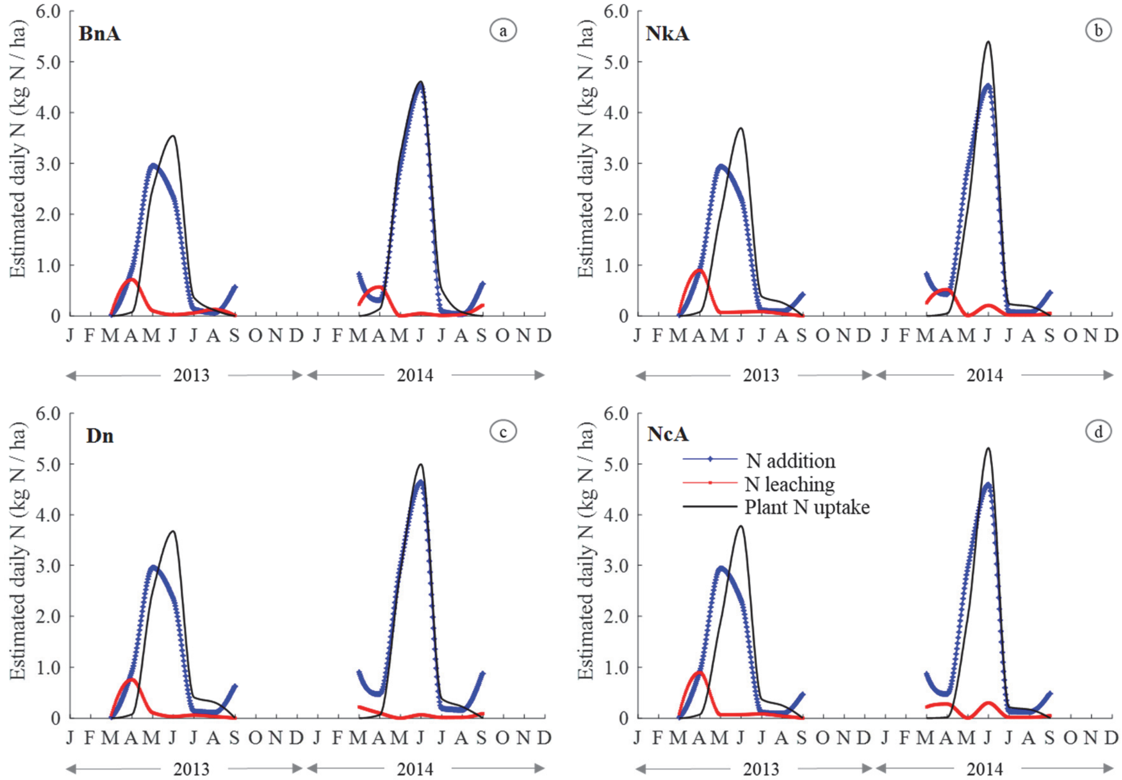

Figure 2. Estimated daily plant N uptake with N addition to the soil and N leaching during the 2013 and 2014 corn growing seasons. RZWQM2 simulations were conducted for four sandy soil series. N addition to the soil is plant-assimilable N, i.e., ammonium (NH_4^+) and nitrate (NO_3^-), and includes preplant fertilizer, fertigation, N in rainwater, and N released by residue and dead roots. Urease enzyme released by microorganisms is essential to degrade urea (CH_4N_2O) into NH_4^+; *Nitrosomonas* and *Nitrobacter* are needed for conversion to NO_3^-.

Table 6. Temporal distribution of total seasonal N leaching (%) for the four soil series in two growing seasons.

	Rate A (2014)				Rate B (2013)			
Month	BnA	NkA	Dn	NcA	BnA	NkA	Dn	NcA
March	21%	24%	44%	25%	5%	7%	6%	7%
April	51%	48%	19%	31%	65%	71%	71%	72%
May	0%	1%	0%	0%	10%	6%	11%	6%
June	4%	19%	13%	34%	2%	6%	3%	6%
July	1%	2%	3%	2%	6%	7%	6%	7%
August	3%	2%	3%	2%	12%	4%	3%	4%
September	20%	5%	18%	6%	0%	0%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%

the monthly distribution of N leaching during the two growing seasons. The percentage distribution shows that 56% to 79% of the N leaching occurs during the first two months of the season. The peak in N leaching at the beginning of the season may be explained by the lag between available N and plant N needs. At the beginning of the season, the N addition was essentially from preplant N application and residue mineralization. Because plant N demand is low at the early growth stage, the N addition was exposed to leaching, particularly in sandy soils with poor nutrient holding capacity.

Field-Scale Soil Variability and N Management Scenarios

The results indicated room to improve N nutrient management by minimizing the N leaching rate. In particular, the high rate of N leaching at the beginning of the crop season complicates the usefulness of preplant fertilization. Hence, the calibrated RZWQM2 model was used to simulate four scenarios of N management based on rates A, A′, B, and B′ described in table 3. Each of the four N management scenarios was simulated separately with individual soil series for nine consecutive corn growing seasons (2010 to 2018). Variables including grain yield, biomass yield, biomass N content, grain N content, total N leaching, and average monthly N stress were analyzed for the nine-year simulations. As shown in figures 3 and 4, for each soil series, there is a clear contrast between corn yield components at the high and low N application rates. Tables 7 and 8 report W-test statistics comparing the medians between rates A and A′ (table 7) and between rates B and B′ (table 8) for each soil series.

The statistics in tables 7 and 8 show significant or nonsignificant patterns depending on the soil series and N management (i.e., high N rates versus low N rates). At low N rates, elimination of the preplant N application is likely to expose the plants to N stress regardless of the soil series (a low value of N stress means frequent N stress later in the crop season). At high N rates, only the BnA and NkA soil

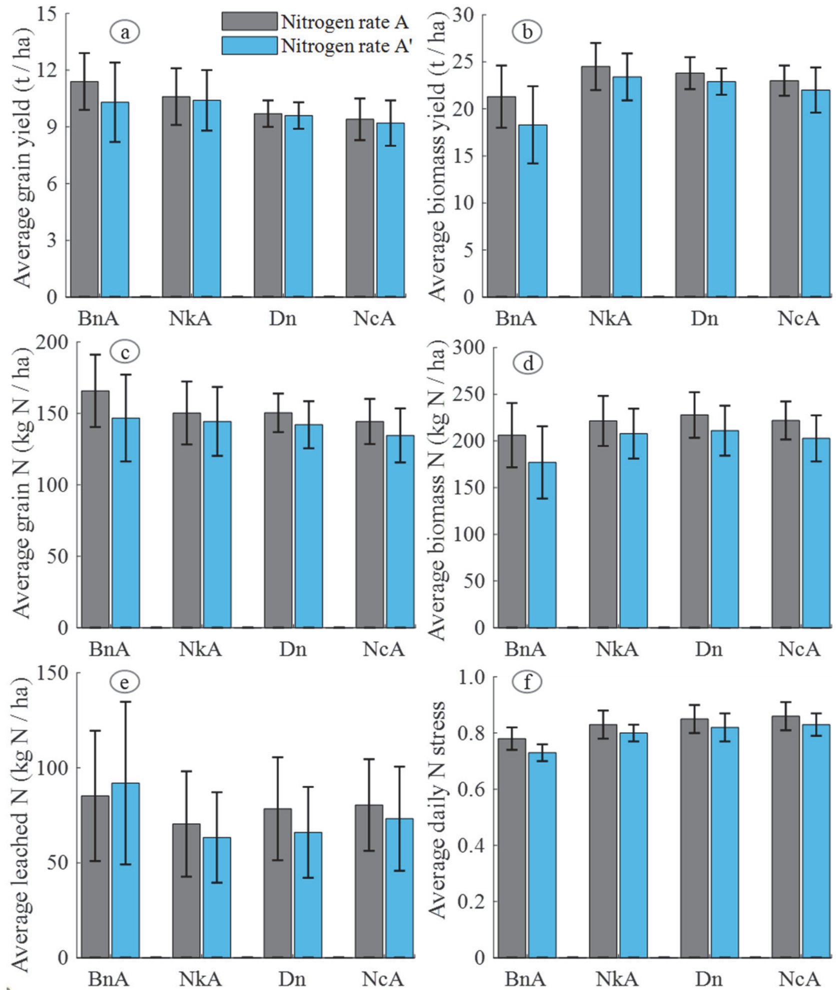

Figure 3. Multiyear RZWQM2-simulated corn yield components for four sandy soil series (BnA, NkA, Dn, and NcA) for two high N application rates (A and A′). Error bars indicate standard deviations.

series showed significant N stress differences due to elimination of the preplant N application. At both high and low N rates (i.e., management scenarios A and B), elimination of the preplant N application significantly reduced average N leaching by 10% to 17% for the NkA and Dn soil series. Interestingly, for the Dn soil at both low and high N rates, grain yield did not change significantly with elimination of the preplant N application, even though the biomass was affected at the low N rate. Likewise, elimination of the preplant N application on the NcA soil did not significantly affect the grain yield, but the biomass was affected at the low N rate. In contrast, elimination of the preplant N application on the BnA soil significantly affected grain yield and biomass at both the low and high N rates, while the difference in N leaching was not significant. For the NkA soil, elimination of preplant N was likely to significantly reduce N leaching, and this reduction would have a significant effect on the biomass, while the grain yield would be unaffected. These results suggest that knowledge of the N dynamics at the soil series level is relevant when making decisions on preplant N ap-plication, as it could help reduce N use and N leaching without affecting corn production at the field scale.

Synthesis and Discussion

In light of the simulation results, RZWQM2 performed reasonably well in reproducing corn yield components and N dynamics on the Bonneau, Norfolk, Dunbar, and Noboco soil series under supplemental irrigation. Indeed, evaluation of the model simulations during the experimental period showed acceptable values of the performance indicators (e.g., $-4.12\% \leq$ Pbias $\leq 13.16\%$, $0.37 \leq$ RSR ≤ 0.75, and $0.57 \leq R^2 \leq 0.91$). Analysis of the N dynamics at the high and low N rates (i.e., management scenarios A and B) showed that N leaching is the main source of N loss. In particular, figure 2 and table 6 revealed that a substantial fraction of the available N was leached from the soil profile at the beginning of the crop season. This pattern could be associated with the temporal gap between available soil N and plant N demand at the beginning of the crop season because 56% to 79% of N leaching likely occurred during the first two months of the season (table 6). A lower N supply at the beginning of the crop season could reduce the amount of N leaching, but the potential impact on corn yield needs to be evaluated for each of the sandy soil series. For that purpose, the calibrated RZWQM2 model was used to simulate nine

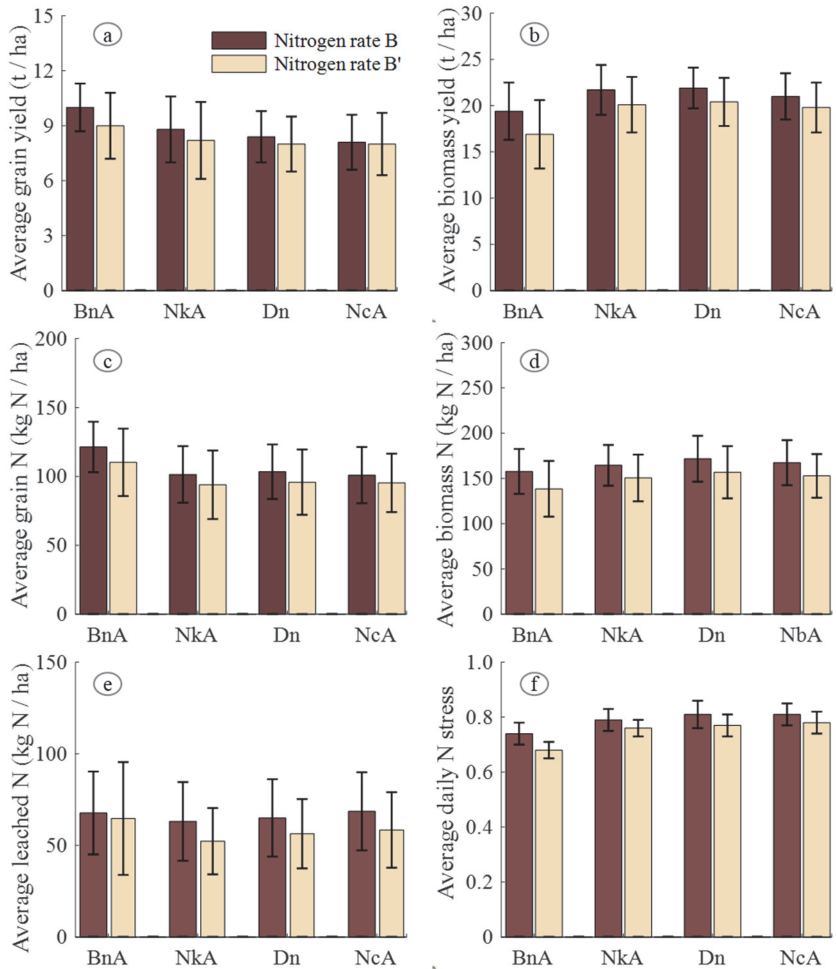

Figure 4. Multiyear RZWQM2-simulated corn yield components for four sandy soil series (BnA, NkA, Dn, and NcA) for two low N application rates (B and B′). Error bars indicate standard deviations.

Table 7. Non-parametric Wilcoxon signed-rank test (W-test) of median equality to compare effects of high N rates. Rate A is 224 kg N ha^{-1} fertigation and 25 kg N ha^{-1} as preplant fertilization. Rate A′ is rate A without the 25 kg N ha^{-1} preplant fertilization.[a]

	Grain Yield (t ha^{-1})			Biomass (t ha^{-1})			N Leached (kg N ha^{-1})			N Stress		
Soil Series	A	A′	W-test	A	A′	W-test	A	A′	W-test	A	A′	W-test
BnA	11.91	10.95	**	21.89	19.15	**	79.52	75.03	ns	0.78	0.73	**
NkA	11.15	11.04	ns	24.50	24.08	*	63.03	58.92	**	0.81	0.79	*
Dn	9.45	9.81	ns	24.25	23.34	ns	73.39	53.69	**	0.84	0.82	ns
NcA	9.95	9.29	ns	23.00	22.32	ns	75.65	71.35	ns	0.85	0.81	ns

[a] Following the non-parametric Wilcoxon signed-rank test of median comparison between A and A′, asterisks (** and *) indicate that the medians are significantly different (at p = 0.01 and 0.05, respectively), and ns indicates that the hypothesis of median equality cannot be rejected (at p = 0.05).

Table 8. Non-parametric Wilcoxon signed-rank test (W-test) of median equality to compare effects of low N rates. Rate B is 157 kg N ha^{-1} fertigation and 25 kg N ha^{-1} as preplant fertilization. Rate B′ is rate B without the 25 kg N ha^{-1} preplant fertilization.[a]

	Grain Yield (t ha^{-1})			Biomass (t ha^{-1})			N Leached (kg N ha^{-1})			N Stress		
Soil Series	B	B′	W-test	B	B′	W-test	B	B′	W-test	B	B′	W-test
BnA	10.39	9.72	**	20.01	17.40	**	68.22	64.70	ns	0.73	0.68	**
NkA	9.45	9.20	ns	21.75	20.12	**	57.09	48.85	*	0.80	0.75	**
Dn	8.49	8.62	ns	22.20	21.01	**	61.59	48.97	**	0.79	0.76	**
NcA	8.22	8.56	ns	20.98	19.52	*	70.89	54.17	*	0.79	0.77	**

[a] Following the non-parametric Wilcoxon signed rank of median comparison between B and B′, asterisks (** and *) indicate that the medians are significantly different (at p = 0.01 and 0.05, respectively), and ns indicates that the hypothesis of median equality cannot be rejected (at p = 0.05).

years of consecutive corn seasons under four N managements scenarios, including two high N rates (A and A′) and two low N rates (B and B′).

With each of the soil series (BnA, NkA, Dn, and NcA), the multi-year RZWQM2 simulations of corn crops under the different N management scenarios corroborated the general tendency of a positive corn yield response to N fertilization (D’Andrea et al., 2008; Cerrato and Blackmer, 1990). Compared to the low N scenarios, the high N scenarios showed higher grain yields and lower N stresses. The yield difference between the high and low N rates was clearly a consequence of frequent N stress that occurred at the low N rates. This is confirmed by the N stress values in table 7 (high N scenarios), which are higher than those in table 8 (low N scenarios). The RZWQM2 simulations of grain yields aligned with the experimental results of Stone al. (2016), who reported higher corn grain yield in 2014 (high N application rate) compared to 2013 (low N application rate).

However, variable patterns were noticed depending on the soil series, and these patterns could be exploited for efficient N management. For instance, with the NkA and Dn soils at both the high and low N rates, the elimination of preplant N application significantly reduced N leaching, while the grain yield did not change significantly. This was not the case for the BnA and NcA soils, even though the RZWQM2 simulations were conducted for the same conditions. Hence, the observed differences were likely driven by the specific proprieties of the soils. For instance, in table 2, NkA and Dn showed lower K_{sat} values compared to BnA and NcA. These lower K_{sat} values are likely to slow N leaching and contribute to better nutrient holding in the NkA and Dn soil profiles. Therefore, the results indicate room to improve N management by applying variable rates of N based on field-scale soil variability.

In practice, nutrient management based on field-scale soil variability could be used to enhance N use efficiency in corn production by synchronizing the N supply with corn N uptake. In this scheme, the split application of N fertilizer (Spackman et al., 2019) must be combined with knowledge of the N dynamics in the different soil series. This does not rule out the yield goal system, which emphasizes split N application (Clemson, 2019). Rather, the consideration of soil series variability at field scale would be useful to maximize N use efficiency by reducing N leaching. Indeed, the sandy soils in the Southeastern Coastal Plain are naturally deficient in N due to their poor nutrient holding capacity. This justifies the customary practice of preplant N application as starter fertilization. The role of the starter fertilization is to stimulate root growth during corn seedling, but the effect is not systematic because it depends on the soil, weather, and placement (Spackman et al., 2019; Steusloff et al., 2019; Niehues et al., 2004). The RZWQM2 simulations of the N management scenarios showed that elimination of preplant N would reduce the amount of N loss via leaching, but its effect on corn yield would depend on the soil series. Adequate water and N are both essential for high corn yield (Xu et al., 2020). By assuming supplemental irrigation, N stresses were isolated from water stresses in the RZWQM2 simulations. This modeling approach adds to previous studies that recommended supplemental irrigation for corn production in Coastal Plain sandy soils. For instance, Sohoulande et al. (2019) asserted that supplemental irrigation is needed to stabilize and maintain high corn yields in the Southeastern Coastal Plain. With no irrigation and no stover removal from the corn fields, Cantrell et al. (2014) reported an average grain yield of 4.82 t ha^{-1} during 2010 to 2012. For the same period, our RZWQM2 simulations for the sandy soils under supplemental irrigation showed a higher average grain yield (i.e., 8.39 t ha^{-1}), which aligns with the results reported by Stone et al. (2016).

CONCLUSIONS

This study used RZWQM2 to model corn (*Zea mays* L.) yields and N dynamics for four sandy soil series under different N management scenarios. The RZWQM2 simulation results were comparable with the experimental data, and the performance indicators suggested good performance of the model for the sandy soils of the Southeastern U.S. Coastal Plain. This study is an addition to the RZWQM2 literature because prior applications of RZWQM2 in the conditions of the Southeastern Coastal Plain are virtually unreported in the literature. The multi-year RZWQM2 simulations of corn crops showed possibilities to significantly reduce N leaching while maintaining corn yields. In particular, preplant N application as starter fertilizer seemed to be ineffective depending on the soil series. These results corroborate previous studies that reported various responses of corn to starter fertilizer depending on the soil type (Niehues et al., 2004). Adaptation of these results for effective consideration of field-scale soil variability in N management could be enabled with advances in precision agriculture. For instance, inclusion of digital soil maps in an automated fertilization system could be used to apply variable N rates within a field (Chandel et al., 2016; Reyes et al., 2015). However, N is unstable in most soils; to compensate its temporal deficiency, split applications of N fertilizer are useful to align the N supply with corn N uptake (Spackman et al., 2019). From this standpoint, the consideration of field-scale soil variability could be integrated into the yield goal system to enhance N management for Southeastern Coastal Plain sandy soils under supplemental irrigation.

REFERENCES

Ahuja, L., Rojas, K. W., & Hanson, J. D. (2000). *Root Zone Water Quality Model: Modeling management effects on water quality and crop production*. Highlands Ranch, CO: Water Resources Publications.

Alva, A. K., Collins, H. P., & Boydston, R. A. (2002). Corn, wheat, and potato crop residue decomposition and nitrogen mineralization in sandy soils under an irrigated potato rotation. *Comm. Soil Sci. Plant Anal., 33*(15-18), 2643-2651. https://doi.org/10.1081/CSS-120014469

Cantrell, K. B., Novak, J. M., Frederick, J. R., Karlen, D. L., & Watts, D. W. (2014). Influence of corn residue harvest management on grain, stover, and energy yields. *Bioenergy Res., 7*(2), 590-597. https://doi.org/10.1007/s12155-014-9433-9

Cerrato, M. E., & Blackmer, A. M. (1990). Comparison of models for describing corn yield response to nitrogen fertilizer. *Agron. J., 82*(1), 138-143. https://doi.org/10.2134/agronj1990.00021962008200010030x

Chandel, N. S., Mehta, C. R., Tewari, V. K., & Nare, B. (2016). Digital map-based site-specific granular fertilizer application system. *Curr. Sci., 111*(7), 1208-1213. https://doi.org/10.18520/cs/v111/i7/1208-1213

Clemson. (2019). Fertility recommendations. Clemson, SC: Clemson University Regulatory Services, Agricultural Service Laboratory. Retrieved from https://www.clemson.edu/public/regulatory/ag-srvc-lab/soil-testing/pdf/agronomic_crops.pdf

D'Andrea, K. E., Otegui, M. E., & Cirilo, A. G. (2008). Kernel number determination differs among maize hybrids in response to nitrogen. *Field Crops Res., 105*(3), 228-239. https://doi.org/10.1016/j.fcr.2007.10.007

Gillette, K., Malone, R. W., Kaspar, T. C., Ma, L., Parkin, T. B., Jaynes, D. B., ... Kersebaum, K. C. (2018). N loss to drain flow and N_2O emissions from a corn-soybean rotation with winter rye. *Sci. Total Environ., 618*, 982-997. https://doi.org/10.1016/j.scitotenv.2017.09.054

Godwin, D. C., & Singh, U. (1998). Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. In Tsuji, G. Y., Hoogenboom, G., Thornton, P. K. (Eds.), *Understanding options for agricultural production* (pp. 55-77). Dordrecht, The Netherlands: Kluwer Academic.

Karlen, D. L., Sadler, E. J., & Busscher, W. J. (1990). Crop yield variation associated with Coastal Plain soil map units. *SSSA J., 54*(3), 859-865. https://doi.org/10.2136/sssaj1990.03615995005400030041x

López-Cedrón, F. X., Boote, K. J., Piñeiro, J., & Sau, F. (2008). Improving the CERES-Maize model ability to simulate water deficit impact on maize production and yield components. *Agron. J., 100*(2), 296-307. https://doi.org/10.2134/agronj2007.0088

Ma, L., Ahuja, L. R., Nolan, B. T., Malone, R. W., Trout, T. J., & Qi, Z. (2012). Root Zone Water Quality Model (RZWQM2): Model use, calibration, and validation. *Trans. ASABE, 55*(4), 1425-1446. https://doi.org/10.13031/2013.42252

Ma, L., Hoogenboom, G., Ahuja, L. R., Ascough, J. C., & Saseendran, S. A. (2006). Evaluation of the RZWQM-CERES-Maize hybrid model for maize production. *Agric. Syst., 87*(3), 274-295. https://doi.org/10.1016/j.agsy.2005.02.001

Malone, R. W., Herbstritt, S., Ma, L., Richard, T. L., Cibin, R., Gassman, P. W., ... Fang, Q. X. (2019). Corn stover harvest N and energy budgets in central Iowa. *Sci. Total Environ., 663*, 776-792. https://doi.org/10.1016/j.scitotenv.2019.01.328

Malone, R. W., Jaynes, D. B., Ma, L., Nolan, B. T., Meek, D. W., & Karlen, D. L. (2010). Soil-test N recommendations augmented with PEST-optimized RZWQM simulations. *J. Environ. Qual., 39*(5), 1711-1723. https://doi.org/10.2134/jeq2009.0425

Malone, R. W., Kersebaum, K. C., Kaspar, T. C., Ma, L., Jaynes, D. B., & Gillette, K. (2017). Winter rye as a cover crop reduces nitrate loss to subsurface drainage as simulated by HERMES. *Agric. Water Mgmt., 184*, 156-169. https://doi.org/10.1016/j.agwat.2017.01.016

Malone, R. W., Weatherington-Rice, J., Shipitalo, M. J., Fausey, N., Ma, L., Ahuja, L. R., ... Ma, Q. (2004). Herbicide leaching as affected by macropore flow and within-storm rainfall intensity variation: A RZWQM simulation. *Pest Mgmt. Sci., 60*(3), 277-285. https://doi.org/10.1002/ps.791

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. *Trans. ASABE, 58*(6), 1763-1785. https://doi.org/10.13031/trans.58.10715

Morris, T. F., Murrell, T. S., Beegle, D. B., Camberato, J. J., Ferguson, R. B., Grove, ... Meisinger, J. J. (2018). Strengths and limitations of nitrogen rate recommendations for corn and opportunities for improvement. *Agron. J., 110*(1), 1-37. https://doi.org/10.2134/agronj2017.02.0112

Niehues, B. J., Lamond, R. E., Godsey, C. B., & Olsen, C. J. (2004). Starter nitrogen fertilizer management for continuous no-till corn production. *Agron. J., 96*(5), 1412-1418. https://doi.org/10.2134/agronj2004.1412

Oreskes, N., Shrader-Frechette, K., & Belitz, K. (1994). Verification, validation, and confirmation of numerical models in the Earth sciences. *Science, 263*(5147), 641-646. https://doi.org/10.1126/science.263.5147.641

Reyes, J. F., Esquivel, W., Cifuentes, D., & Ortega, R. (2015). Field testing of an automatic control system for variable-rate fertilizer application. *Comput. Electron. Agric., 113*, 260-265. https://doi.org/10.1016/j.compag.2015.03.003

Ribaudo, M., Delgado, J., Hansen, L., Livingston, M., Mosheim, R., & Williamson, J. (2011). Nitrogen in agricultural systems: Implications for conservation policy. Economic Research Report No. 127. Washington, DC: USDA Economic Research Service. https://doi.org/10.2139/ssrn.2115532

Saseendran, S. A., Ma, L., Malone, R., Heilman, P., Ahuja, L. R., Kanwar, R. S., ... Hoogenboom, G. (2007). Simulating management effects on crop production, tile drainage, and water quality using RZWQM-DSSAT. *Geoderma, 140*(3), 297-309. https://doi.org/10.1016/j.geoderma.2007.04.013

Sigua, G. C., Stone, K. C., Bauer, P. J., Szogi, A. A., & Shumaker, P. D. (2017). Impacts of irrigation scheduling on pore water nitrate and phosphate in Coastal Plain region of the United States. *Agric. Water Mgmt., 186*, 75-85. https://doi.org/10.1016/j.agwat.2017.02.016

Sohoulande, C. D., Stone, K., Szogi, A., & Bauer, P. (2019). An investigation of seasonal precipitation patterns for rainfed agriculture in the southeastern region of the United States. *Agric. Water Mgmt., 223*, 105728. https://doi.org/10.1016/j.agwat.2019.105728

Spackman, J. A., Fernandez, F. G., Coulter, J. A., Kaiser, D. E., & Paiao, G. (2019). Soil texture and precipitation influence optimal time of nitrogen fertilization for corn. *Agron. J., 111*(4), 2018-2030. https://doi.org/10.2134/agronj2018.09.0605

Stanford, G. (1973). Rationale for optimum nitrogen fertilization in corn production. *J. Environ. Qual., 2*(2), 159-166. https://doi.org/10.2134/jeq1973.00472425000200020001x

Steusloff, T. W., Nelson, K. A., Motavalli, P. P., & Singh, G. (2019). Fertilizer placement affects corn and nitrogen use efficiency in a claypan soil. *Agron. J., 111*(5), 2512-2522. https://doi.org/10.2134/agronj2019.02.0108

Stone, K. C., Bauer, P. J., & Sigua, G. C. (2016). Irrigation management using an expert system, soil water potentials, and vegetative indices for spatial applications. *Trans. ASABE, 59*(3), 941-948. https://doi.org/10.13031/trans.59.11550

Stone, K. C., Bauer, P. J., & Sigua, G. C. (2019). Potential water conservation using site-specific variable-rate irrigation. *Appl. Eng. Agric., 35*(6), 881-888. https://doi.org/10.13031/aea.13108

Sun, M., Huo, Z., Zheng, Y., Dai, X., Feng, S., & Mao, X. (2018). Quantifying long-term responses of crop yield and nitrate leaching in an intensive farmland using agro-eco-environmental model. *Sci. Total Environ., 613-614*, 1003-1012. https://doi.org/10.1016/j.scitotenv.2017.09.080

Swaney, D. P., Howarth, R. W., & Hong, B. (2018). Nitrogen use efficiency and crop production: Patterns of regional variation in the United States, 1987-2012. *Sci. Total Environ., 635*, 498-511. https://doi.org/10.1016/j.scitotenv.2018.04.027

USDA-NRCS. (2006). Land resource regions and major land resource areas of the United States, the Caribbean, and the Pacific Basin. USDA Handbook 296. Washington, DC: USDA Natural Resources Conservation Service.

Wilcoxon, F., Katti, S. K., & Wilcox, R. A. (1970). Critical values and probability levels for the Wilcoxon rank sum test and the Wilcoxon signed rank test. *Selected tables in mathematical statistics, 1*, 171-259. Institute for Mathematical Statistics.

Woolson, R. F. (2007). Wilcoxon signed-rank test. In *Wiley encyclopedia of clinical trials*. https://doi.org/10.1002/9780471462422.eoct979

Xu, J., Cai, H., Wang, X., Ma, C., Lu, Y., Ding, Y., ... Saddique, Q. (2020). Exploring optimal irrigation and nitrogen fertilization in a winter wheat-summer maize rotation system for improving crop yield and reducing water and nitrogen leaching. *Agric. Water Mgmt., 228*, article 105904. https://doi.org/10.1016/j.agwat.2019.105904