Predicting the Spatial Distribution of Aflatoxin Hotspots in Peanut Fields using DSSAT CSM-CROPGRO-PEANUT-AFLATOXIN

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Abstract.

Aflatoxin contamination in peanut (Arachis hypogaea L.) is a persistent concern due to its detrimental effects on both profitability and public health. Several plant stress-inducing factors, including high soil temperatures and low soil moisture, have been associated with aflatoxin contamination levels. Understanding the correlation between stress-inducing factors and contamination levels is essential for implementing effective management strategies. This study uses the DSSAT CSM-CROPGRO-Peanut-Aflatoxin model to identify stress-inducing factors that may indicate the potential of aflatoxin contamination in peanut fields. The model considers a set of optimum temperatures that will lead to most rapid synthesis of aflatoxin. Calibrating soil-related parameters in the model significantly impact simulated aflatoxin contamination patterns so using good field data is imperative. The ultimate goal of the project is to use the CSM-CROPGRO-Peanut-Aflatoxin model to identify areas within fields that have the potential to become aflatoxin hotspots. This knowledge will allow peanut growers to harvest their fields differentially to avoid cross-contamination and enable peanut shellers to segregate peanuts from potential hotspot areas for additional testing prior to storage. During the first year of the project, data were collected from three rainfed farmer fields and one research field in southern Georgia, USA. Field data are being used to calibrate the CSM-CROPGRO-Peanut model. Once calibrated, levels of plant stress factors will be quantified and correlated with corresponding aflatoxin contamination measurements. The model will then be used to evaluate the spatial distribution of aflatoxin in peanut fields by running the model individually for management zones delineated from physiographic features such as soil texture, soil EC, and elevation using the Management Zone Analyst software (Fridgen et al., 2003). Our results for 2023, confirms the spatial distribution of aflatoxin in peanut fields. The DSSAT model simulation results for management zones designated by soil texture and soil EC shows different levels of aflatoxin as well. More years of model calibration is needed, as the aflatoxin concentrations were low during 2023.

Keywords.

modeling, management zones, aflatoxin, peanut, spatial variability

Introduction

Arachis hypogea L., also known as groundnut or peanut, is an annual herbaceous legume belonging to the Fabaceae family. Initially cultivated in Central and South America 3500 years ago, its cultivation has since expanded to temperate and tropical regions worldwide due to its high demand as an oil and food product (Syed et al., 2021). Peanut is cultivated across approximately 26 million hectares of land in 120 countries (Salano, 2024).

Aflatoxins are secondary metabolites produced by fungi and are known for their high toxicity, leading to their classification as mycotoxins. Their names are derived from the genus Aspergillus (a), the species (flavus), and the term "toxin" is a Greek word indicating poison. *Aspergillus flavus* and *Aspergillus parasiticus* are the major producers of aflatoxins, although other species such as *Aspergillus australis* may be important in southern hemispheric countries (IARC 2002). Aflatoxins have detrimental effects on both human and animal health. According to the World Health Organization (WHO), aflatoxin B1 has been classified as a Group 1 carcinogen (Pisoschi et al., 2023). As a result, there are limits on the concentration of aflatoxin allowed in edible products and farmers suffer from the economic losses associated with contamination levels higher than the accepted thresholds. Hence, health and economic concerns have been driving research efforts for a considerable duration.

Total aflatoxin levels in foods are limited to avoid unintentional exposure of consumers to aflatoxins. Guidelines from the FDA permit, at most 20 $\mu g\ kg^{-1}$ (ppb- parts per billion) of total aflatoxin in food or feed and 0.5 ppb cumulative aflatoxin in milk. The EU aflatoxin limit is stricter, with a maximum of 4 ppb for total aflatoxins and 2 ppb for aflatoxin B1. Economic losses from mycotoxins in the US are associated with regulatory losses, as opposed to lowered production, illness, and/ or deaths from the effects of the toxins. The USDA National Peanut Research Laboratory estimated peanut industry losses due to aflatoxin contamination to be about $126 million annually (Smith, 2021).

There have been different approaches to understand the factors involved in aflatoxin contamination in different crops, including peanut. Among these approaches are predictive models most of which use environmental conditions as inputs. Model output consists of the prediction of mycotoxin contamination during the growing season and at harvest.

The Decision Support System for Agrotechnology Transfer (DSSAT) is a universally used decision support tool (DST) that includes dynamic crop growth simulation models for over 42 crops (Boote, 2019). DSSAT has been well calibrated for a variety of crops and cultivars, allowing the users to simulate the growth and development of the crop of interest under different management practice scenarios and environmental conditions. The CROPGRO-Aflatoxin model can be run as stand alone or in DSSAT (Boote, 2018). DSSAT-CROPGRO-Peanut is a model within DSSAT that has been used to predict aflatoxin production by associating it with model variables such as water stress occurrence during the water deficit sensitive periods such as pod filling. The CROPGRO-Aflatoxin model and the DSSAT-CROPGRO-Peanut model are associated through their integration within the DSSAT framework and their use in predicting aflatoxin production.

On the other hand, the DSSAT-CROPGRO-Peanut model, which is a component of the DSSAT system, simulates peanut growth and development. It has been utilized to predict aflatoxin production by linking aflatoxin risk to key model variables, such as water stress occurrences during critical periods like pod filling. When integrated, the DSSAT-CROPGRO-Peanut model provides the necessary environmental and phenological data, such as periods of water deficit, that the CROPGRO-Aflatoxin model uses to assess the likelihood of aflatoxin production. Thus, the DSSAT-CROPGRO-Peanut model supports the CROPGRO-Aflatoxin model by supplying relevant stress and growth data that influence aflatoxin contamination.

In a preliminary study conducted in southern Georgia, USA, Vellidis et al. (2006) found that aflatoxin contamination was spatially aggregated within a rainfed peanut field. Based on that, we hypothesize that aflatoxin concentrations in rainfed peanut fields are spatially distributed and a function of measurable physical and biological conditions. The overall goal of this work is to evaluate the potential of using DSSAT-CROPGRO-Peanut to develop spatially explicit aflatoxin risk maps in rainfed peanut fields.

Materials and Methods

Field studies

During the 2023 growing season, 4 fields were chosen for experimental data collection. Three fields were rainfed grower fields while the fourth consisted of large plots on a University of Georgia (UGA) Tifton Campus research farm. The grower fields were selected to have medium levels of spatial variability of soils and topography to improve the likelihood of observing spatial variability in aflatoxin concentrations. The fields also were selected to be in different ecoregions of the Georgia Coastal Plain where most of the peanut crop in Georgia is grown.

The cultivar utilized in the research is Georgia-06G (Reg. no. CV-94, PI 644220), a high-yielding, Tomato Spotted Wilt Virus (TSWV)-resistant, runner-type peanut (*Arachis hypogaea* L. subsp. hypogaea var. hypogaea) released by the Georgia Agricultural Experiment Stations in 2006 (Branch, 2007b).

Data collection for model calibration

Data needed for model calibration and evaluation (Hoogenboom et al., 2012) were collected from all three fields and included environmental, physical, and biological measurements as described below.

Soil electrical conductivity (EC)

After field selection and prior to planting, apparent soil electrical conductivity (EC_a) was measured continuously in 18 m parallel swaths using a Veris 3100 instrument. EC_a is a measurement that correlates with physico-chemical soil properties that affect crop productivity including salinity, soil texture, water holding capacity, organic matter content, cation exchange capacity (CEC) and soil porosity (Grisso et al., 2005).

Soil cores

Following EC_a mapping, a 0.4 ha (1 ac) grid were overlain over the field boundaries. The center point of each grid cell served as the sampling location for physical and biological measurements in the fields. A total of 77 sampling locations were established across the three fields. Intact 90 cm soil cores were then collected at the center point of each grid cell. Each core was divided into six 15 cm increments and each increment analyzed for texture (sand, silt, clay), organic matter content (OM), pH, macronutrients (N, P, K, Ca, P) and micronutrients (Al).

Soil moisture data

University of Georgia Smart Sensor Array (UGA SSA) soil moisture sensor nodes (Vellidis et al., 2013) were installed in 50 of the 77 grid cell center points. Locations were selected to represent a wide range of measured EC_a. The UGA SSA measures soil moisture in terms of soil water tension (the absolute value of soil matric potential). Each UGA SSA node measures soil water tension (SWT) hourly at three depths (10, 20, 40 cm) and soil temperature hourly at 5 and 10 cm used to collect soil water tension from fields for the entire growing season.

In the DSSAT model, the input file for the soil water content is required to be in form of volumetric water content (cm^3cm^{-3}). The Van Genuchten model (Equation 1) was used to convert the SWT measurements into volumetric water content (VWC).

$$\theta(h) = \theta_r + \frac{\theta_s + \theta_r}{[1+(\alpha h)^n]^{1-\frac{1}{n}}} \quad (1)$$

Where θ is soil VWC (cm^3cm^{-3}), h is the pressure head (cm); θ_s and θ_r are the saturated and residual VWC (cm^3cm^{-3}), respectively; α is an empirical parameter which is often referred to as the inverse of the air entry point (cm^{-1}); and n is an empirical constant affecting the shape of the curve (Van Genuchten, 1980). Rosetta version 1 was used to obtain the Van Genuchten parameters. Field capacity (FC), soil water tension (SWT) at FC, permanent wilting point (PWP), and available water content (AWC) at FC in different soils in fields were then identified using the method applied by Liang et al. (2016).

Meteorological data

Air temperature, precipitation, solar radiation, relative humidity, and wind speed among others were collected at 15 min intervals using an ATMOS 41W (METER Group, Inc., WA, USA) all-in-one compact weather station.

Growth and development data

Whole plant samples were collected biweekly in all fields at approximately 60% of the grid sampling points. As with the soil moisture sensor nodes, sampling locations were selected to represent a wide range of measured EC_a. Designated sampling rows were established around the grid cell center point. Biweekly, three intact peanut plants were collected and divided into leaves, stems, pods, and seeds. Leaf area was measured using a LiCor model LI-3100 leaf area meter (LI-COR Ltd., Nebraska, USA) while stems, pods, and seeds were used to determine yield components. All plant components and the remaining part of the large sample were oven dried at 60°C for approximately 48 hours and then weighed to determine dry matter. The whole sample dry matter was used for biomass measurement. During each sampling event, peanut plants were carefully evaluated for their phenological stage (emergence, flowering, pegging, beginning pod, beginning seed, seed maturity).

Aflatoxin concentration data

4-5 plants were collected beginning with approximately 90 days after planting for aflatoxin analyses at each biweekly sampling event. The pods were detached, and oven dried at 60 ̊C for 24 h. Based on the literature, subsampling 25 g from 100 g of peanut seeds is adequate to detect aflatoxin concentrations with a reliable estimation (Luis, 2014). The dried samples were analyzed by Waters Agricultural Laboratory for aflatoxin concentrations using the Enzyme-linked immunosorbent assay (ELISA) method (Hidayat and Wulandari, 2021).

Yield measurement

Yield data are one of the important parameters in the crop simulation models. Final yield is the parameter widely used in model calibration. To measure the yield performance, peanut pods were harvested in a 100-feet length in each plot, and the collected pods were weighed. Then, considering the moisture content of the pods and the area harvested, the final value would be reported by the units accepted in the model (kg ha^{-1}).

Management zone creation

Due to the necessity of setting up different files for different treatments in the DSSAT model, and to catch the indicators of spatial aflatoxin distribution in the field, MZA (Management Zone Analyst; Fridgen et al., 2004) was used to perform a cluster analysis. MZA provides the user with two cluster performance indices: the fuzziness performance index (FPI), and the normalized classification index (NCI). To select the optimal number of clusters, the minimum value, representing the least membership sharing (FPI) or greatest amount of organization (NCI) would be considered. Nevertheless, the final decision may require additional verification. To run the experimental files for a group of plots based on the soil type or soil EC, each field’s soil data were clustered using MZA software, into the dominant soil texture types and EC data and run separately.

DSSAT-CROPGRO file set up

DSSAT Version 4.8.2 (Hoogenboom et al., 2023) is being used as the model in this study. X-files (experimental files) in the DSSAT model were set up for different management zones. ATCreate was used to create two types of crop measurement files, including File A that is a summary, primarily end of season average performance; and File T for a time course experiment file. Soil moisture, soil temperature, LAI, aflatoxin concentrations, biomass and yield components are organized as T-files. End of season yields, and aflatoxin levels (ppb) are used as A-files for the initial calibration of the model. WeatherMan is a tool used to organize required weather data and running the simulations for different weather conditions. Once the management zones were designated, the available soil data for each soil horizon within a zone were calculated as the average of the plots in that zone. SBUILD is the tool in DSSAT for creating and modifying soil files. Soil files are essential for model calibration, validation, and accurate yield predictions.

The DSSAT model calibration

DSSAT does not offer automated procedures for calibration. Changes to parameters of the model to calibrate it for specific conditions must be made by the user. Making quantitative comparisons of model output to observations requires the data to be exported to an analysis package. To accomplish this in a precision farming simulation, this process must be repeated for every management zone (Throp et al., 2008). All zones were used to calibrate the model, as the Georgia-06G cultivar has not been calibrated and incorporated into the DSSAT model. Model performance was evaluated by using standard model evaluation metrics such as root mean squared error (RMSE), coefficient of determination (R^2) of simulated versus observed values, and the index of agreement (*d*).

Results

Sand and clay content of 15 cm topsoil (figures 1.a and 1.b) and soil EC_a (figure 1.c) were used to allocate plots to management zones. The field in figure 1 is one of the 2023 three grower fields. Aflatoxin concentrations at harvest (figure 1.d) show promising results related to the parameters used in MZA software. However, one more year of data collection will be done to recalibrate the model. It also will be useful to assess other parameters in zoning fields.

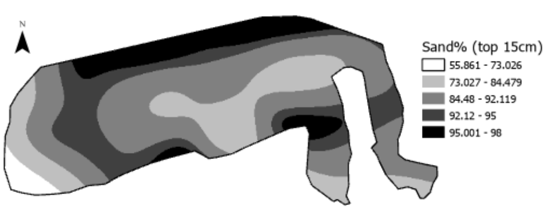

Figure 1.a - Sand percentage in topsoil

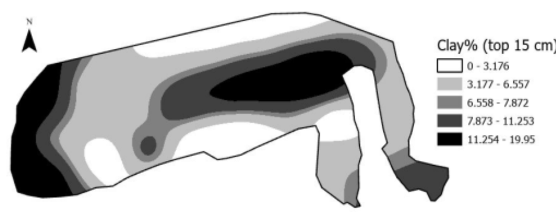

Figure 1.b - Clay percentage in topsoil

Figure 1.c - Soil EC

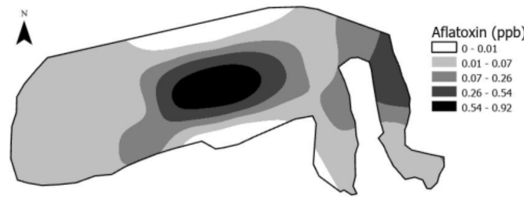

Figure 1.d - Aflatoxin (ppb) at harvest

Calibration of the DSSAT-CROPGRO-Peanut Model for Georgia-06G Cultivar

The DSSAT-CROPGRO-Peanut model is well calibrated for several peanut cultivars. In our research, Georgia-06G was incorporated into the model for the first time. Since the yield of Georgia-06G is similar to that of Georgia Green, the coefficient calibration began with the values for Georgia Green. These values were then manually adjusted, first individually and then collectively, to obtain the optimal coefficients. More seasons of data collection and model calibration are needed to obtain more precise coefficients.

In figures 2 and 3, DSSAT-simulated versus observed values for tops weight (kg ha^{-1}) and stem weight (kg ha^{-1}) are shown. Tops weight represents above-ground biomass. The lines indicate simulation results while the individual data points represent discrete field measurements.

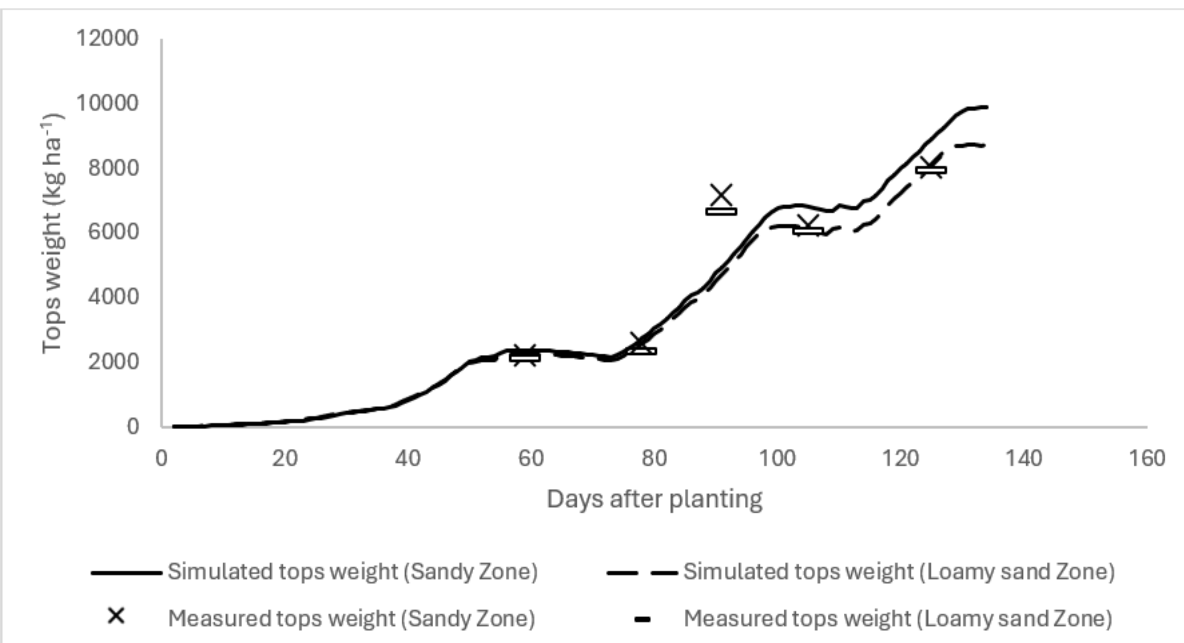

Figure 2. Simulated and measured tops weight (kg ha^{-1}) in two zones of the field.

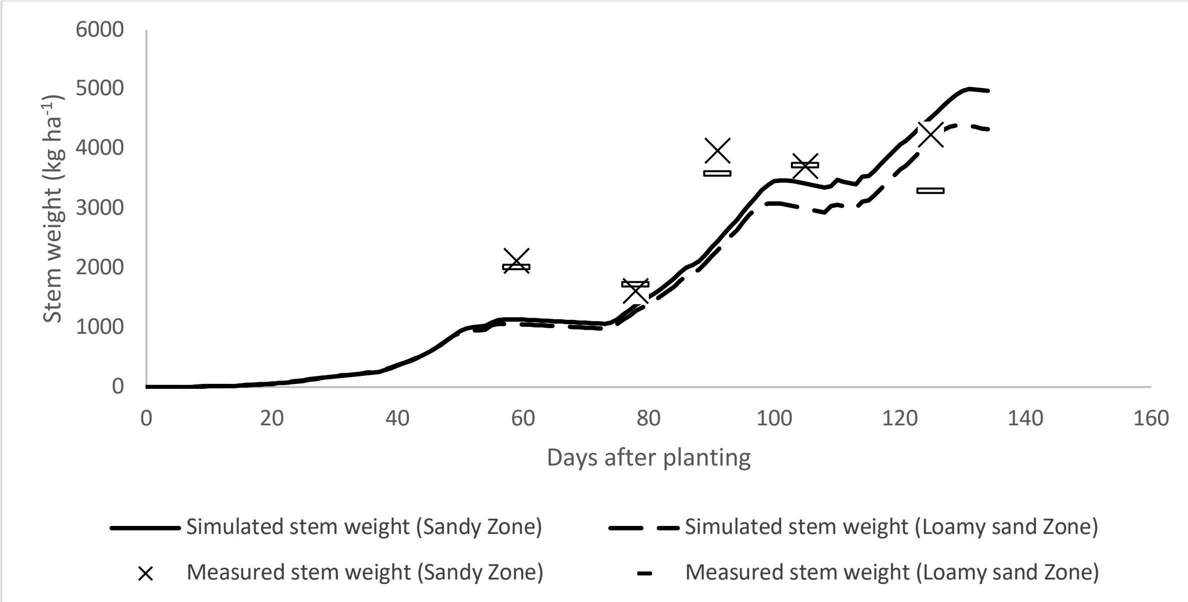

Figure 3. Simulated and measured stem weight (kg ha^{-1}) in two zones of the field.

Simulated versus observed values in some zones showed a significantly high correlation. However, when evaluating within other zones, we found that there is a need to revise the root growth factor and soil profile depth. It is likely that the water stress simulated in soil with a higher clay percentage could be optimized by soil depth considerations.

The DSSAT model aflatoxin output

Figure 4 shows the simulated versus observed values for aflatoxin content (ppb) in one the fields used for model calibration. In 2023, aflatoxin levels were low, and although there were differences among zones, in the figure, these differences are not visually noticeable because the simulated levels were much higher. Nevertheless, the spatial distribution of aflatoxin across different zones occurred, influenced by variations in soil texture and the resulting differences in water and heat stress levels. Although the aflatoxin module in DSSAT was able to predict different aflatoxin concentrations in different zones, the magnitude of the predicted aflatoxin concentrations was an order of magnitude higher than measured in the field. The aflatoxin module requires additional calibration with more years of data.

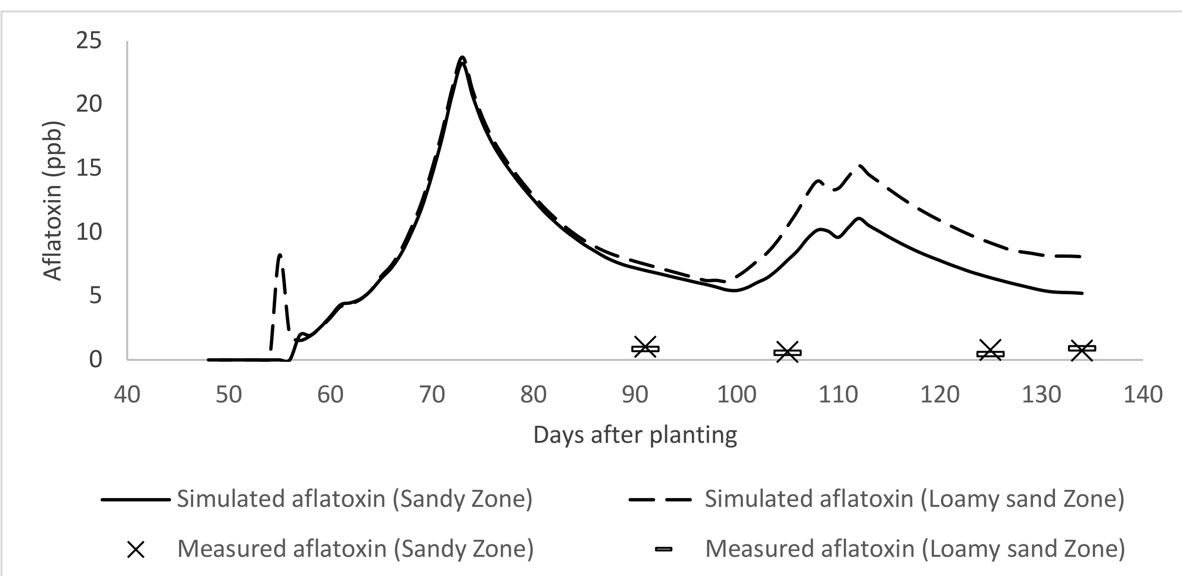

Figure 4. Simulated and measured aflatoxin concentrations (ppb) in two zones of the field.

Discussion and conclusions

Model simulations for different field zones revealed varying aflatoxin concentration patterns throughout the season. The interesting point is that simulated aflatoxin levels continue to vary during the last stages of physiological maturity and harvest maturity. Hence, the DSSAT model might be a useful tool for establishing harvest window selection for differential harvesting. There is evidence that selection of an earlier harvest time, despite increased insect damage and contamination by Aspergillus section *Flavi* in the soil and peanuts, can be a way of reducing aflatoxin under stress conditions without compromising yield (Martins et al., 2023).

Certain factors that affect the growth and phenological development of peanuts are not included in the DSSAT model. However, these factors should still be monitored and considered when interpreting stress-inducing conditions. For instance, variables such as specific pest pressures, microclimatic variations, and localized soil nutrient deficiencies can influence peanut development and stress responses but are not accounted for in the model.

Furthermore, obtaining more detailed information on root growth conditions in relation to soil parameters would enhance the model's accuracy and applicability. This includes understanding how soil texture, moisture levels, and nutrient availability impact root development. Such detailed data would be beneficial not only for peanuts but also for improving the modeling applications for other crops, leading to more precise simulations and better-informed agricultural practices.

Our results confirm the past research indicating spatial distribution of aflatoxin contamination in peanut fields (Vellidis et al., 2006). Since there is a large difference between simulated and measured aflatoxin concentrations, the aflatoxin model requires more calibration. For 2023, measured aflatoxin concentrations were very low, compared with the simulated contamination. It highlights the necessity of collecting data through more years and regions. During the 2024 growing season, our study continues with three more rainfed grower fields to calibrate and evaluate the DSSAT-CROPGRO-Peanut-Aflatoxin model.

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