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Simulating soybean productivity under rainfed conditions for major soil types using APEX model in East Central Mississippi

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ABSTRACT

Knowledge of soybean yield constraints under rainfed conditions on major soil types in East Central Mississippi would assist growers in the region to effectively utilize the benefits of water/irrigation management. The objectives of this study were to use the Agricultural Policy/Environmental eXtender (APEX) agro-ecosystem model to simulate rainfed soybean grain yield (GY) for nine major soils during 14 years (2002–2015) and then to evaluate selected model inputs/outputs in relation to irrigation management that may decrease difference in simulated GY among the different soils. Values for GY ranged broadly from 2.24 to 6.14 Mg ha^{-1} across soils and years, giving a maximum yield difference of 3.90 Mg ha^{-1}. For the average GY of nine soils, the range was from 3.52 to 5.42 Mg ha^{-1} over 14 years. Averaged across 14 years, GY ranged from 3.66 to 4.90 Mg ha^{-1} across the nine soils and was affected by difference in soil texture (clay and sand percentages) and soil available water content (AWC). Simulations revealed relatively high water stress during the R4, R5 and R6 stages of plant development (early- to mid-fruit development), suggesting great potential to enhance soybean yield if some irrigation is provided during these critical water stress periods; whereas, the potential was accordingly less in the normal and wet years. Results indicated installing irrigation on Griffith, Sumter or Demopolis soils would have a large impact through increased crop productivity and yield stability.

1. Introduction

Soybean is an important crop in American agriculture and a major crop in Mississippi, with an area of 817 × 10^3 ha in 2014 accounting for 44% of the total cropland area (NRCS, 2015). Approximately 70%–85% of total soybean acreage in Mississippi is rainfed, meaning the land does not have irrigation facility (Thomas and Blaine, 2014). Worldwide, there is concern that crop productivity under rainfed conditions will need to be enhanced to meet increasingly growing demand for food (Bhatia et al., 2008).

Even in humid climatic regions, such as Mississippi, rainfall is variable from year-to-year and during the crop growing season (Paz et al., 2007). Studies on year-to-year variation in rainfed productivity have found knowledge of yield difference can help in developing management strategies to improve the productivity of peanut, soybean and rice (Naab et al., 2004; Bhatia et al., 2008; Worou et al., 2013).

Determining the productivity and yield variability of rainfed soybean through field experiments under different soil types and rainfall conditions requires multiple years to make reasonable and meaningful references. Additionally, field experiments have uncertainty regarding the growth of soybean due to the impact of multiple factors from climatic factors, soil properties, and even the human management. In recent years, many process-based crop growth dynamic simulation models have been developed and applied to predict crop growth, leaf area index (LAI), grain yield (GY) and biomass using systems method that integrate knowledge of the underlying processes and interaction of different components of crop production (Boote et al., 1996; Van Ittersum et al., 2013). For example, Sun and Ren (2014) used the Soil and Water Assessment Tool (SWAT) to assess crop yield and water productivity in the Haihe plain, China. Bhatia et al. (2008) used CROPGRO model to analyze the potential yields and yield gaps of rainfed soybean in India. Saseendran et al. (2015) used Root Zone Water Quality Model (RZWQM) to estimate the average corn crop water production func-

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tion. Hence, it is possible to use a growth model to simulate rainfed soybean productivity and yield difference on different soil types under different climatic conditions.

The Agricultural Policy/Environmental eXtender (APEX) is a tool for managing whole farms or small watersheds to achieve sustainable production and maintain environmental quality (Williams et al., 2008). APEX can be used as a Best Management Practice model by simulating a variety of land management scenarios (Borah et al., 2006). Since its inception in 1996, APEX has been used in a number of studies to evaluate the impact of agricultural practices (Saleh et al., 2004; Cavero et al., 2012) at both watershed (Wang et al., 2008; Cavero et al., 2012) and regional scales (Powers et al., 2011). Studies which suggest soil management impacts on runoff, sediment yield, corn productivity and soil organic carbon were successfully simulated by APEX (Wang et al., 2008). Powers et al. (2011) used APEX to simulate water and soil quality environmental impacts associated with bioenergy crop production and biomass removal in the Midwest USA. Cavero et al. (2012) conducted APEX simulation of best irrigation and N management strategies in three Mediterranean watersheds. Such studies indicated the APEX model is capable of successfully modeling the impacts of climate, soil, cropping system, tillage, irrigation and management practices on crop growth and productivity.

Knowledge is needed on rainfed soybean productivity under different soil types and rainfall category years in order to improve agricultural sustainability through strategies that may reduce yield variability. The objectives of this study were to: (1) calibrate and validate APEX model using the NRCS SSURGO database and field experimental datasets from twelve treatments conducted in 2014 and 2015 in Eastern Central Mississippi that involved four soil types and three irrigation levels; (2) simulate the rainfed soybean GY and assess yield difference on nine major agricultural soil types and in 14 rainfall category years from 2002 to 2015; and, (3) explore the possible reasons for yield differences among soils and years, and recommend irrigation management measures for the different soils to improve GY stability.

Table 1a
A full list of the abbreviations used in this paper.

Abbreviation	Full explanation
APEX	Agricultural Policy/Environmental eXtender
GY	grain yield
BIOM	daily dry biomass including roots and above ground plant material
ET_c	weekly evapotranspiration
LAI	leaf area index
FLAI	fraction of growing season when LAI starts to decline
SW	soil water storage from 0 to 100 cm depth
HI	harvest index
RD	root depth
CH	crop height
VA	Vaiden soil type
OK	Okolona soil type
DE	Demopolis soil type
BR	Brooksville soil type
BER	biomass energy ratio
RUE	radiation use efficiency
EF	Nash-Sutcliffe modeling efficiency
RMSE	root mean square error
RRMSE	relative root mean square error
MAE	mean absolute error
RMAE	relative mean absolute error
WS	water stress
AWC	soil available water content
AYNS	average yield of nine soils types in each category year
ERUE	effective rainfall use efficiency
TRL	total rainfall loss in growing season

2. Materials and methods

2.1. Study area and APEX model description

2.1.1. Noxubee county

Noxubee county is an important crop planting region in East Central Mississippi, with cropland area of approximately 22.9×10^3 ha in 2014, accounting for 12.3% of total area in the county. Soybean is the major crop grown on approximately 8.3×10^3 ha, accounting for 36.2% of crop land in Noxubee county (NRCS, 2015). The dominant agricultural soil types are Vaiden, Catalpa, Leeper, Brooksville, Okolona, Kipling, Griffith, Sumter and Demopolis, which account for 97.0% of total cropland (Fig. 1; USDA, 2003) (Table 1a). Vaiden, Catalpa, Leeper, Brooksville, Okolona, Griffith and Sumter are silty clay (Table 1b). Kipling is silty clay loam and Demopolis is clay loam, and both of these soil types have a relatively large sand percentage. The soil available water content (AWC, the amount of water at field capacity minus the amount at permanent wilting point) ranges from approximately 0.09 m/m to 0.19 m/m. The AWC and other soil properties were decided in 0.30 m surface soil, as evinced by the two-year field experiments in 2014 and 2015 approximately 80% roots were located in 0.30 m soil depth in Mississippi, a humid region (Table 1b). Based on the USDA-NRCS descriptions, soils in the area are characterized as having a thermic temperature regime, a udic or aquic moisture regime, and a smectitic or carbonatic mineralogy.

2.1.2. APEX model description and input parameters

The WinAPEX software, a user-friendly Windows interface designed by the Blackland Research and Extension Center (Williams et al., 2008; Steglich et al., 2014) was used for the simulations, because it provides an environment for executing the latest APEX version 0806. WinAPEX inputs include weather data, soil properties, crop data and management. Weather data were input daily and included precipitation, maximum and minimum air temperature, solar radiation, average wind speed and average relative humidity. These data were used to estimate potential evaporation and evapotranspiration using the Penman method (Penman, 1948; Williams et al., 2008).

The model computes water evaporation from soils and plants separately, as described by Ritchie (1972). The volume of runoff water was estimated using the infiltration equation of Green and Ampt (1911). The APEX model uses a generic crop growth model (Williams et al., 1989) that is capable of simulating growth for approximately 100 annual and perennial crops. Potential increase in biomass for a day was computed according to Monteith (1977) and daily crop LAI was simulated according to Acevedo et al. (1971) and Watts (1972).

Convenient interfaces are supplied by APEX for assembling inputs and interpreting outputs (Williams et al., 2012). Soil properties by layer for the nine soil types were used for APEX simulation. These data were primarily from NRCS SSURGO database (USDA, 2003) and included layer depth, bulk density, field capacity, wilting point, percentage sand, percentage silt, percentage organic carbon and saturated hydraulic conductivity. Field experiments conducted in 2014 and 2015 (described below) provided inputs on soybean growth, GY, LAI, harvest index (HI), root depth (RD), crop height (CH), biomass and plant population, as well as crop management inputs such as the rate and/or date of plough, sowing, fertilizer, irrigation, pest control, cultivar and harvest.

2.2. Field experiments for calibration and validation of APEX model

Experiments were conducted in a 7.04 ha irrigated field in 2014 and in a 1.21 ha irrigated field in 2015 that were located in Noxubee County, Mississippi. A soybean group IV cultivar was planted at

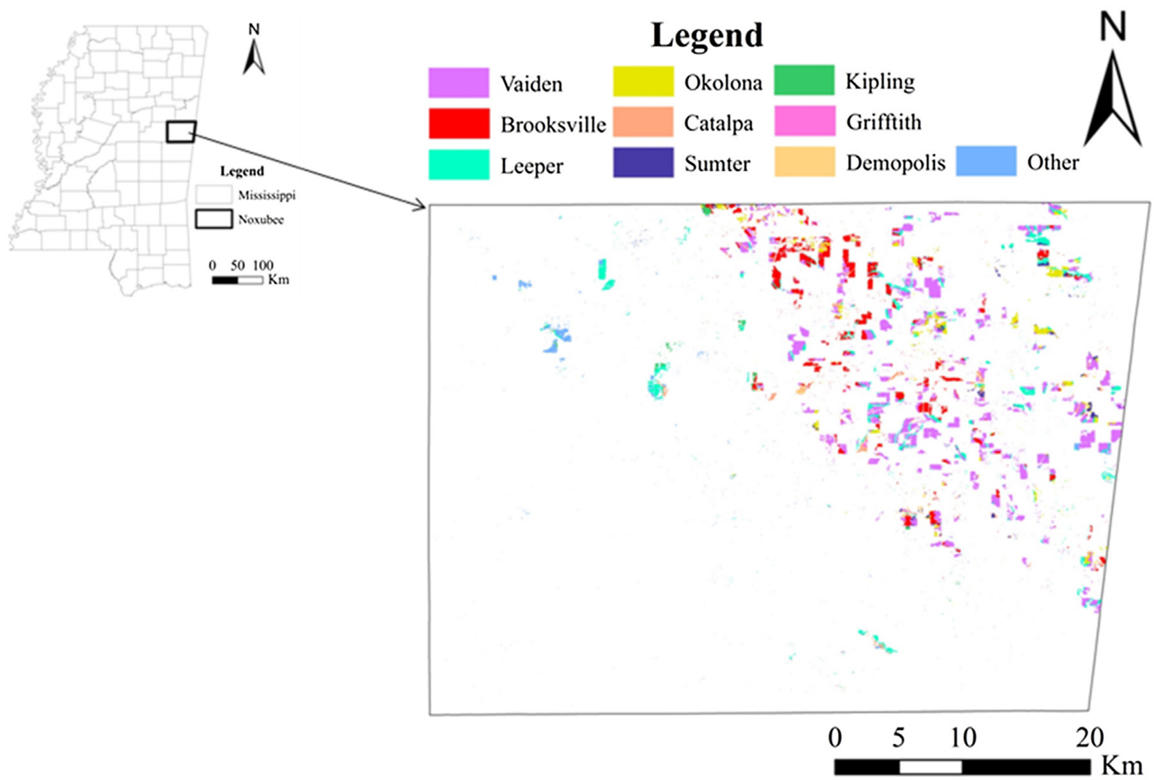

Fig. 1. Location and the nine major soil types growing crop of study area, Noxubee county.

Table 1b
Nine soil types used in simulating studies and their properties in 0.3 m surface soil layer thickness[a].

Soil type	AWC	Sand content	Silt content	Clay content	Soil texture	Description
	(m/m)	(%)	(%)	(%)		
Vaiden	0.19	8.40	40.10	51.50	Silty clay	Very-fine, smectitic, thermic Aquic Dystruderts
Catalpa	0.17	7.82	50.55	41.63	Silty clay	Fine, smectitic, thermic Fluvaquentic Hapludolls
Leeper	0.18	7.56	48.86	43.58	Silty clay	Fine, smectitic, nonacid, thermic Vertic Epiaquepts
Brooksville	0.16	7.00	48.00	45.00	Silty clay	Fine, smectitic, thermic Aquic Hapluderts
Okolona	0.17	7.20	45.40	47.40	Silty clay	Fine, smectitic, thermic Oxyaquic Hapluderts
Kipling	0.16	13.67	49.60	36.73	Silty clay loam	Fine, smectitic, thermic Vertic Paleudalfs
Griffith	0.09	7.67	51.33	41.00	Silty clay	Fine, smectitic, thermic Aquic Hapluderts
Sumeter	0.13	6.42	49.25	44.33	Silty clay	Fine-silty, carbonatic, thermic Rendollic Eutrudepts
Demopolis	0.16	23.97	48.03	28.00	Clay loam	Loamy, carbonatic, thermic, shallow Typic Udorthents

[a] Soil properties were obtained from USDA-NRCS (http://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx). AWC is soil available water content.

296,525 seeds per hectare on May 8, 2014 and May 19, 2015. Grain was harvested on September 10, 2014 and September 20, 2015. These fields were composed of four soils mapped as Vaiden (VA), Okolona (OK), Demopolis (DE) and Brooksville (BR) (3.76, 2.35, 0.93 and 1.21 ha, respectively; USDA, 2003). Experimental design was completely randomized with four replicates. The irrigation treatments are defined as (i), 'SM', irrigation when measured root zone soil moisture is 50% of total plant available water (TAW) and the amount of irrigation is the water needed to recharge to field capacity; (ii), 'halfSM', the irrigation trigged time is the same as with 'SM', but irrigation provided only half the amount of 'SM' treatment; (iii), 'RF or Rainfed', not irrigated or 0 mm irrigation; and (iv), 'WB', irrigation when root zone soil moisture based on a water balance method (initial soil water minus daily water consumption based ET_c as calculated using weather data) is 50% of TAW and the amount of irrigation is the water needed to recharge to field capacity. The 'SM', 'halfSM' and 'RF' treatments were applied to all four soil types and 'WB' treatment was conducted on BR soil only. Because rainfall was evenly distributed in 2014, the VA, OK and DE soils were provided three irrigation levels of 25.4, 12.7 and 0 mm for 'SM', 'halfSM' and 'RF' during the soybean growing season; these treatments are hereafter refered to as VASM, VAhalfSM, VARF, OKSM, OKhalfSM, OKRF, DESM and DERF, respectively. Similarly, irrigation levels of 114, 57 and 0 mm were supplemented for BR soil, whose treatment names were BRSM, BRhalfSM and BRRF, respectively. While the treatment of BRWB expressed BR soil irrigated with 76 mm based on 'WB' method. Thus, the field experiments in 2014 and 2015 consisted of twelve treatments, hereafter referred to as VASM, VAhalfSM, VARF, OKSM, OKhalfSM, OKRF, DESM, DERF, BRSM, BRhalfSM, BRRF and BRWB.

The weather station is located in Macon, Noxubee county, USA (33.13°N, 88.48°W), which is part of weather data network supported by Mississippi State University (http://ext.msstate.edu/anr/drec/stations.cgi). The study area is a humid region, with long-term

(1895–2014) average annual precipitation of 1307 mm, and average rainfall in April (before sowing) of 126 mm that typically would make soil moisture near field capacity. Initial volumetric soil water content at sowing on May 3, 2014 was 0.46, 0.37 and 0.28 m/m for Vaiden, Okolona, and Demopolis soils, respectively and 0.41 m/m for Brooksville soil on May 13, 2015. In each plot, 5 TM soil moisture sensors (Decagon Inc.) in 2014 and time-domain reflectometry sensors (Acclima Inc.) in 2015 were installed to measure daily soil moisture at depths of 0–15, 15–30, 30–60, 60–100 cm. The LAI was measured destructively using a LI-3100 Area Meter (Li-Cor Inc) in 2014 and non-destructively using a AccuPAR LP-80 (Decagon Inc) in 2015. Most important parameters of weather, soil, crop and management required by the APEX model were measured. Measurements of CH, RD, LAI, canopy cover, and dry biomass of leaf, stem and root were made weekly and the values were used for calibration and validation of the APEX model.

2.3. APEX model calibration

Before a model is applied, it needs to be thoroughly calibrated and validated for given site/region to establish its credibility (Boote et al., 1996). Calibration should start with a sensitivity analysis followed by manual or automated adjustment of the input parameters (Moriasi et al., 2007; Sophocleous et al., 2009). Sensitivity analysis of APEX using manual adjustment indicated soybean biomass and GY were responsive to several input parameters, including crop biomass energy ratio (BER), HI, the maximum LAI, the maximum RD and the fraction of growing season when LAI starts to decline (FLAI), and as expected, soil property, weather situation, and general management practice. Therefore model calibration and validation were conducted using values for GY, daily dry biomass including roots and above ground plant material (BIOM), LAI, weekly evapotranspiration (ET_c) in the whole growing season and soil water storage from 0 to 100 cm depth (SW).

Based on Wang et al. (2008) and Cavero et al. (2012), as well as the present simulations derived using APEX, model calibration should be proceed according to the following order: GY, biomass, LAI, components of water balance, crop parameters, soil property and management. According to Ahjuja and Ma (2011), users should first select a dataset of measured observations for model calibration and the rest for model validation. Considering the diversity of treatments available in 2014 and 2015, six treatments of VASM, VAhalfSM, OKRF, DESM, BRWB and BRRF were used for model calibration and another six treatments of VARF, OKSM, OKhalfSM, DERF, BRSM, BRhalfSM were used for validation.

2.4. APEX model evaluation

A model generally is considered well calibrated and validated if it responds to management practices with reasonable accuracy in terms of root mean squared error (RMSE), the mean absolute error (MAE) and Nash-Sutcliffe modeling efficiency (EF) (Ahjua and Ma, 2002; Maniruzzaman et al., 2015; Hassanli et al., 2016). The RMSE reflects difference in mean values between measured observations and simulated results; however, it is not easy to evaluate model performance. Hence, the relative root mean square error (RRMSE) was taken as an indicator of model fit. The RRMSE is the root mean square error normalized to the mean of the observed values defined as (Ma et al., 1998; Ma et al., 2012):

$$RRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}}{\bar{O}} \quad (1)$$

where P_i and O_i are the model predicted and the experimental measured points, respectively; $\bar{O}$ is the mean of observed values. Small RRMSE means a better model performance, so RRMSE = 0 indicates a perfect match between experimental and modeling results.

A similar measure is the mean absolute error (MAE), which was defined as:

$$MAE = \frac{\sum_{i=1}^{N}|P_i - O_i|}{N} \quad (2)$$

As with RMSE, to evaluate MAE more quantitatively and easily, the relative MAE (RMAE) may be calculated from MAE as:

$$RMAE = \frac{MAE}{\bar{O}} \quad (3)$$

Alternatively, some model users simply use the percentage difference between simulated and measured values as a criterion for goodness of model parameterization (Hanson et al., 1999). For example, the Nash-Sutcliffe modeling efficiency (EF) (Nash and Sutcliffe, 1970) is defined as:

$$EF = 1.0 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \quad (4)$$

EF = 1 indicates a perfect match between predictions and measurements. A high EF, which has maximum value of 1.0, indicates strength of agreement between simulated and measured values. In this paper, calibration and validation of model outputs relied on EF, RMSE and RRMSE for statistical analysis, and RMAE for comparison of graphic analysis.

2.5. Empirical frequency analysis to classify rainfall into different category year

Classification of category year (that is, wet, normal and dry year) to analyze crop productivity has varied in different studies. Studies have shown years can be divided into categories according to either the number of precipitation days in a year (Nagy et al., 2007) or through comparison of annual precipitation with long-term average value (Yang et al., 2003; Liu et al., 2013).

In the present study, empirical frequency analysis (EFA) was used to classify rainfall category year according to rainfall amount in each soybean growing season from 2002 to 2015. Because EFA needs more than 30 years of data, rainfall recorded at the same weather station in the 1960–2001 growing seasons were joined into a dataset. Daley (1991) reported rainfall at a location for a specified time period usually does not have a normal distribution but obeys the Pearson type III distribution. Reports that empirical probability calculated by EFA method agrees well with theoretical probability from the Pearson type III distribution provide confidence in using EFA to determine rainfall category year (Wang et al., 2009; Liu et al., 2013; Zhang et al., 2013). The EFA method is as follow:

(a) Rank rainfall in growing season of each year in descending order with a total n value, where n is the number of growing seasons.
(b) Assign each descending order as a rank m, from the largest as 1 and the smallest as n.
(c) Calculate the empirical probability (P) by Weibull equation (Chow et al., 1988) as follows:

$$P = m/(n + 1) \times 100\% \quad (5)$$

(d) Divide n observations into rainfall category year according to P value (Liu et al., 2013; Zhang et al., 2013): if $P \leq 25\%$, it is categorized as 'wet' year; if $25\% < P < 75\%$, it is categorized as 'normal' year; and if $P \geq 75\%$, it is categorized as 'dry' year.

2.6. Definition of water stress

The APEX model can simulate daily crop water stress (WS), which was used to identify both the timing and duration of water limiting conditions that might result in yield difference among the nine soils. The WS factor is computed by considering plant water supply and demand in the equation of Williams et al. (2012):

$$WS = S/D \quad (6)$$

where S is actual plant uptake, which is equal to actual crop transpiration at some day affected by all available water sources that can be utilized in growth, such as irrigation, rainfall and soil water, mm d^{-1}; D is potential plant water use rate which is equivalent to the potential transpiration given the leaf area index achieved at some day, mm d^{-1}. So, D is the maximum amount of water that can be transpired from the crop if the available water is not limited. Values for WS range from 0 to 1, and plant stress increases as WS decreases.

To validate the outcomes of APEX simulations, the Kolmogorov-Smirnov non-parametric test was used to determine if the distributions of simulated and observed LAI are characteristic of the same or different populations. Analysis of Variance (ANOVA) was used to test the effects of soil types, year categories, and the interaction of soil types and year categories with respect to the mean GY. Multiple comparison analysis by the Fisher's least significant difference (LSD) was conducted to compare the differences among soil types and year categories. All statistical computation and tests for this paper were implemented using SAS software, version 9.2.

3. Results and discussion

3.1. Model calibration and validation

Table 2 presents calibrated results of crop parameters in APEX model, which were used to conduct further validation and simulation studies. Biomass energy ratio (BER) is the amount of crop biomass produced (g m^{-2}) per unit of intercepted solar radiation (MJ m^{-2}), and is equivalent to radiation use efficiency (RUE) (g biomass MJ^{-1}) (Monteith, 1977). GY is calculated through multiplying biomass by HI. Hence, the first step is to calibrate RUE to obtain a good fit between simulated and measured biomass. The second step is to calibrate HI to obtain a good fit between simulated and measured GY. Third is the components of water balance, such as ET_c and SW. Fourth is the maximum LAI. Then is FLAI, the maximum RD and CH. Obviously, to achieve reasonable simulated results, the above steps need to be repeated back and forth many times. Given adequate nutrients and water, soybean RUE is often relatively constant and ranges from approximately 1.32–2.52 g MJ^{-1} (Sinclair and Muchow, 1999). As compared to APEX default maximum values, the field experiments in 2014 and 2015 gave somewhat smaller mean values for RD, CH, FLAI, and HI (Table 2).

Table 2
Calibrated results of soybean crop parameters in APEX model.

Parameters	Crop default range	Soybean calibrated results
Biomass energy ratio (g MJ^{-1})	1–10	2.4
Fraction of growing season when LAI starts to decline	0.1–1.0	0.8
Maximum LAI	1–15	7.4
Maximum crop height (m)	0.1–30	1.2
Maximum root depth (m)	0.6–3.6	1
Harvest index	0–2.5	0.5

Moriasi et al. (2007) recognized that performance for watershed models was acceptable when EF > 0.5. Among the above-mentioned statistics, RRMSE or RMAE is the most unbiased model comparison parameter (Legates and McCabe, 1999). If the RRMSE or RMAE value is within 10% of the measured mean values for all measurements, it is a 'very good' calibration. A value within 20% is considered 'good', within 30% is considered 'satisfactory', and greater than 30% is considered 'poor' for agricultural models (Jamieson et al., 1991).

3.1.1. Model calibration

Simulated values for GY, BIOM, LAI, ET_c and SW were in good accordance with those measured in the calibration dataset (Table 3). Simulated GY was close to measured GY for calibration (5.06 ± 1.34 Mg ha^{-1} versus 5.25 ± 1.83 Mg ha^{-1}), and so was for BIOM (11.89 ± 2.06 Mg ha^{-1} versus 12.09 ± 2.11 Mg ha^{-1}). According to Moriasi et al. (2007), the calibration was acceptable for GY, BIOM, LAI, ET_c and SW, with EF ranging from 0.58 to 0.92 (Table 3). For RRMSE, the calibration is very good for GY, BIOM, LAI, ET_c and SW whose RRMSE value is within 10% (Jamieson et al., 1991), namely, 9.88%, 6.17%, 8.44%, 6.59% and 5.14%, respectively. Meanwhile, in terms of RRMSE and RMAE, Hanson et al. (1999) recommended 15% error for biomass, yield and LAI.

The RMAE for BIOM in the VASM, VAhalfSM, OKRF, DESM, BRWB and BRRF treatments was less than 10%, with values of 6.38%, 5.14%, 5.73%, 5.93%, 6.94% and 4.65% (Fig. 2), respectively, indicating very good comparison between predicted and measured values in the calibration dataset (Jamieson et al., 1991). The trend line of simulated daily BIOM conformed well to soybean growth, suggesting the calibration result for daily BIOM was acceptable (Fig. 2). Similarly, analysis of daily LAI showed a reasonably good calibration for VASM, VAhalfSM, OKRF, DESM, BRWB and BRRF with RMAE values of 11.65%, 9.64%, 8.64%, 7.54%, 8.42 and 7.75% (Fig. 3), respectively, below the 15% error level recommended by Hanson et al. (1999). Although a relatively large bias was observed between measured and simulated LAI for VASM and VAhalfSM, the predicted trend line

Table 3
Summary statistics of calibration results for grain yield (GY), daily dry biomass including roots and above ground plant material (BIOM), daily leaf area index (LAI), weekly evapotranspiration (ET_c), soil water storage from 0 to 100 cm depth (SW).

	N[a]	Simulated		Measured		EF	RMSE	RRMSE
		Mean	STDEV	Mean	STDEV			
GY (Mg ha^{-1})	6	5.06	1.34	5.25	1.83	0.90	0.52	9.88%
BIOM (Mg ha^{-1})	38	11.89	2.06	12.09	2.11	0.87	0.75	6.17%
LAI	36	5.44	0.47	5.35	0.71	0.58	0.45	8.44%
ET_c (mm)	108	23.64	12.57	24.06	12.88	0.92	1.58	6.59%
SW (mm)	502	303.45	36.90	312.75	41.92	0.71	17.64	5.14%

[a] N, number of calibrated and measured observations; EF, Nash-Sutcliffe efficiency; RMSE, root mean square error; RRMSE, root mean square error normalized to the mean of the observed values.

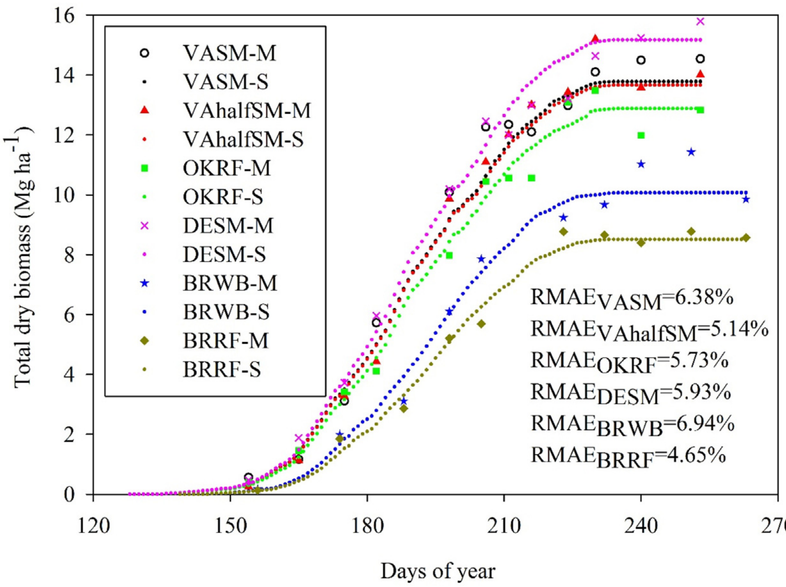

Fig. 2. Relationship between measured (-M) and simulated (-S) total daily dry biomass including the root and above ground pant material (BIOM) for six treatments (VASM, VAhalfSM, OKRF, DESM, BRWB and BRRF) during the calibration period; RMAE, the ratio of the mean absolute error (MAE) to the mean measured values for all treatments.

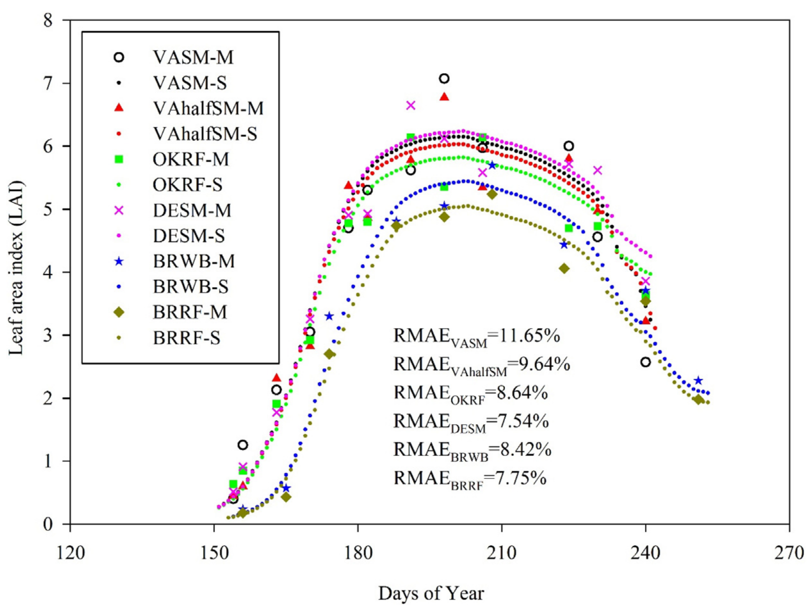

Fig. 3. Relationship between measured (-M) and simulated (-S) daily leaf area index (LAI) for six treatments (VASM, VAhalfSM, OKRF, DESM, BRWB, and BRRF) during the calibration period; RMAE, the ratio of the mean absolute error (MAE) to the mean measured values for all treatments.

of daily LAI for the above six treatments agreed closely with data collected during the field experiments (Fig. 3).

3.1.2. Model validation

The calibrated model reasonably simulated values for GY, BIOM, LAI, ET_c and SW in the validation period, with EF from 0.52 to 0.87 and RRMSE from 7.17% to 11.43%. Simulated GY agreed closely with measured values for the validation (5.11 ± 1.05 Mg ha^{-1} versus 5.02 ± 1.35 Mg ha^{-1}) (Table 4). Additionally, GY values were closely related between predicted and observed values, with EF = 0.78, which met established criteria for satisfactory correlation (Moriasi et al., 2007). The RMSE for GY was 0.57, while RRMSE was 11.43% indicating a good validation (Jamieson et al., 1991). Simulated and measured BIOM values were similar during the validation period (11.85 ± 1.69 Mg ha^{-1} versus 12.08 ± 1.86 Mg ha^{-1}). The statistical parameters also demonstrated satisfactory validation for BIOM with EF = 0.74 and RRMSE = 7.17% based on the constructed criterion (Table 4). Simulated LAI also indicated an acceptable model validation for LAI with values of EF = 0.52 and RRMSE = 8.29% (Table 4). Based on Moriasi et al. (2007) and Jamieson et al. (1991), statistical results of validation indicated acceptable accuracy in modeling ET_c with EF = 0.87 and RRMSE = 8.12% (Table 4). Though the predicted and experimental values for SW were somewhat different (310.42 ± 31.52 mm versus 321.91 ± 42.60 mm), the simulated values appeared reasonable based on EF = 0.59 and RRMSE = 7.32%. The Kolmogorov-Smirnov non-parametric test suggested simulated and observed LAI were not from different

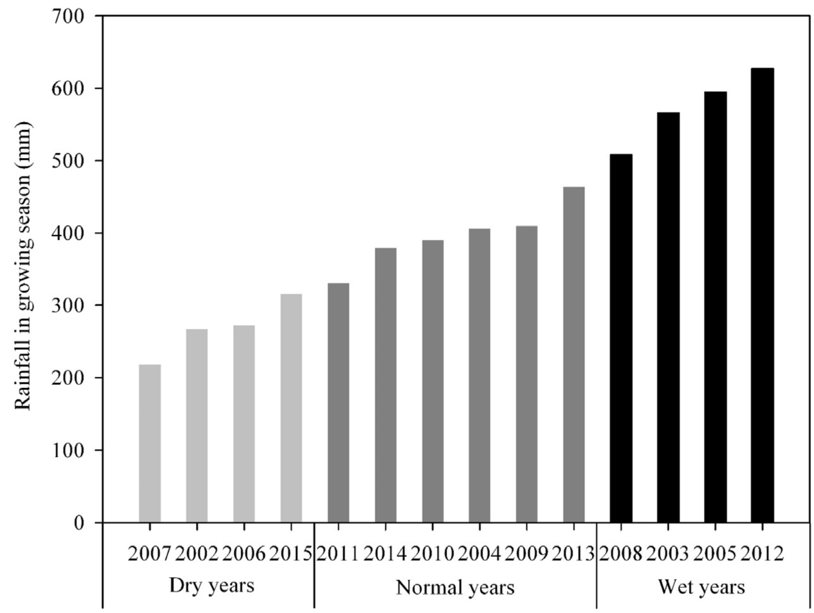

Fig. 4. Ranking of the rainfall category years for the 14-year study period from 2002 to 2015.

Table 4
Summary statistics of validation results for grain yield (GY), daily dry biomass including roots and above ground plant material (BIOM), daily leaf area index (LAI), weekly evapotranspiration (ET_c), soil water storage from 0 to 100 cm depth (SW).

	N[a]	Simulated		Measured		EF	RMSE	RRMSE
		Mean	STDEV	Mean	STDEV			
GY (Mg ha^{-1})	6	5.11	1.05	5.02	1.35	0.78	0.57	11.43%
BIOM (Mg ha^{-1})	38	11.85	1.69	12.08	1.86	0.74	0.93	7.17%
LAI	36	5.49	0.43	5.42	0.66	0.52	0.45	8.29%
ET_c (mm)	108	23.60	12.50	23.96	12.66	0.87	1.95	8.12%
SW (mm)	502	310.42	31.52	321.91	42.60	0.59	23.56	7.32%

[a] N, number of validated and measured observations; EF, Nash-Sutcliffe efficiency; RMSE, root mean square error; RRMSE, root mean square error normalized to the mean of the observed values.

populations, indicating they have the same distributional characteristics ($P > 0.4727$).

3.2. Characteristics of simulated grain yield in 14 years with different rainfall

Based on EFA results (Eq. (5)), 2002, 2006, 2007 and 2015 were categorized as dry years, with growing season rainfall ranging from 218 to 316 mm; 2004, 2009, 2010, 2011, 2013 and 2014 were categorized as normal years, with growing season rainfall ranging from 330 to 464 mm; and 2003, 2005, 2008 and 2012 were categorized as wet years, with growing season rainfall ranging from 508 to 627 mm (Fig. 4).

3.2.1. Overall characteristics of simulated grain yield in category years

Simulated GY ranged broadly from 2.24 to 6.14 Mg ha^{-1} over the 14 years and nine soil types, a difference of 3.90 Mg ha^{-1} (Table 5). When data were averaged across nine soil types, GY for wet, normal and dry years was approximately 4.88, 4.51 and 3.68 Mg ha^{-1}, respectively. Regression analysis indicated a positive correlation between mean GY and rainfall across 14 years ($y = 0.0037x + 2.8651$, $R^2 = 0.60$). Multiple comparison tests showed significant difference among wet, normal and dry category years for GY (LSD = 0.25), in the order of wet > normal > dry.

The highest 'average yield of nine soil types in each category year (AYNS)' was approximately 5.42 Mg ha^{-1} in 2005, which belonged to a wet year (Table 5). The lowest AYNS was 3.52 Mg ha^{-1} in 2015, which belonged to a dry year. So the biggest yield difference in AYNS was 1.90 Mg ha^{-1}. On the whole, the wet and normal years had a higher AYNS ranging from 4.39 to 5.42 Mg ha^{-1} except for normal year 2010 with 3.68 Mg ha^{-1}, while the dry years had the lowest AYNS values, ranging from 3.52 to 4.06 Mg ha^{-1} (Table 5).

Simulated GY had a standard deviation (STDEV) of 0.63, 0.70 and 0.74 Mg ha^{-1} in wet, normal and dry category years, respectively (Table 5). The wet category years of 2003, 2005 and 2012 had relatively small yield variation across soil types, with STDEV of 0.05, 0.49 and 0.28 Mg ha^{-1}, respectively; however, 2008 had relatively large STDEV of 0.97 Mg ha^{-1}. For dry category years, the yield variation was relatively high with STDEV ranging from 0.43 to 1.01 Mg ha^{-1} (Table 5).

The maximum GY of 6.14 Mg ha^{-1} belonged to a normal year, as compared with the maximum GY for wet years of 5.88 Mg ha^{-1} and for dry years of 4.85 Mg ha^{-1}. Wet years had the highest minimum yield of 3.30 Mg ha^{-1}, while dry years had the lowest minimum yield of 2.24 Mg ha^{-1} (Table 5). The lowest value of maximum and minimum GY values were both in dry years. The minimum GY in normal years of 2.43 Mg ha^{-1} was somewhat lower than that in wet years of 3.30 Mg ha^{-1}.

As compared with dry category years, wet and normal years generally had higher simulated GY and lower variation among nine soil types, probably because the model 'saw' rainfall throughout the growing season. In dry years, the simulated plant growth was under water stress at critical developmental stages, which may be the main reason to cause greater GY variability. Hence, considering the results of high and stable GY in wet years, supplemental water

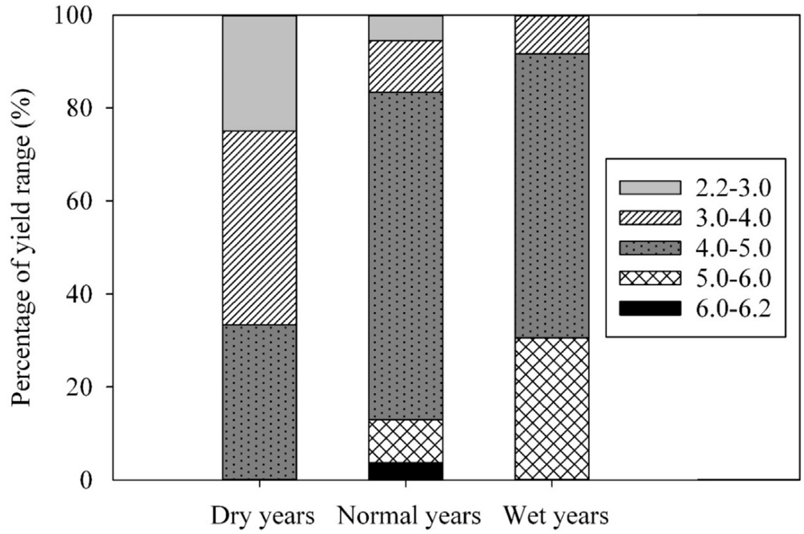

Fig. 5. Selected yield ranges for nine soil types during the categorized wet (n = 36), normal (n = 54) and dry years (n = 36).
Note: Percentage of yield range is the number of simulated yields in this range in ratio to the total number of yields in dry, normal and wet category years.

Table 5
Simulated grain yield statistics across nine soil types for wet, normal and dry years.

Category years	Number of simulations	Average	STDEV	Minimum	Maximum
		$Mg\ ha^{-1}$			
2003	9	4.67	0.05	4.58	4.70
2005	9	5.42	0.49	4.67	5.84
2008	9	4.67	0.97	3.30	5.88
2012	9	4.77	0.28	4.23	4.96
Wet years	36	4.88[a]	0.63	3.30	5.88
2004	9	4.41	0.07	4.28	4.45
2009	9	4.92	1.00	3.66	6.14
2010	9	3.68	0.84	2.43	4.31
2011	9	4.39	0.45	3.70	4.69
2013	9	4.99	0.01	4.98	5.00
2014	9	4.70	0.19	4.28	4.81
Normal years	54	4.51[b]	0.70	2.43	6.14
2002	9	4.06	0.43	3.34	4.42
2006	9	3.60	1.01	2.24	4.85
2007	9	3.55	0.89	2.40	4.66
2015	9	3.52	0.61	2.82	3.94
Dry years	36	3.68[c]	0.74	2.24	4.85

Note: Means with the same letter are not significantly different ($P < 0.05$).

by irrigation probably is an effective way to increase and stabilize GY of soybean in East Central Mississippi.

3.2.2. Simulated grain yield range and distribution among category years

Soybean GY was simulated on nine soil types in four 'wet' (36), six 'normal' (54) and four 'dry' (36) category years, giving a total of 126 yield observations. The highest yield range of 6.0–6.2 $Mg\ ha^{-1}$ was rarely observed, just 3.7% of the total observations and in normal years only (Fig. 5). The occurrence of a 5.0–6.0 $Mg\ ha^{-1}$ yield range was 9.3% in normal years, increasing to 30.6% in wet years; it was 0% in dry years. The yield range of 4.0–5.0 $Mg\ ha^{-1}$ was proportionally large for wet, normal and dry category years, accounting for 61.1%, 70.3% and 33.3%, respectively. The occurrence of 3.0–4.0 $Mg\ ha^{-1}$ yield range mainly distributed in dry years which accounted for 41.7%, as compared with 8.3% in wet years and 11.1% in normal years. The yield range of 2.2–3.0 $Mg\ ha^{-1}$ was distributed accordingly less in dry and normal years, accounting for 25.0% and 5.6%, respectively. All the yields in wet years exceeded 3.0 $Mg\ ha^{-1}$, so it lacked the yield range of 2.2–3.0 $Mg\ ha^{-1}$ (Fig. 5).

Hence, the GY in wet and normal years mainly distributed in yield range of 4.0–6.2 $Mg\ ha^{-1}$, which accounted for 91.7% and 83.3%, respectively; while that for dry years just accounted for 33.3% (Fig. 5). In yield range 2.2–4.0 $Mg\ ha^{-1}$, it mainly distributed in dry years, which account for 66.7%; while normal and wet years had less distribution, of just 16.7% and 8.3%, respectively. Meanwhile, the wet years had no distribution in the lowest yield range 2.2–3.0 $Mg\ ha^{-1}$ and the dry years had no distribution in yield range of 5.0–6.2 $Mg\ ha^{-1}$.

3.3. Simulated grain yield characteristics among different soil types

3.3.1. Yield statistics and difference of 14 years in each soil type

For the average yield of 14 years, Vaiden, Catalpa and Leeper had the highest GY among nine soil types, with values of 4.90, 4.78 and 4.70 $Mg\ ha^{-1}$, respectively (Fig. 6). In contrast, Griffith, Sumter and Demopolis had the lowest average GY, with values of 3.90, 3.79 and 3.66 $Mg\ ha^{-1}$, respectively. Brooksville, Okolona and Kipling had moderate average GY values of 4.63, 4.58 and 4.51 $Mg\ ha^{-1}$,

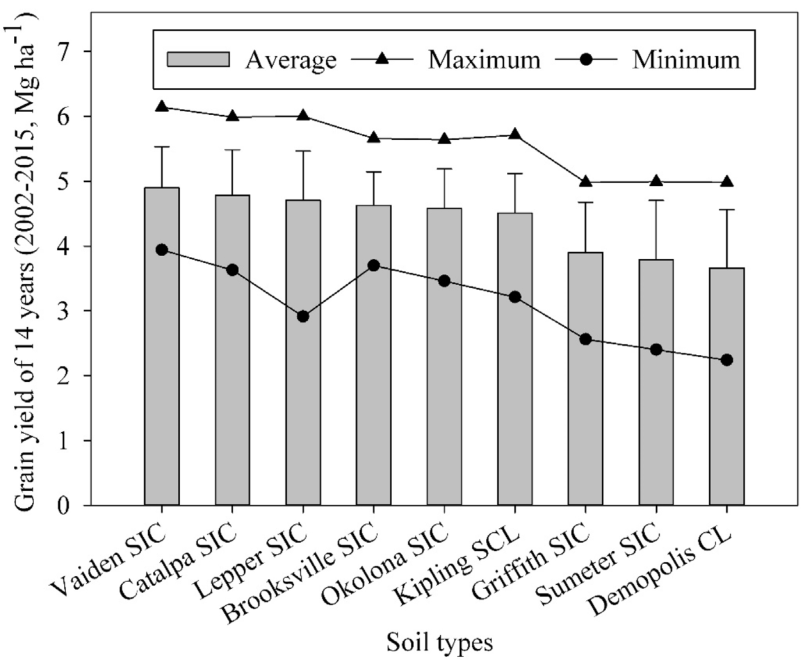

Fig. 6. Average, maximum, minimum grain yield (GY) of 14 years in each soil type.
Note: Error bar means the standard deviation (STDEV).
SIC = silty clay; SCL = silty clay loam; CL = clay loam.

respectively. Meanwhile, multiple comparison test showed that soil types of Vaiden, Catalpa, Leeper, Okolona, Brooksville, and Kipling had relatively higher GY compared to the soil types of Griffith, Sumter, and Demopolis (LSD = 0.43). Hence, the average GY across 14 years had great difference among nine soil types, ranging from 3.66 to 4.90 Mg ha^{-1}, with a difference of 1.24 Mg ha^{-1}. Based on soil textural classification, Kipling is a silty caly loam, Demopolis is a clay loam, and the remaining seven soils are silty clay (Table 1b). Apparently, difference in soil texture had a large effect on soybean productivity, and variation in GY was also evident among soils with silty clay texture.

Griffith, Sumter and Demopolis had large GY variation from 2002 to 2015 with STDEV values from 0.78 to 0.91 Mg ha^{-1}, and that for Vaiden, Catalpa and Leeper was accordingly lower, with STDEV from 0.64 to 0.76 Mg ha^{-1} (Fig. 6) However, GY for Brooksville, Okolona and Kipling varied the least, with STDEV from 0.52 to 0.61 Mg ha^{-1}.

3.3.2. Yield statistics and difference of wet, normal and dry years in each soil type

Vaiden, Catalpa and Leeper produced high average GY in the wet years from 5.17 to 5.34 Mg ha^{-1}, in the normal years from 4.88 to 4.89 Mg ha^{-1}, and in the dry years from 3.98 to 4.47 Mg ha^{-1} (Fig. 7). In contrast, Griffith, Sumter and Demopolis had low average GY in the wet years from 4.22 to 4.41 Mg ha^{-1}, in the normal years from 3.89 to 4.05 Mg ha^{-1}, and in the dry years from 2.75 to 3.24 Mg ha^{-1}. Simulated GY was moderate for Brooksville, Okolona and Kipling soils in the wet years from 5.01 to 5.09 Mg ha^{-1}, in the normal years from 4.63 to 4.70 Mg ha^{-1}, and in the dry years from 3.84 to 4.08 Mg ha^{-1}. Analysis of variance showed that year category by soil type interaction did not significantly affect mean GY ($P = 0.9991$); however, year category and soil type effects were significant ($P < 0.0001$).

Across the nine soil types, difference in GY between wet and normal years (DIF_{w-n}) ranged from 0.29 to 0.44 Mg ha^{-1}, while the difference between wet and dry years (DIF_{w-d}) ranged from 0.87 to 1.58 Mg ha^{-1}. Vaiden, Catalpa, Leeper, Brooksville, Okolona and Kipling soils had relatively small DIF_{w-d} values that ranged from 0.87 to 1.20 Mg ha^{-1}; whereas, Griffith, Sumter and Demopolis soils had large DIF_{w-d} values of 1.10, 1.58 and 1.48 Mg ha^{-1}, respectively (Fig. 7).

Hence, in years with dry growing season, there was a great potential for yield increase through supplemental irrigation and improved soil moisture for additional soybean growth, particularly on the Griffith, Sumter and Demopolis soils.

3.4. Impacting factors analysis of grain yield under rainfed conditions

3.4.1. Avenue of rainfall loss

The total rainfall loss during the growing season (TRL) is equal to the sum of interception, runoff, and percolation. Large year-to-year variation was evident for TRL between 2002 and 2015, and soils also differed in TRL (Fig. 8). In the dry years, TRL for nine soils was relatively low, ranging from 46 to 80 mm, probably due to low rainfall in these growing seasons (Fig. 4). Values ranged from 79 to 189 mm in the normal years. The wet years had relatively high TRL from 106 to 255 mm (Fig. 8). Large TRL in wet years may explain the relatively low simulated GY. For example, even though 2003 was a wet category year, average GY of nine soils was just 4.67 Mg ha^{-1}, and TRL ranged from 205 to 255 mm (Table 5). In another wet year of 2012, TRL differed widely across the nine soils, as compared to the remaining 13 years, and values were approximately 275 mm in Demopolis, 221 mm in Kipling, and 199 mm in Griffith soil (Fig. 8). Additionally, the TRL of these three soils was somewhat greater than for the remaining six soils in 2003, 2004, 2005, 2009, 2010, 2012 and 2013 (Fig. 9), which may be one reason for their low simulated GY values (Fig. 6).

Rainfall interception within each of the 14 years was similar among the nine soil types and was somewhat greater in wet (63 mm) and normal (60 mm) years than in dry years (51 mm) (Fig. 8). In contrast, runoff varied among the nine soil types in wet years of 2003, 2005, 2008 and 2012, with the largest difference reaching 46 mm (Fig. 8). Runoff in the remaining nine years was

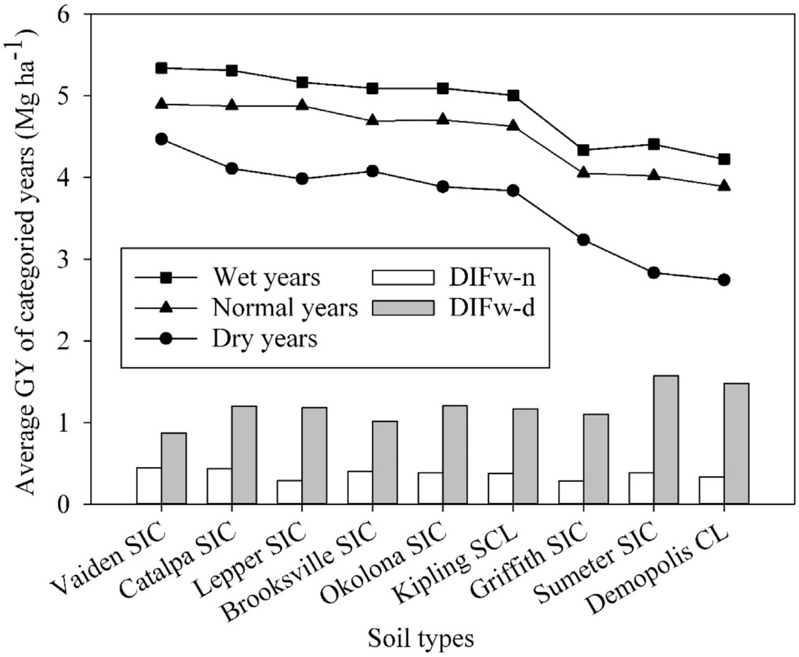

Fig. 7. Grain yield (GY) and difference of wet, normal and dry years in each soil type.
Note: DIFw-d is the difference between average yield of four wet years and average yield of four dry years for each soil type; DIFw-n is the difference between average yield of four wet years and average yield of six normal years for each soil type.
SIC = silty clay; SCL = silty clay loam; CL = clay loam.

Table 6
Effective rainfall use efficiency (ERUE) of 14 years in each soil type.

ERUE (kg ha^{-1} mm^{-1})	Vaiden	Catalpa	Leeper	Brooksville	Okolona	Kipling	Griffith	Sumeter	Demopolis
Average	18.0	16.8	16.4	16.8	17.1	16.6	14.1	12.8	13.3
Minimum	10.8	10.2	10.3	10.7	11.2	12.2	9.2	8.9	9.1
Maximum	29.2	23.2	22.6	26.2	28.4	24.3	19.3	18.1	18.1

accordingly smaller. In general, runoff was low in Demopolis and Kipling soils, probably owing to relatively high sand content. Additionally, Percolation for nine soil types was zero in 2002 and 2007, and ranged from 0 to 10 mm in 2011 (Fig. 8). Demopolis, Kipling and Griffith had relatively high percolation (Fig. 8); Demopolis soil type reached to 181 mm in 2012, which may explain low simulated GY of Demopolis (Fig. 6).

3.4.2. Simulated rainfall use efficiency

In assessing rainfall use efficiency among nine soil types in growing seasons from 2002 to 2015, the different soil types appeared to differ in percolation and runoff even in the same year. So, effective rainfall use efficiency (ERUE, kg ha^{-1} mm^{-1}) was defined as: ERUE = Y/ER, where Y is the simulated GY of some soil type and some year, kg ha^{-1}; ER is effective rainfall (mm), which is equal to Rainfall − (interception + runoff + percolation).

Soybean ERUE under rainfed conditions broadly ranged from 8.9 to 29.2 kg ha^{-1} mm^{-1} across 14 years in Noxubee county of East Central Mississippi (Table 6). The ERUE in 2007 was not only higher, but also varied greatly among nine soil types, ranging from 14.5 to 29.2 kg ha^{-1} mm^{-1}. Possible reasons for this difference were the large variation in simulated GY in 2007, from 2.40 to 4.66 Mg ha^{-1}, and low growing season rainfall of 218 mm. When data were averaged across 14 years, Griffith, Sumter and Demopolis had low ERUE ranging from 12.8 to 14.1 kg ha^{-1} mm^{-1}, while Vaiden, Catalpa, Leeper, Brooksville, Okolona and Kipling had high ERUE ranging from 16.4 to 18.0 kg ha^{-1} mm^{-1} (Table 6). Therefore, it is essential to take measures to minimize percolation and runoff losses so as to increase ERUE for Demopolis, Sumter and Griffith soils.

3.4.3. Relationship between soybean grain yield and soil properties

Averaged across the 14 years, simulated GY for each soil type was related to corresponding values for soil available water content (AWC) in 0.3 m soil surface, with R^2 of 0.50. High AWC indicates large capacity to store water for plant use when weather was dry, which may translate to improved productivity (Table 1b). The higher average GY values for Vaiden, Catalpa and Leeper soil types ranging from 4.70 to 4.90 Mg ha^{-1} (Fig. 6) were in accord with a higher AWC of 0.17–0.19 m/m (Table 1b). In contrast, Griffith and Sumter had lower average GY of 3.90 and 3.79 Mg ha^{-1}, consistent with the low AWC values of 0.09 and 0.13 m/m. Brooksville, Okolona and Kipling had moderate average GY across 14 years, ranging from 4.51 to 4.63 Mg ha^{-1}, in association with moderate AWC values, ranging from 0.16 to 0.17 m/m. In contrast, Demopolis had the lowest average GY though AWC reached to 0.16 m/m, probably due to higher sand content of 23.97% (Table 1b), and higher percolation (Fig. 8). Apparently, AWC was the key factor to determine yield difference in different soil types, because AWC would affect soil water balance components, such as runoff and percolation.

Based on soil texture triangle, Vaiden, Catalpa, Leeper, Brooksville, Okolona, Sumter and Griffith belong to silty clay, and average GY was high and similar in Vaiden, Catalpa, Leeper, Brooksville and Okolona ranging from 4.58 to 4.90 Mg ha^{-1} (Fig. 6). However, average GY for Sumter and Griffith was relatively low, with 3.79 and 3.90 Mg ha^{-1}, respectively. So, for the seven soil types classified as silty clay in texture, simulated GY ranged broadly from

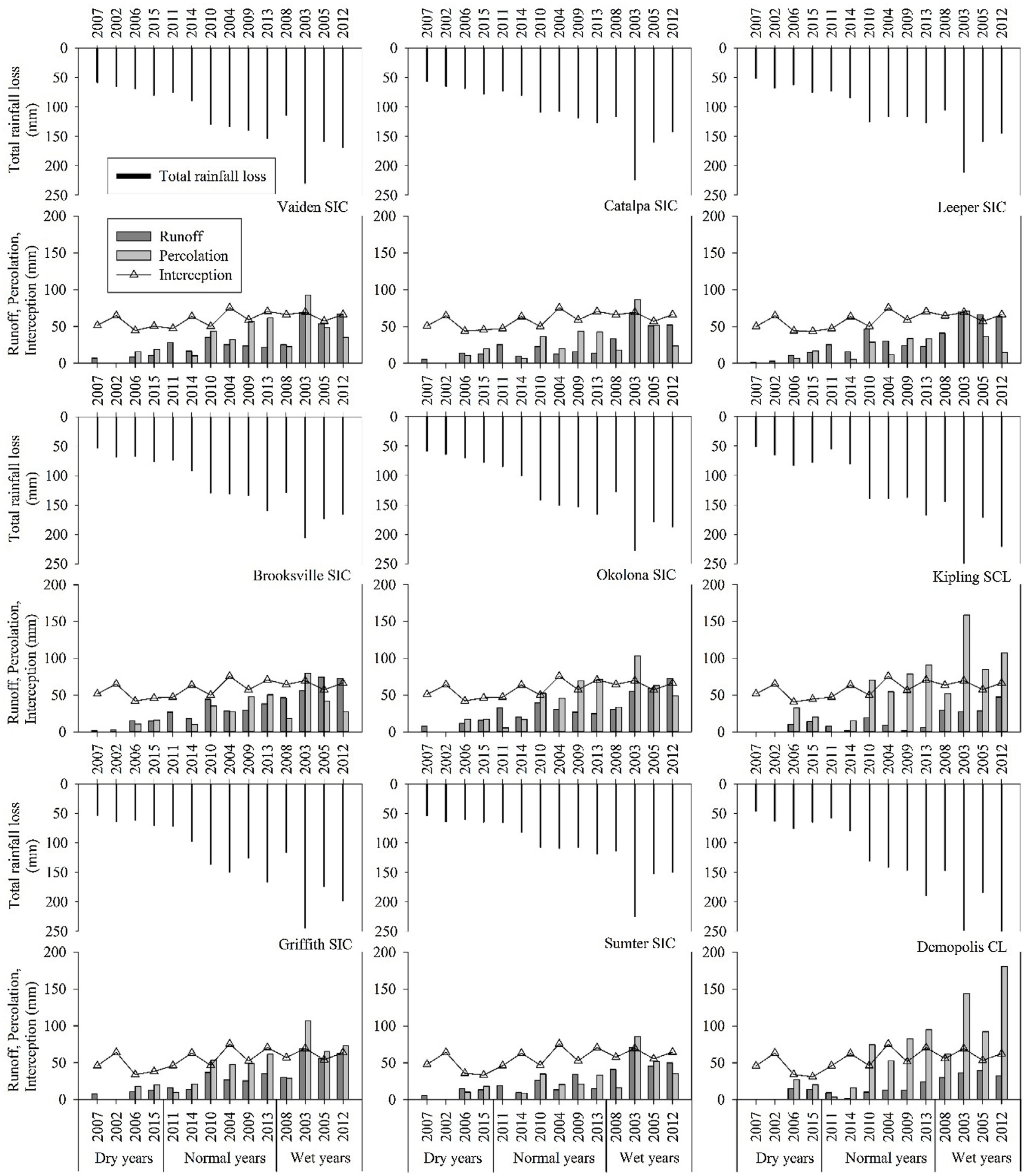

Fig. 8. Runoff, percolation, interception and total rainfall loss during growing season on nine soil types from 2002 to 2015.
Note: SIC = silty clay; SCL = silty clay loam; CL = clay loam.

approximately 3.79–4.90 Mg ha^{-1}, probably due to difference in silt and clay contents by as much as 11.23% (Table 1b).

3.4.4. *Water stress and irrigation management of soybean*

As expected, simulated GY of soybean was responsive to the number of days of water stress (WS) during the growing season. The nine soil types had similar GY values in 2003 and 2013 (Table 5) when WS was close to zero (Fig. 9). Griffith, Sumter and Demopolis had large WS values in each year from 2002 to 2015 (Fig. 9), consistent with their low GY (Fig. 6). Vaiden, Catalpa and Leeper had small WS every year, except 2007 (Fig. 9), consistent with their high GY (Fig. 8). Brooksville, Okolona and Kipling had moderate WS values except in 2007 (Fig. 9), consistent with moderate GY.

Average WS among nine soil types was 23.9 days in dry category years, which accounted for approximately 19% of total soybean growing days. The normal and wet category years had similar average WS values of 7.2 and 7.4 days, respectively. Plants experienced considerable WS in dry years, particularly in 2006, 2007 and 2015,

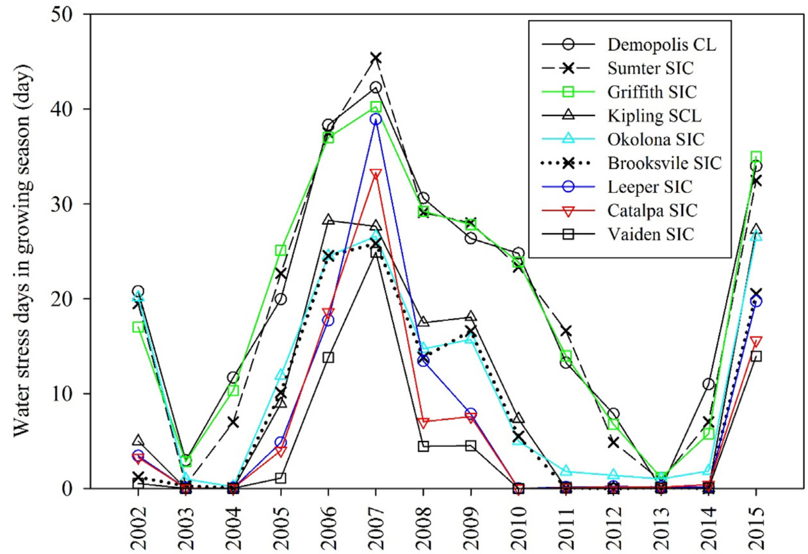

Fig. 9. Simulated water stress among nine soil types over 14 years.

which led to low GY for all soil types. Stressful conditions such as high temperature or moisture deficiency reduce soybean yield, and WS is considered one of the most important factors to limit crop growth and GY, particularly during the grain filling period (Boyer, 1982).

According to simulated results on soybean growth, even in a wet year of 2008 when rainfall in growing season was 508 mm, serious WS among nine soils ranged from 4.5 to 30.6 days. This may have resulted from uneven rainfall distribution, as indicated by the rainfall reaching 50 mm two times and reaching 70 mm two times, combined with increased runoff and percolation of as much as 46 and 62 mm (Fig. 8). Hence, uneven rainfall resulted in higher runoff and percolation, and then led to more WS causing the reduction in simulated GY. So, poor rainfall distribution in growing season often constitutes a more common cause of reduced productivity than low cumulative rainfall (Ochola and Kerkides, 2003; Muhammad and Reason, 2004; Barron and Kwacha, 2005).

Since it is not possible to influence the timing and amount of rainfall (Shaxson and Barber, 2003; Stroosnijder et al., 2008), the best way to produce crops in such an area is through irrigation. According to simulated results on WS timing, WS in dry years mainly happened at Vc, V1, R4, R5, R6, R7 and R8 developmental stages. While in wet and normal years, WS mainly happened at Vc, R5, R6, R7 and R8 developmental stages. Stegman et al. (1990) reported drought stress in R4 to R6 stages was most detrimental to yield. Korte et al. (1983) found a single irrigation during R3-R4 increased seeds per plant and irrigation during R5-R6 increased weight per seed. Yields from a single irrigation at R4, R5 or R6 were similar and approximately 20% greater than plants receiving no irrigation (Sweeney et al., 2003). Interestingly, values for WS in the present study were relatively high at R4, R5, and R6. Hence, in humid regions, such as Mississippi, rainfall can be highly variable and supplemental irrigation is often needed during critical developmental stages, such as R4, R5 and R6, to ensure a high harvest yield.

4. Conclusions

Calibration and validation results demonstrated that simulated soybean grain yield (GY) and growth agreed closely with corresponding measured values. Hence, the APEX model was reasonably accurate in simulating soybean performance under rainfed conditions in East Central Mississippi. Under rainfed conditions, the average GY for wet, normal and dry category years was 4.88, 4.51 and 3.68 Mg ha^{-1}, respectively. High yields in wet years had somewhat less variability across years, as standard deviation was 0.63, 0.70 and 0.74 Mg ha^{-1} for wet, normal and dry category years, respectively. The high yield range of 4.0–6.2 Mg ha^{-1} was found mainly in wet and normal categories years, accounting for 91.7% and 83.3% of the total observations, respectively. In contrast, the relatively low yield range of 2.2–4.0 Mg ha^{-1} in dry category years accounted for approximately 66.7% of total observations, as compared with only 16.7% in normal years and 8.3% in wet years. Even in a humid region like Mississippi, rainfall also varied greatly year by year, and the large yield difference between wet and dry years indicated supplemental irrigation can increase and stabilize GY

Soil texture had a large effect on soybean productivity, and even for the seven soils classified as silty clay in texture (Vaiden, Leeper, Catalpa, Brooksville, Okolona, Griffith and Sumter) GY varied from 3.79 to 4.90 Mg ha^{-1}. Averaged across 14 years, GY was greatest on Vaiden, Leeper and Catalpa soils; less on Griffith, Sumter and Demopolis-clay loam soils; and moderate on Brooksville, Okolona and Kipling-silty clay loam soils. The GY of each soil type was related to soil available water content (AWC) in 0.3 m soil surface, with R^2 of 0.50, suggesting AWC was a key factor influencing yield in the different soil types by affecting runoff and percolation. Results for low rainfall years suggest potential to substantially increase GY if enough irrigation water can be supplied during critical soybean growth stages, such as R4, R5 and R6. By comparison, a small potential to increase yield through irrigation was apparent in wet and normal rainfall years. Additionally, sustainable soybean production on Griffith, Sumter and Demopolis soils may rely on management practices that consider improvements in soil-plant-water relations and their influence on final GY.

Acknowledgements

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