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Preliminary evaluation of the SPOTCOMS model for simulation of Sweetpotato growth and development in the southern United States

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Abstract
Sweetpotato [*Ipomoea batatas* (L.) Lam.] is an economically and nutritionally important root crop, yet the application of process-based crop models for its simulation remains limited, particularly when compared with major cereal crops. Process-based models provide powerful tools for evaluating crop responses to environmental variability, management strategies, and climate- and policy-driven scenarios. This study evaluated the applicability and performance of the SPOTCOMS (Sweet Potato Computer Simulation) model in simulating sweetpotato growth, development, and yield formation. Field experiments were conducted over two consecutive growing seasons (2022 and 2023) using the widely grown 'Covington' cultivar under conventional production practices in Alabama. Comprehensive datasets were collected, including phenological and growth parameters (vine length, leaf area, branch number, and storage root development at multiple growth stages), soil physicochemical properties, and daily weather variables. These data were used to derive cultivar-specific genetic coefficients and to calibrate and validate the SPOTCOMS model. The SPOTCOMS model successfully captured key phenological stages of sweetpotato development, demonstrating high predictive accuracy for storage root number and total yield, with greater than 90% agreement between simulated and observed values. Vine length was also well simulated (R^2 = 0.90). In contrast, predictions of leaf number and branching showed moderate agreement with observations (R^2 = 0.50), indicating model limitations in simulating vegetative architecture. Sensitivity analysis identified early-season growth and mid-season leaf expansion as critical drivers of final storage root yield. Overall, these findings highlight the potential of SPOTCOMS as a decision-support tool for predicting sweetpotato performance and optimizing production in the southeastern United States. Further calibration and validation across multiple cultivars, environments, and management systems are recommended to improve model robustness and broader applicability.

Keywords: Nanourea, conventional urea, growth, LAI, yield and wheat

1. Introduction
Sweetpotato [*Ipomoea batatas* (L.) Lam.] is an important root vegetable crop cultivated in over 100 countries, but predominantly in tropical and subtropical regions [1]. Global production ranged from 88 to 92 million metric tons (Mt), with Asian countries—led by China—accounting for 62%-67% of total production, while African countries contributed 29%-34% [2]. The United States is among the top global ex-porters by volume, with the annual export value rising from $14 million to $187 million between 2001 and 2021 [3].
In the USA, sweet potato production is concentrated in the South due to favorable growing conditions, with North Carolina being the leading state, contributing approximately 60% of total storage roots grown in the country [4]. Although Alabama is not a major sweetpotato producer, the crop remains an important component of the food system for both household consumption and commercial sales. Recently, it was certified as an official vegetable of the state of Alabama [5].
Globally, sweetpotato ranks as the seventh most important staple crop, following wheat, rice, maize, potato, barley, and cassava, and is the fifth most significant food crop in the tropics [7]. It

is an excellent source of carbohydrates, vitamins A (beta-carotene) and C, fiber, and minerals [8, 9]. Beyond its nutritional value, sweetpotato offers numerous health benefits, including antioxidants, cardioprotective, anti-inflammatory, anti-cancer, anti-diabetic, antimicrobial, and anti-obesity properties [10]. Additionally, the storage roots have various applications in the food industry, such as making flour, bread, pastries, fries, and brewing [11], while the leaves can be used for animal feed [12]. In comparison to other food crops, sweetpotatoes are adaptable to marginal growing conditions (such as high temperatures, drought, and low soil nutrients), have short production cycles, and can produce high yield potential under low production costs. Because of these attributes, the crop has been identified as a candidate in contrasting environmental conditions, such as climate change scenarios [13, 14]

Despite its importance, studies on sweetpotato modelling are lagging compared to major cereals and grains [15]. Crop modeling has been used worldwide as an efficient and strategic tool in agricultural research to assess environmental impacts, make informed decisions about crop management, and optimize resource allocation with limited time and resources [16]. These models can be classified based on their purpose in-cluding empirical models (based on the statistical relationship between crop growth and environmental factors); Stochastic models (use a probability of inputs and outputs to stimulate plant growth and environmental interactions); Explanatory models (based on quantitative description of the mechanisms and processes that cause the behavior of crop growth systems); Mechanistic models (explains the relationship between weather parameters and yield as well as the mechanism which influences yield) and the pro-cess-based models which simulate the progression of the crop through over time using differential equations to describe crop development processes as a function of weather and soil conditions as well as crop management [17, 18].

Process-based simulation models are widely used to predict crop performance under diverse biotic and abiotic conditions, providing cost-effective tools for optimizing management strategies [18]. These models play an important role in improving crop management, breeding programs, and policymaking [19]. They are also valuable for analyzing yield gaps [20] and optimizing the utilization of resources such as fertilizer and water/irrigation [21, 22]. Furthermore, they are used to determine the impact of extreme weather on crop growth, assess the effects of climate change on crop production, and select potential adaptation measures [21, 23]. However, the robustness of these models requires evaluation of their performance under similar or the same environmental conditions, and establishing specific genetic coefficients of the intended crop [24, 25].

Process-based models such as Decision Support System for Agrotechnology Transfer (DSSAT) and APSIM (Agricultural Production Systems simulator) have been extensively developed and utilized for grains, cereals, and other commercial crops [26, 27], but less so for root and tuber crops [15, 28]. The existing sweetpotato models include SPOTCOMS (Sweetpotato Computer Simulation), a process-based model [29]; the Climate-Crop Modeling System (CLICROP), an empirical/statistical regression-based model [30]; and the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT), an economic model [31]. Each of these models has its advantages and drawbacks. For instance, SPOTCOMS requires detailed data on sweet potato growth and development, soil, and weather conditions, but allows impact assessments at any location with some calibration. In contrast, CLICROP, uses few data for analyzing climate-crop yield interactions but is limited to yield and climate rela-tionship assessments. IMPACT is designed for large-scale Agriculture policy analysis but cannot be used in yield assessments under conditions that may lie outside the range in which the model was developed [17].

SPOTCOMS, an advanced version of MADHURAM has demonstrated potential in modeling sweetpotato growth in diverse environmental conditions [29]. However, its validation has been limited to specific regions, such as India and East Africa, and varieties grown in those areas, restricting its broader applicability [32]. To enhance its adoption, the model must be tested across a wider range of genotypes, soil types, and climatic conditions. This study aims to evaluate the applicability of SPOTCOMS for simulating the growth and development of sweet potato varieties cultivated in Alabama.

2. Materials and Methods

2.1. Study location

Experiments were conducted at the George Washington Carver Agricultural Experiment Station, Tuskegee University, Alabama, U.S.A. Prior to the present study, the site had been under vegetable cultivation. The climate in Tuskegee is humid subtropical with mild winters and hot, humid summers. The study was conducted over two consecutive crop seasons, summer 2022 and 2023. During the period of the experiments, the mean high and low temperatures ranged between (31.3 and 31.6 °C) and (18.8-19.2 °C) for 2022 and 2023, respectively, with irregular precipitation patterns and humidity (Figure 1). The soil was sandy loam, acidic with a pH range of 5.1 to 6.1, low P and K, and high Mg and Ca concentrations.

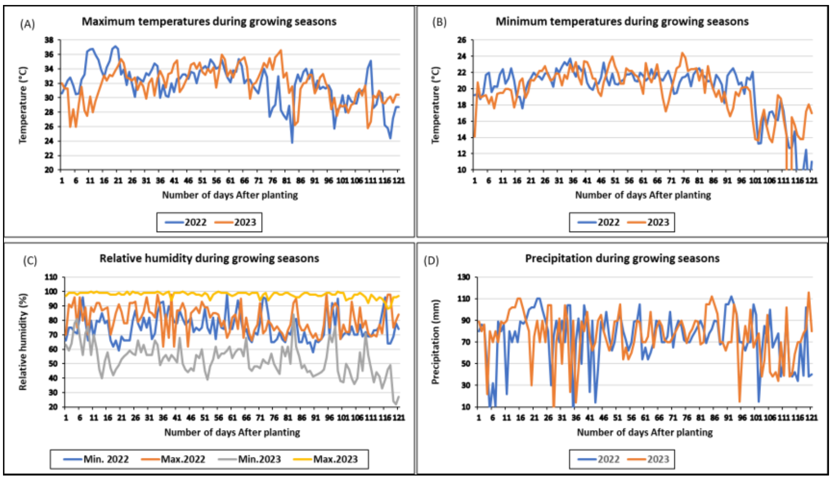

Fig 1: Mean daily weather data, including maximum and minimum temperatures (A and B, respectively), total precipitation (B), and relative humidity (C), in the study area during the 2022/2023 growing seasons

2.2. Land Preparation and Soil Analysis
The experimental field was conventionally tilled (plowed and harrowed) to promote soil aeration and root penetration, optimizing conditions for sweetpotato vine establishment. Prior to planting, soil samples were collected from a 15 cm depth using a zig-zag sampling pattern across the field, homogenized into composite samples, and analyzed for pH, available P K, Mg), and Ca. Fertilizer was applied in single bands 15 cm from the plants 14 days after planting, following soil test recommendations. A 5-4-3 NPK organic fertilizer was applied at a rate of 80-120-150 kg/ha based on soil test recommendations.

2.3. Sweet potato variety
Covington, a cultivar developed by North Carolina State University (NCSU), was used for the study. Fully developed leaves of this variety are cordate to triangular with slight lobing, while young leaves are purple and green when mature. Flowering occurs sporadically during the season, typically triggered by stress conditions. Plants reach maturity 100-120 days after planting, achieving average storage root yields of 45.3 t ha^{-1}, although storage roots can stay in the ground longer without splitting [33].
Storage roots are small to medium, long, slender, with slightly curved, tapered ends, averaging 5 to 8 cm in diameter, and are highly prized for their uniform size, shape, and extended shelf life. The flesh is orange, firm, dense, and creamy with a malty flavor, great for boiling, roasting, or baking. Nutritionally, they are rich in vitamins A, C, and B6, as well as Mg, Fe, and K. Since the early 2000s, Covington began dominating the sweetpotato industry, even surpassing Beauregard, the standard in industry in garden and commercial production due to its consistent quality and adaptability [33]

2.4. Experimental design and planting
The experiments were conducted as a random complete block with one treatment factor: harvest time, and four replications. Each plot was 3m by 1.2 m, in which 30 cm long stem cuttings were planted on ridges at 1.8 m apart and 0.3 m between plants. Cuttings were planted on June 3, 2022, and June 6, 2023, and harvested at 119 and 120 days after planting, respectively.

2.5. Plant management
Standard cultural practices were followed, including fertilizer application and a combination of cultivation and manual weed control until the vines grew out and provided canopy cover. Moisture was provided twice per week through drip irrigation.

2.6. Phenological data collection
Phenological data were measured and recorded at 14-day intervals to monitor the growth and development of the crop. Four plants were randomly selected from each replication and sampled for measurement, including vine length, number of branches, leaves, leaves per vine, and leaf area. At harvest, fresh storage roots were collected, and 25-g subsamples were taken from the middle 10 cm of three US#1 storage roots were dried in an oven at 65-72 °C for 48-72 hours, and dry weights were estimated using a fresh to dry weight ratio.

2.7. Weather Information
Daily weather data for maximum and minimum temperature (°C), relative humidity (%), day length in hours (Hr), and precipitation (mm) were recorded using an onsite weather station. Data was exported into Excel and formatted according to the data format for the SPOTCOMS model.

2.8. Soil data
The soil data used to run the model were obtained from the initial soil analysis before the establishment of the experiments. The parameters used to build soil files for the SPOTCOMS model included texture, pH, P, and K. Soil classification information was obtained from the existing soil reports from previous studies.

Table 1: Soil characteristics of the soil in the experimental field.

Soil property	pH	N	P	K	Mg	Ca
Unit		%	-------------------(lbs/acre)----------------			
Value	5.1	0.08	14	53	32	186

2.9. Calibration and validation of SPOTCOMS crop model
2.9.1. Research modeling framework
The SPOTCOMS (Sweet potato computer Simulation) model [29]. The model simulates phenological development in relation to photothermal time, net assimilation, resource allocation to different plants above and below plant organs, transpiration, and soil water dynamics on a daily time step and crop growth as a function of growing degree days and divides sweet potato growth into three phases. Establishment Phase (0-30 days) extends from planting to root development and initial vine growth., Storage Root Initiation and Development Phase (30-60 days) from storage root initiation to the beginning of storage root bulking and vigorous vegetative growth, and Storage Root Bulking and Maturation Phase (60-120 days) from the beginning of storage root enlargement to final harvest. The parameters that drive the model were determined using the nine equations below:
Equation 1 describes growing degree days (GDD), which are used to estimate sweetpotato growth and development during the growing season and are calculated at different growth stages.

$$GDDd = \sum_{i=1}^{d} TMEAN_i - d\ X\ TBase \qquad (1)$$

Where: d= Days after planting (DAP), i=number of days after planting, TMEANi =the mean temperature on i^{th} DAP, and $TBase$= = Base temperature

Equation 2 defines the GDD requirement for the first growth phase of sweet potato.

$$phsgdd = GDDi \qquad (2)$$

Where: GDD= Growing degree days i = 28 days under tropical conditions and 66 days under non-tropic

Equation 3 defines the GDD requirement for the second growth phase of sweetpotato. It reflects growing degree days between 4 and 7 weeks after planting for tropical and 9.5 weeks and 16 weeks after planting under nontropical conditions.

$$phs2gdd = \nabla \mathrm{GDDi} \qquad (3)$$

where phs2gdd is the difference between 4 weeks and 7 weeks after planting for tropical and 9.5 weeks and 16 weeks after planting under nontropical conditions ie. $phs2gdd$= $GDD49$-$GDD28$ for tropical conditions and $GDD112$- $GDD66$ under non tropical conditions.

Equation 4 describes the development of vines.

$$Vlen = \frac{vli}{GDDi} \quad (4)$$

where: VLi = vine length on the ith DAP; GDDi = GDD on i^{th} DAP

Equation 5 describes the development of roots.

$$tgrate = \frac{nTBRi}{GDDi} \quad (5)$$

where: nTBRi = the number of tubers on ith DAP and GDDi = GDD on ith DAP

Equation 6 defines the branching of the crop.

$$brgap = BRi\ X\ LFi \quad (6)$$

where: BRi = the number of branches on ith DAP and LFi = the number of leaves on the branches on i th DAP

Equation 7 specifies the number of leaves on a sweet potato plant

$$lfactor = \frac{Lfi}{GDDi} \quad (7)$$

where: LFi = The number of plant leaves on ith DAP and GDDi = GDD on i th DAP

Equations 8 define the leaf area of sweet potatoes at different growing stages.

$$lafactor = \log LFi\ X\ ALAi \quad (8)$$

where: ALAi =the average leaf area on ith DAP, LFi = The number of plant leaves on i^{th} DAP

Equation 9 defines the leaf area as a cultivar for the whole growing season.

$larea$ = *Average leaf area* for a cultivar for the whole growing season (9)

The initial conditions for the SPOTCOMS model were: (1) Optimum Temperature for Sweet potato = 25.0 °C, (ii) Base Temperature for Sweet potato= 8.10 °C, and (iii) Maximum Temperature for Sweet potato = 380 °C

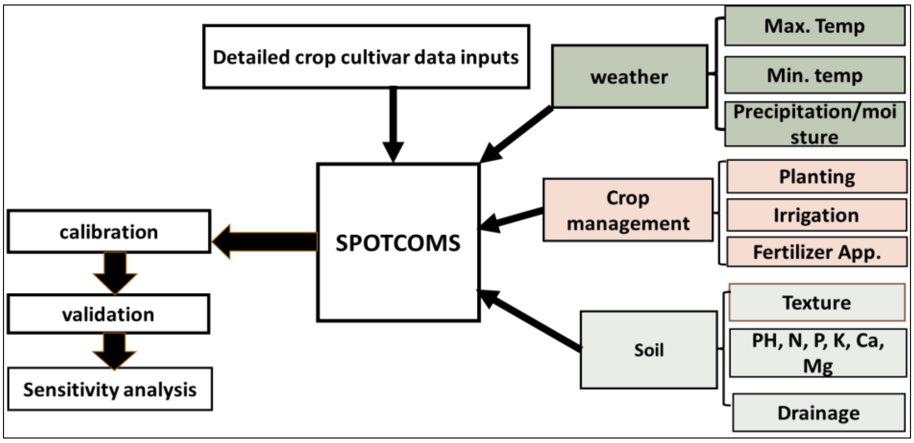

Fig 2: Summary of SPOTCOMS model framework operation

2.9.2. Calibration and performance evaluation of SPOTCOMS model

Calibration and testing of SPOTCOMS were performed using data sets from the two experiments of the 2022 and 2023 growing seasons. The suitable crop data were determined from the average of plant attributes and were then used to calculate the crop parameters using equations i, ii, iii,., and viii above. The calculated sets of parameters were then used to run the SPOTCOMs model. A descriptive statistical analysis was used to evaluate the relationship between the simulated and the observed storage root yields from the two experiments. The combination with the best fit was chosen for the model simulations. Two descriptive statistics were used in both model calibration and evaluation. The first was the coefficient of determination (R^2), derived from the Pearson correlation coefficient that measured the level of agreement between the observed and simulated values (equation 11). A R^2 value of 1 indicates a strong agreement, while a value of 0 implies a weak agreement. The second is the Bias, which measures the degree of error between observed and simulated values (equation 12)

The model performance in the simulation of final yield in terms of weight and number of storage roots was evaluated by percentage change using the equation below:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(\bar{Y} - Y_i)^2} \quad (10)$$

Where:y_i=observed value, x_i=simulated values, and n=Number of data points

$$\text{BIAS} = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \quad (11)$$

Where: P_i = simulated value; 0i = observed value; and n is the number of observations

$$\%\ \text{change} = (yo - yi)\ /\ yo)100 \quad (12)$$

Where: y_0= observed value and y_i simulated value

2.10. Data Analysis

2.10.1. Trend analysis for the field data collected

Trend analysis was performed on the eight variables, including vine length, number of leaves, total leaf area, number of branches and number of storage roots, and fresh and dry weight of shoots and storage roots.

2.10.2. Sensitivity analysis of cultivar coefficients in SPOTCOMS

The purpose of performing a sensitivity analysis on cultivar coefficients was to generate output responses associated with the variation in input and to assign the simulated output variability to the model coefficients that affect it most [34]. Sensitivity was used to provide a normalized measure in comparing all model coefficients. The sensitivity of the final yield output (t ha^{-1}) to the perturbations in each plant parameter was computed using the base and the ±5% changes in the base values. The relative change in output and the change in parameter were used to calculate the sensitivity indices, such that all eight coefficients determined were individually used to determine the sensitivity indices using the equation proposed by Pathak *et al.* [35] as shown below:

coefficients determined were individually used to determine the sensitivity indices using the equation proposed by [35] below:

$$\beta\left(\frac{Y}{\theta}\right)=\frac{(Y-Yi)/Y}{(\beta-\beta i)/\beta} \qquad (13)$$

where i represent individual coefficients: phsgdd, phs2gdd, Vlen, tgrate, brgap, lfactor, lafactor, or larea, Y is the simulated storage root yield using the initial set of determined coefficients and Yi is the simulated storage root yield obtained for each level of an individual model parameter (βi) while keeping all other model parameters at their base values.

3. Results

3.1. Trend of growth parameter

Trends of plant attributes including vine length, number of branches, number of leaves, and total leaf area for the entire growing season are presented in Figure 3. Vine length increased steadily from transplanting to the maturity stage (Fig. 3a). Increases were quite substantial up to about day 55 but the magnitude declined thereafter to maturity. Secondary and tertiary branching of the vines began around 35 DAP and increased sharply 60-100 days after planting and declined thereafter towards maturity (Figure 3b). Similarly, the number of leaves and total leaf area increased with time to 100 days after planting and then declined marginally towards maturity (Figure 3 c&d).

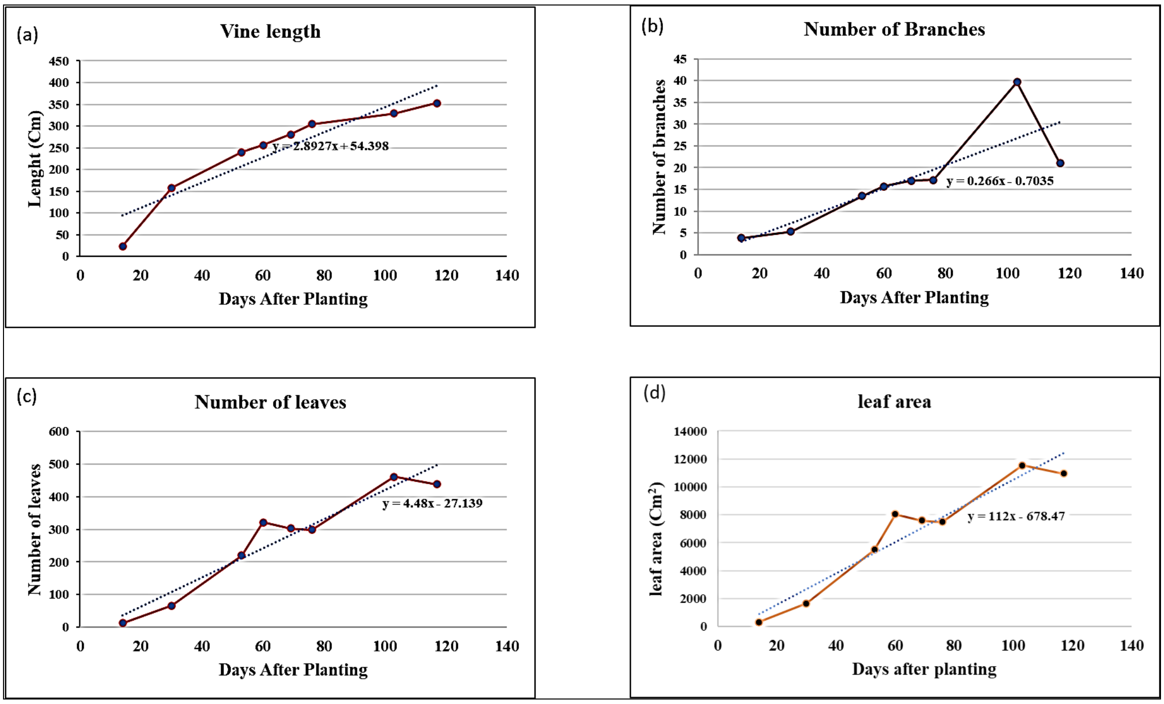

Fig 3: Mean values of vine length (a), number of branches (b), number of leaves (c), and total leaf area (d) during the growing seasons.

3.2. Cultivar coefficients

The mean cultivar coefficients (Table 2) were determined from four replications, from which a mean coefficient and the maximum and minimum values were also determined. Among the variables, Vlen, Ifactor, and brgap showed a high variation, all of which are functions of foliage growth for vine length, number of leaves, and number of branches, respectively.

Table 2: Summary of cultivar parameters determined from field experiments.

Cultivar coefficients	Vlen	Tgrate	br_gap	lfactor	lafactor	Larea
Mean	0.1989	0.0022	196.7781	0.0346	82.4947	38
Minimum	0.0901	0.00094	53.3333	0.00217	56.1603	35.2
Maximum	0.2776	0.00299	282.8571	0.0505	96.1329	49.3

Note: the summary of cultivar genetic coefficient for the Covington cultivar planted at the spacing of when phsgdd = 377 and phs2gdd = 779.

3.3. Sensitivity of cultivar coefficients from field data

Table 3 shows the results of the sensitivity analysis at 5% of the variety coefficient on final yields. The findings indicated that the sensitivity analysis of cultivar coefficients, which are a function of growing degree days, phsgdd, and phs2gdd were the most sensitive at a 5% increase. And phs2gdd, and lafactor, were more sensitive than at the 5% decrease range. On average phsgdd, and lafactor were the most sensitive followed by vlen and larea while br_gap was the least sensitive (Figure 4)

Table 3: Summary of genetic coefficients of cultivar parameters sensitivity to final yield.

Parameter	Optimum coefficients	5%increase in parameter	Simulated yield (tha^{-1})	β_5% increase	5% decrease in parameter	Simulated yield (tha^{-1})	β_5% decrease	Av β
phsgdd	335.000	351.75	25.780	-2.870	318.250	28.700	0.930	-0.970
phs2gdd	779.000	808.50	29.100	-0.880	731.000	27.790	1.250	0.190
vlen	0.300	0.315	30.580	0.320	0.285	29.380	0.480	0.400
tgrate	0.018	0.018	30.100	0.000	0.017	29.360	0.490	0.250
br_gap	186.000	195.300	30.330	0.150	176.700	30.600	-0.330	-0.090
lfactor	0.030	0.032	31.190	0.720	0.029	31.720	-1.080	-0.180
lafactor	130.000	136.500	29.110	-0.660	123.500	30.690	-0.390	-0.530
larea	49.000	51.450	30.750	0.430	46.550	29.890	0.140	0.290

Note: Summary of cultivar sensitivity influence on final yield(tha^{-1}), calculated at 5% increase or decrease (β_5%) and respective average (Av β) values. Calculations are based on the baseline/optimal simulated yield of 30.1 t ha^{-1}.

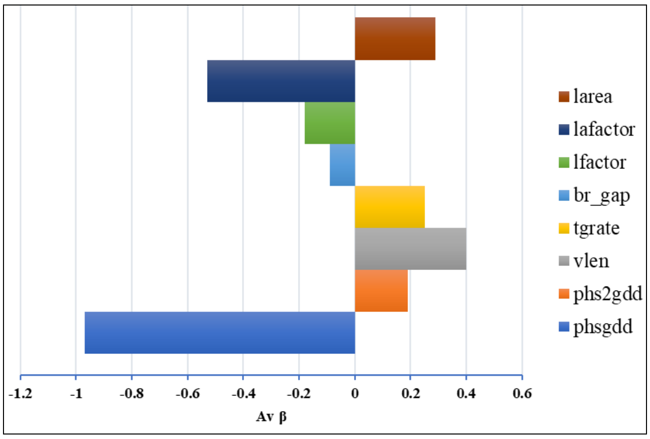

Fig 4: Summary of sensitivity analysis showing mean cultivar coefficients (β)of 5% increase and decrease of the mean values

3.4. Model evaluation

The SPOTCOMS model simulation results for growth variables, including vine length, number of branches, leaves, storage roots, and yield, are shown in Figure 5a-c. The simulated values for vine length are reasonably close to the observed value, with an R^2 of 0.90. Predicted values of the number of branches and number of leaves deviated considerably from the observed values, with R^2 values of 0.48 and 0.51, respectively. Thus, in the case of the number of branches and leaves, only approximately half of the observed variation in branch and leaf number can be explained by the inputs into the modelIn terms of bias measurement, the model underestimated vine length and number of branches compared to the observed values by an average of 51 and 9.7 units, respectively. Additionally, the model overestimated the number of leaves by an average of 15 units (Table 4).

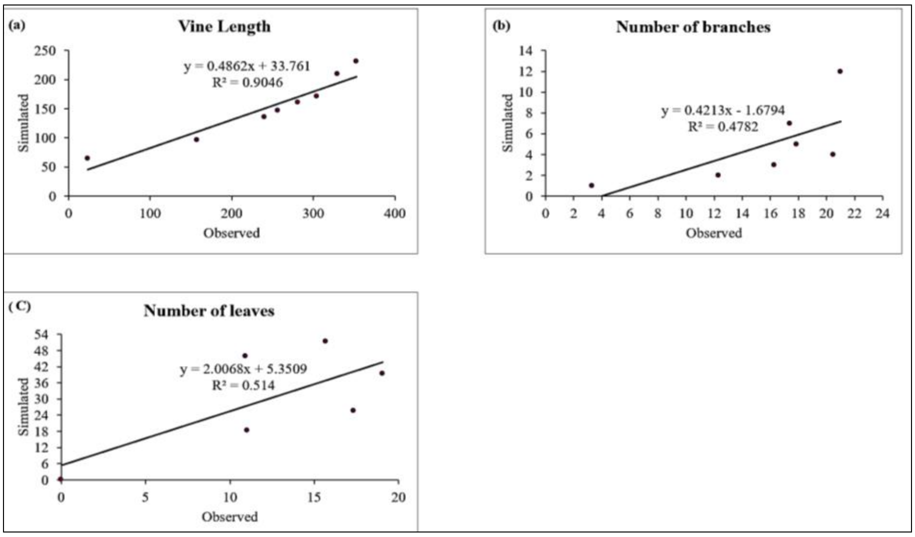

Fig 5: Plots showing observed vs predicted values of vine length (A), number of branches (B), and number of leaves (C) collected throughout the growing season.

Table 4: Coefficient of determination and bias estimates for vine length, number of branches and number of leaves

Parameter	Vine length	Number of branches	Number of leaves
Coefficient of determination (R^2)	0.9	0.47	0.5
Bias	-51	-9.7	15

Predicted values for the number and yield of storage roots are presented in Table 5. Simulated values are very close to observed values with a small deviation of 0.4 (storage root/plant) and 2.4 for the number of storage roots and yield, respectively.

Table 5: Observed vs predicted values of the number of storage roots per plant and storage root final yield (T/ha).

Parameter	Observed	Simulated	Difference	%change
Number of storage roots/plant	3.6	4.0	+0.4	11.1
Storage root yield (tha^{-1})	32.5	30.1	-2.4	-7.3

4. Discussion

The trends observed in the growth parameters and calculated cultivar coefficients show the relationship between environmental variables, sweet potato growth and development, and final yield. Initially, vine length exhibited elongation steadily until the mid-growth stage, followed by a slight rise towards the maturity phase, likely this response aligns with resource allocation theory, where plants prioritize vegetative growth early to establish photosynthetic capacity before transitioning to storage root development. The secondary branching of the vines initiated at 35 DAP and peaking between 60-100 DAP, is probably associated with the plant's strategy to expand its architecture during the middle phase to optimize light interception and photosynthesis capacity during the critical storage root bulking phase [36]. Similarly, the number of leaves and total leaf area increased consistently until 100 days after planting and declined thereafter due to senescence. This physiological response is potentially linked to source-sink relationships, where resource remobilization (eg. N and carbohydrates) tends to be re-translocated from senescing leaves to sustain storage root bulking to development as the plant approaches maturity [37,38]. Harvesting at 119-120 DAP corresponded to a cumulative growing degree day (GDD) of 1324, aligning closely with established GDD-based yield prediction models for sweet potato. This value is consistent with prior studies using GDD-based yield prediction models, hence validating its utility for yield prediction [39].

The cultivar-specific coefficients, particularly vlen, lafactor, and larea, were within the range reported on other sweet potato cultivars such as $NASPOT_1$, SPK004, and $NASPOT_{10}$ that are common in East Africa [40]. Additionally, the coefficients for br_gap and lfactor were within a range reported from other cultivars common in Asia [29]. This observation suggests conserved developmental strategies within sweet potato species. In contrast, the coefficient for tgrate (description of root development) was unique for the assessed variety, Covington. This implies that even though there were similarities among cultivars from different locations because they are the same genus and species, the root development traits have shown distinctness to the Convington cultivar; this may probably be due to genotype-environment-specific interaction, which influences traits such as root expansion and dry matter allocation.

Sensitivity analyses revealed that changes in cultivar coefficients such as phsgdd, Vlen, lafactor, and tgrate that determine root initiation, vine length, leaf, and storage root development, respectively, had a significant influence on simulated yields. Notably, the sensitivity of these coefficients to change at 5% increments or decrements shows their influence on final yield, emphasizing the importance of adjusting these variables during yield simulation. A similar trend of sensitivity of phsgdd, and lafactor was reported in the estimation of a coefficient of other sweetpotato cultivars [29, 40].

The SPOTCOMS model demonstrated strong mechanistic accuracy in simulating sweetpotato storage root yields and vine elongation with predictions falling within the error margins similar to other studies using crop models [41]. However, for other variables such as the branching of vines and the number of storage roots, SPOTCOMS was less precise, likely due to its limited parameterization of stochastic processes governing branching initiation. Future versions of this model may require adjustments to the algorithms used for estimating the number of branches and storage roots.

Like most models, SPOTCOMS showed some limitations that will need to be addressed in future studies. For example, SPOTCOMS needs to be set such that it has a threshold beyond which if the temperature is exceeded, sweetpotato growth would be inhibited. This has not yet been set in the model and therefore, the researcher is mandated to remove locations with average high temperatures exceeding 38^0C. Also, the model does not account for the effects of weeds, pests, and diseases and therefore tends to overestimate yield. Finally, the model currently uses topsoil data and does not account for the variation of soil nutrients in the soil profiles as has been significantly developed in other crop models such as the DSSAT crop models.

5. Conclusion

Overall, the SPOTCOMS sweet potato model simulated storage root yield and number, number of leaves, and vine length very precisely for Covington. However, it demonstrated limitations in predicting the number of branches and roots, emphasizing the need for improved parameterization of these variables in future studies.

The generated genetic coefficients for the Covington variety are readily available for future reference and for any impact assessment studies on Covington and related varieties. However, to improve the model's robustness in Alabama and other states, there is a need for further calibration and validation are needed in diverse regions to account for variations in weather, soil conditions, and the common sweetpotato varieties grown in those areas. This will help improve the model's applicability and robustness.

Author Contributions

Devotha Mwazembe, D.G. Mortley, V.S. Santhosh Mithra, and R. O, Ankumah conceptualized the research. Devotha Mwazembe, D.G. Mortley, V. S. Santhosh Mithra conducted the research experiments. V. S. Santhosh Mithra provided access to the software. R. Shange, J. Quansah1, S. Fall, and O. Idehen provided inputs for the validation of the model outputs. Devotha Mwazembe, D.G. Mortley, and V. S. Santhosh Mithra wrote the original manuscript draft. D.G. Mortley supervised the research work and secured research funds. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper

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