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RESEARCH

Performance of the SWAP–WOFOST Model for Simulating Cotton Growth and Yield Under Tropical Cerrado Conditions

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Abstract

Process-based agro-hydrological models are essential tools for assessing crop growth and yield under contrasting management and environmental conditions. This study assessed the performance of the coupled Soil-Water-Atmosphere-Plant and World Food Studies Simulation Model (SWAP–WOFOST) to simulate cotton (*Gossypium hirsutum* L., cv. FiberMax 975 Wild Strike®) growth and yield under tropical Cerrado conditions in western Bahia, Brazil. Field experiments were carried out during the 2014/2015 growing season under three nitrogen management treatments: ammonium sulfate®, prilled urea®, and a control without nitrogen fertilization. The SWAP component was calibrated to simulate soil water dynamics, whereas WOFOST was used to represent crop growth and yield. Model performance was evaluated using the coefficient of determination (R^2), Willmott's agreement index (d-index), Root Mean Square Error (RMSE), Nash–Sutcliffe efficiency (NSE), and the performance index (c-index). The SWAP model showed limited performance in simulating soil volumetric water content, with low precision (R^2), agreement (d-index) and efficiency (NSE), indicating limitations in representing near-surface soil water dynamics, particularly after rainfall events. In contrast, the WOFOST component showed excellent performance in simulating leaf area index, reproductive structure biomass, and total aboveground biomass across all treatments. These results indicate that, despite limitations in soil water content representation, the coupled SWAP–WOFOST framework was robust for simulating cotton growth and yield responses under contrasting nitrogen management strategies. The model may support assessments of crop performance and nitrogen fertilization strategies under tropical Cerrado conditions.

Keywords Crop modelling · Soil–plant–atmosphere system · Nitrogen fertilization · Tropical agriculture

Introduction

Cotton (*Gossypium hirsutum* L.) is a crop of great economic and social importance, mainly because of its role as a source of natural textile fiber, although cottonseed is also used for oil and animal feed production (Thorp et al., 2014; Constable & Bange, 2015). Cotton remains a major global agricultural *commodity*, with world production projected at approximately 121.9 million bales in the 2025/26 season, the highest level since 2012/13. The main producing countries include India, China, Brazil, and the United States, with Brazil consolidating its position among the leading global producers and exporters of cotton fiber (OECD/FAO, 2025; USDA ERS, 2026).

High-quality cotton fibers are mostly produced by domesticated species of the genus *Gossypium*, whose evolutionary origin dates back approximately 12.5 million years (Wendel et al., 2010). In Brazil, cotton production has expanded and gained technological importance due to the crop's adaptability to tropical agricultural environments, advances in cultivar development, and the adoption of highly mechanized production systems. In recent years, Brazilian cotton

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production has been concentrated mainly in the Cerrado regions of Mato Grosso and Bahia, where favorable climate conditions, large-scale farming systems, and improved crop management have supported high yields and strong international competitiveness. For the 2025/26 marketing year, Brazil's cotton production is forecast at 17.8 million bales, equivalent to approximately 3.87 million metric tons, with a cultivated area of about 2.13 million ha (USDA FAS, 2025).

As a result of the significant importance of the cotton crop and the agronomic challenges associated with its production in different environments, it is essential to understand the processes that govern its growth and yield. Hence, crop modeling emerges as an essential tool, capable of integrating multiple factors and simulating diverse scenarios to aid decision-making and to optimize yield while minimizing environmental impacts (Monteiro et al., 2005; Ezui et al., 2018; Tribouillois et al., 2018; Lei et al., 2021). Thorp et al. (2014) highlighted that there are generic crop models that simplify plant growth for application in different crops; however, their use for cotton crops is still scarce. The Soil-Water-Atmosphere-Plant (SWAP) coupled with World Food Studies Simulation Model (WOFOST) model stands out as one of them.

Process-based models such as SWAP have been widely used to simulate soil–plant–atmosphere interactions (Jarvis et al., 2022; Shin et al., 2023). These models integrate subcomponents that represent soil water flow, solute and heat transport, evapotranspiration, plant growth, and yield (Kroes et al., 2008).

The SWAP model simulates soil water movement, a process essential for crop growth and yield, based on the Richards equation, whose deterministic solution represents the water flow in variably saturated soils accurately, with variable time steps (Ma et al., 2011; Kroes et al., 2017; Singh et al., 2017; Sinnathamby et al., 2017; Heinen et al., 2024).

This approach is operationalized through a detailed multilayer scheme that describes water redistribution in the soil profile based on physical principles (Kroes et al., 2017). To this end, the model requires careful calibration of the soil's hydraulic properties, allowing the definition of stratified profiles, in which each layer is characterized by specific parameters that describe the relationship between pressure head, soil water content, and hydraulic conductivity (van Genuchten, 1980; Kroes et al., 2008; Lei et al., 2021).

The robustness of SWAP has been demonstrated in several studies, with good levels of agreement between simulations and observed soil water content data (Bonfante et al., 2010; Shafiei et al., 2014; de Jong van Lier et al., 2015). SWAP can be coupled with the WOFOST (World Food Studies Simulation Model) model, developed by researchers at Wageningen University (van Diepen et al., 1989; van Ittersum et al., 2003), which simulates the growth, development, and yield of agronomic crops from emergence to maturity, based on phenotypic traits (Eitzinger et al., 2004; Kroes et al., 2008; Thorp et al., 2014).

WOFOST is a mechanistic, explanatory, and dynamic model that operates at daily resolution and considers canopy-level physiological and ecological processes like assimilation, respiration, transpiration, biomass accumulation, and partitioning among leaves, stems, roots, and storage organs, as well as the influence of environmental conditions on these processes (de Wit et al., 2019, 2020). The model performs simulations of potential and real growth (Kroes et al., 2008; Vazifedoust et al., 2008; de Wit et al., 2019). Although it has a simplified soil module, its integration with SWAP results in the coupled SWAP-WOFOST model.

SWAP-WOFOST system calibration, however, requires specific and complex field experiments and a robust computational structure, due to the need for accurate estimates of numerous hydrological, phenological, and physiological coefficients, which depend on reliable and high-quality experimental data.

Simulating cotton growth and yield in the Brazilian Cerrado, particularly in sandy or medium-textured soils of western Bahia, is challenging due to the interaction between soil physical limitations and marked seasonal climatic variability. These soils often present low organic carbon contents and limited water-holding capacity, which may increase crop sensitivity to irregular rainfall distribution and periods of water deficit (Campos et al., 2020; Amorim et al., 2022). In addition, cotton production in the Cerrado is strongly influenced by rainfall amount, thermal conditions, radiation availability, and soil quality during critical phenological stages such as flowering and boll filling (Echer et al., 2024). Therefore, the temporal variability of soil water availability and atmospheric conditions reinforces the need for dynamic crop simulation models capable of representing crop responses over time, rather than relying solely on static field observations (Amorim et al., 2022; Rodrigues et al., 2025).

Despite advances in process-based modeling, there is still a lack of calibrated parameters for the SWAP–WOFOST model applied to cotton, mainly under tropical Cerrado conditions. Most previous studies have focused on other crops or different environmental settings, limiting the direct applicability of model parameterizations to region-specific management practices. This gap restricts the reliability of simulations when used as a decision-support tool, particularly under varying fertilization strategies.

Nitrogen (N) is widely recognized as one of the key nutrients controlling cotton growth, yield formation, and fiber quality, and its management plays a crucial role in determining nitrogen-use efficiency and overall crop performance (Ali, 2015; Constable & Bange, 2015; Snider et al., 2021; van der Sluijs, 2022). However, under tropical conditions, especially in sandy or medium-textured soils, N management is complex because fertilizer N may be lost through different pathways, including nitrate leaching after nitrification and ammonia volatilization, particularly when urea-based fertilizers are applied under warm conditions and remain near the soil surface (Furtado da Silva et al., 2020; dos Santos Diniz et al., 2025). In Cerrado soils, ammonia volatilization from urea has been shown to be strongly affected by soil texture, temperature, and fertilizer dose, with greater losses in sandy loam soils than in soils with higher clay content (dos Santos Diniz et al., 2025). This further highlights the importance of using calibrated simulation models to evaluate cotton performance and nitrogen-use efficiency under contrasting soil, climate, and fertilizer-management conditions.

It is important to note that the version of the WOFOST model used in this study does not include a dynamic nitrogen module. Therefore, differences among nitrogen treatments were not mechanistically simulated, but were indirectly represented through the experimental field conditions used for model calibration and evaluation. Consequently, the simulations reflect crop growth responses under given environmental and management conditions rather than explicitly simulating nitrogen dynamics.

In this context, evaluating the SWAP–WOFOST model with locally derived parameters provides an opportunity to assess its ability to simulate cotton growth and yield under tropical Cerrado conditions and to identify possible limitations in the representation of soil water dynamics.

Thus, the aim of this study was to assess the performance of the SWAP–WOFOST model in simulating cotton growth, development and yield under unfertilized conditions and contrasting nitrogen management strategies in western Bahia, Brazil. The specific objectives were: (i) to experimentally determine the soil, crop, and atmospheric parameters required for model calibration; (ii) to calibrate the SWAP–WOFOST model under local conditions; and (iii) to evaluate its ability to reproduce crop growth and yield under different management scenarios.

Materials and Methods

Experimental Data

The observed data were obtained from an experiment carried out between November 30, 2014, and July 20, 2015, on an agricultural farm located in the municipality of Luís Eduardo Magalhães, Bahia, Northeastern of Brazil (12°05’03” S, 45°48’18” W, 778 m of altitude). The municipality is in the far west of Bahia, next to the state of Tocantins, and is part of the Rio Grande River basin.

According to the Köppen climate classification, the region has a Tropical Savannah climate (Aw), with an average annual air temperature of 24 °C and an average annual rainfall of 1200 mm, concentrated mainly between November and March (Moreira & da Silva, 2010). The soil of the experimental area was classified as a Red-Yellow Latosol (Santos et al., 2018) according to the Brazilian Soil Classification System, broadly corresponding to an Oxisol in USDA Soil Taxonomy.

The experimental delineation was randomized blocks, evaluating two ammoniacal nitrogen sources and two rates (0 kg ha^{-1} – control and 200 kg ha^{-1}), in four blocks, characterizing a $2 \times 2 \times 4$ factorial arrangement. The two inorganic nitrogen fertilizer sources tested were a commercial multi-nutrient fertilizer based on ammonium sulfate (Sulfammo-29®), containing 29% nitrogen (N), 9% sulfur (S), 2% magnesium (Mg), 5% calcium (Ca), and 0.3% boron (B), and prilled urea® (45.9% N). Each experimental plot had an area of 27.4 m^2, composed of six planting rows 6 m long and a spacing of 0.76 m between rows. The plants were distributed along the rows with approximately 0.206 m spacing between them, resulting in a final density of 6.4 plants m^{-2}.

The cultivar (FiberMax 975 Wild Strike®) used was a transgenic late-cycle cotton variety with resistance to target insects conferred by the expression of the Cry1Ac and Cry1F proteins, derived from the bacterium *Bacillus thuringiensis* (Bt). This cultivar presents anthesis between 52 and 60 days after sowing (DAS) and has an estimated final fiber yield of 40 to 41%. The soil was prepared without disturbing the surface layers, and cotton seeds were planted under the corn straw. Mechanized sowing was carried out on November 30, 2014. The experimental area has a history of soybean–corn–cotton crop succession. Nitrogen fertilization was applied manually as a side dressing at 40 DAS.

During the experiment, agrometeorological and soil volumetric water content parameters were measured. Weather parameters, including air temperature, relative humidity, wind speed and direction, global solar radiation, and rainfall, were measured using an Automatic Weather Station (AWS). Soil water content (m^3/m^3) and soil temperature were measured at a depth of 0.08 m (model 5TE, Decagon Devices). The instruments were connected to a datalogger system programmed to take measurements every 5 min, and store the average of the air temperature, relative humidity, wind speed and direction, and accumulated rainfall and global solar irradiation.

Reference evapotranspiration (ETo) was estimated based on daily weather data from AWS using the Penman-Monteith FAO-56 method, which is considered the most robust and adaptable (Allen et al., 1998). This method has been validated and successfully applied in the western region of Bahia state (Vieira et al., 2023).

Before planting, composite soil samples (six points) were collected at depths of 0–10, 10–20, 20–40, and 40–60 cm to characterize the fertility of the experimental area. The Red-Yellow Latosol, predominant in the region, has good water retention capacity, attributed to the predominance of fine pores. Its hydraulic conductivity (K) is considered moderate, favoring water movement in the intermediate layers of the profile.

The physical-hydric characterization of the soil was performed based on undisturbed samples collected at 10 cm intervals, from the surface to a depth of 110 cm. This characterization included the experimental determination of the field capacity, the permanent wilting point, the water retention curve, the soil density, and the saturated soil hydraulic conductivity (Table 1). Available soil water was estimated from the difference between moisture contents at -10 kPa (field capacity) and −1500 kPa (permanent wilting point).

Crop Growth, Development, and Yield

During the growing season, nine field campaigns were carried out to evaluate cotton aboveground biomass (AB). On the first three dates (5, 7, and 14 days after sowing - DAS), two plants per plot were randomly sampled, while subsequent collections (38, 52, 79, 114, 179, and 232 DAS) consisted of one plant per plot. Plants were separated into stems, branches, leaves, reproductive structures, and viable bolls. The samples were oven-dried at 55 °C until they reached constant weight and then weighed on a precision balance.

Plant height was measured at 15 points throughout the cycle (up to 232 DAS), monitoring the same plants. The leaf area index (LAI) was calculated as the ratio between the total leaf area per plant and the available soil area. Leaf area was estimated by the specific leaf area (SLA) method, using values of 118.3, 136.6, and 133.4 $cm^2\ g^{-1}$ for cotyledonary, cordate, and lobed leaves, respectively (Monteiro et al., 2005).

The phenological stages were classified into vegetative (V1 to V5) and reproductive (B1 to B7, F1 to F5, and C1 to C5) phases, according to Marur and Ruano (2004), with regular observations in 10 random plants per experimental unit. Harvesting was performed manually at 232 DAS (July 20, 2015), and yield was estimated based on the average production per plant and plant density per hectare.

Cotton growth is related to the accumulation of degree days (DD), calculated by the difference between the average daily air temperature and the lower basal temperature (LBT), fixed at 15.6 °C (Beltrão et al., 2008), since air temperatures in the region do not exceed the upper basal temperature (UBT) (Ritchie et al., 2007; Lyra et al., 2008).

Experimental data on height, biomass, and leaf area index (LAI) were previously fitted to log and exponential growth models (Bender et al., 2020). Based on these fits, the resulting parameters were used to calibrate the SWAP/WOFOST model to evaluate its ability to simulate cotton growth and yield under different nitrogen sources in the far western region of Bahia state.

Operationalization of the SWAP-WOFOST Model

The SWAP-WOFOST model calibration procedure was performed in two stages: (i) field data collection, including weather information, soil characteristics, and cotton crop data in the Cerrado region of Bahia; and (ii) calibration of crop and soil parameters in the SWAP-WOFOST model, aiming to accurately simulate cotton growth. Information about the SWAP model can be found at https://swap.wur.nl/ (accessed March 2025).

The following is a brief description of the main calculation processes performed by SWAP-WOFOST.

Table 1 Result of the physical-hydric analysis of the Red-Yellow Latosol in the experimental area, from the surface to 110 cm in 10 cm intervals. Saturated soil hydraulic conductivity (K_{sat})

Depth	Potential (kPa)							K_{sat}
(cm)	-4	-6	-10	-30	-100	-500	-1500	($cm\ h^{-1}$)
0–10	0.136	0.109	0.078	0.068	0.059	0.047	0.033	6.669
10–20	0.129	0.099	0.081	0.071	0.060	0.048	0.033	4.492
20–30	0.154	0.134	0.093	0.081	0.076	0.065	0.053	5.397
30–40	0.157	0.136	0.100	0.083	0.077	0.068	0.060	6.549
40–50	0.152	0.134	0.104	0.092	0.083	0.076	0.064	4.384
50–60	0.166	0.136	0.107	0.090	0.081	0.079	0.063	4.393
60–70	0.154	0.140	0.104	0.091	0.083	0.069	0.058	5.879
70–80	0.157	0.139	0.104	0.090	0.079	0.070	0.063	8.787
80–90	0.175	0.156	0.118	0.103	0.091	0.078	0.066	7.345
90–100	0.160	0.150	0.116	0.105	0.095	0.075	0.064	4.407
100–110	0.175	0.160	0.122	0.112	0.099	0.087	0.067	7.232

SWAP Model

SWAP is a one-dimensional agro-hydrological model based on field-scale physical processes that simulate the vertical transport of water, solutes, and heat, as well as plant growth in unsaturated and variable saturation soils. Soil water movement is simulated using the well-known Richards equation (Eq. 1):

$$\frac{\partial\,\theta\,(h;t)}{\partial\,t}=\frac{\partial\,\left[K\,(h;t)\left(\frac{\partial\,q(t)}{\partial\,z}+1\right)\right]}{\partial\,z}-Sr\,(h;t)-Sd\,(h) \tag{1}$$

in which θ is the soil volumetric water content ($cm^3\ cm^{-3}$), t is the time (days), h is the pressure head with h≥0 when the soil is saturated and h<0 when it is unsaturated (cm), z is the vertical coordinate, positive upwards (cm), K is the hydraulic conductivity ($cm\ day^{-1}$), and Sr is a sink term referring to root water uptake ($cm^3\ cm^{-3}\ day^{-1}$), and Sd is a source or sink term referring to the interaction with drains ($cm^3\ cm^{-3}\ day^{-1}$).

The Richards equation combines the continuity and Darcy equations, resulting in the general soil water flow equation for saturated and unsaturated conditions (Kroes et al., 2008). In the SWAP model, this equation is solved numerically using an implicit finite-difference scheme (Belmans et al., 1983), detailed by van Dam et al. (2008). The model simulates water transport considering initial and boundary conditions, as well as hydraulic relationships between soil water content (θ), pressure head (h), and hydraulic conductivity (K) in an unsaturated local.

These relationships, which define the soil's capacity to retain, release, and transmit water under different environmental conditions, can be determined in the laboratory based on soil samples collected in the field (Vazifedoust et al., 2008).

In the SWAP calibration, the soil was separated into 11 layers of 10 cm, totaling 110 cm in depth. Table 1 shows the hydraulic conductivity K(h) values used, referring to the physical water analysis. The h values were fitted based on the soil water retention curve obtained from the van Genuchten model.

To solve the Richards equation, SWAP implements the Mualem-van Genuchten function (Mualem, 1976; van Genuchten, 1980), proposing an analytical (h) (Kroes et al., 2008):

$$\theta\ =\theta_{\,res}+\frac{(\theta_{\,sat}-\theta_{\,res})}{\left(1+|\alpha\,h|^{n}\right)^{-m}} \tag{2}$$

in which, $\theta_{\,sat}$ is the saturation water content ($cm^3\ cm^{-3}$); $\theta_{\,res}$ is an asymptotic residual. water content ($cm^3\ cm^{-3}$); α (cm^{-1}), n and m (dimensionless) are empirical shape factors.

The term m, used by SWAP, is defined as being dependent on the factor n, through the following relationship (Kroes et al., 2008):

$$m=1-\frac{1}{n} \tag{3}$$

Considering the relations of (h) presented previously and applying the theory of hydraulic conductivity in unsaturated soils, proposed by Mualem (1976), the function K(θ) is obtained (Kroes et al., 2008):

$$K\,(S_e)=K_{sat}\,S_e^{\lambda}\,\left[1-\left(1-S_e^{\frac{1}{m}}\right)^{m}\right]^2 \tag{4}$$

which K_{sat} is the saturated hydraulic conductivity ($cm\ d^{-1}$); λ is the (dimensionless) shape factor dependent on $\partial\,K/\partial\,h$; S_e is the relative saturation (Kroes et al., 2008), being defined as:

$$S_e=\frac{\theta\ -\theta_{\,res}}{\theta_{\,sat}-\theta_{\,res}} \tag{5}$$

A modification of the Mualem-van Genuchten function (Schaap & van Genuchten, 2006) was implemented in the SWAP model, introducing the minimum capillary height hc and Sc, corresponding to the soil saturation at point he, obtained through the classical model proposed by van Genuchten, which causes smaller changes in the retention curve.

The SWAP model calibration was performed based on data from the field experiment (2014/2015 harvest) carried out in the Cerrado region of Bahia, complemented by information from the literature regarding regions with similar climatic conditions.

WOFOST Model

Cotton growth, development, and yield were simulated using the detailed crop simulation module based on the WOFOST model (Supit et al., 1994; Wolf et al., 2011), integrated with the SWAP model. The latter allows crop growth simulation through two distinct modules: a simple module, in which the user defines the LAI, crop height, and root depth as functions of the phenological stage; and a detailed module, which uses WOFOST, a generic model for simulating the growth, development, and yield of various crops (Supit et al., 1994; Vazifedoust et al., 2008).

WOFOST organizes the factors that influence yield into three hierarchical levels. Defining factors are related to the physical environment, such as carbon dioxide, solar radiation, and air temperature, as well as the crop's physiological and morphological characteristics, which define potential yield. Limiting factors correspond to the water and nutrient availability, which can restrict potential yield. Finally, reducing factors represent losses caused by biotic stresses, such as pests, diseases, and pollutants.

Solar radiation intercepted by the canopy is calculated based on leaf area and available radiation, being converted into carbohydrates through photosynthesis, which is the basis for biomass production. Potential photosynthesis is adjusted by water and nutritional stress factors, resulting in real photosynthesis. The carbohydrates produced are primarily used to meet maintenance energy demands (maintenance respiration); the surplus is allocated to the production of structural biomass. This biomass is distributed among roots, stems, leaves, and reserve organs according to partition coefficients and the plant's development stage, represented by the DVS (*Development Stage*) index.

Dry matter accumulation in leaves directly influences solar radiation interception, promoting a feedback effect on the growth process. Quantifying phenological stages is essential in plant growth models, as these events regulate important physiological and morphological processes.

In cotton, phenological stages are determined by thermal accumulation and seasonal variation in sunlight duration. Before anthesis, development is controlled by day length and air temperature; after this stage, it is controlled only by temperature. Processes such as assimilation, distribution, and tissue senescence are regulated by the DVS, which ranges from 0 (emergence) through 1 (flowering) to 2 (maturation) (de Wit et al., 2020). The DVS is calculated by the accumulated thermal sum, so that high temperatures accelerate development and shorten the crop cycle.

Calibration

Model calibration was performed using experimental data from the 2014/2015 growing season. Crop parameters were primarily calibrated based on observed data of biomass, leaf area index (LAI), and phenology. Due to data availability, the same dataset was used for both calibration and evaluation. Therefore, the results should be interpreted as a model fitting assessment rather than an independent predictive validation. This limitation is explicitly acknowledged and considered in the interpretation of results.

Although several crop parameters listed in Table 3 are indicated as "default," the calibration strategy focused on parameters directly related to crop growth dynamics and site-specific conditions, including phenological development, biomass accumulation, and partitioning coefficients derived from experimental observations. In contrast, parameters associated with general physiological processes, such as light use efficiency (LUE), maximum CO_2 assimilation rate (Amax), respiration coefficients, and light extinction coefficients (kdir and kdif), were maintained as default values from the WOFOST database. These parameters are considered conservative and have been widely validated across crops and environments, reducing the risk of overparameterization.

Model Evaluations and Statistical Analyses

The SWAP model performance was evaluated by analyzing linear regression between simulated values (BT, BER, LAI, and soil water content) and observed values, considering the coefficient of determination (R^2) and root mean square error (RMSE), as a function of the different nitrogen fertilizer sources. Additionally, scatterplots were generated with the fitted linear regression ($Y_i = \beta_0 + \beta_1 X_i$), in which Y represents the simulated value, X the observed value, β_0 is the intercept, and β_1 is the slope and the subscript i represents the data on the i-th day.

$$RMSE = \left[\frac{\sum_{i=1}^{n}(Y_i - X_i)^2}{n}\right]^{1/2} \tag{6}$$

in which *RMSE* is the Root Mean Square Error; *n* is the total number of observations.

The Willmott's agreement index (d-index) and the Nash–Sutcliffe efficiency (NSE) were also applied to quantify the agreement and efficiency of simulations, as proposed by Willmott (1982) and Nash and Sutcliffe (1970), respectively. The d-index values range from 0 to 1, with values closer to 1 indicating greater simulation accuracy. The corresponding equations are:

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i - X_i)^2}{\sum_{i=1}^{n}\left(\left|Y_i - \widehat{\mathrm{X}}\right| + \left|X_i - \widehat{\mathrm{X}}\right|\right)^2}\right] \tag{7}$$

in which $\widehat{\mathrm{X}}$ is the mean of the observed values.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}\left(X_i - \widehat{\mathrm{X}}\right)^2}\right] \tag{8}$$

NSE values close to 1 indicate high predictive accuracy and strong agreement between simulations and observations. Values around 0 suggest that the model performs similarly to using the observed mean as a predictor, whereas negative values indicate that the model performs worse than the observed mean and has limited predictive capability.

Additionally, the performance index (c-index), proposed by Camargo and Sentelhas (1997), was used, calculated as:

$$c = |r * d| \tag{9}$$

in which c is the dimensionless performance index proposed by Camargo and Sentelhas (1997); r refers to Pearson's correlation coefficient (dimensionless); d is Willmott's (1985) agreement index. The interpretation of the c-index follows the following criteria: excellent (c-index > 0.85); very good (0.75 ≤ c-index < 0.85); good (0.65 ≤ c-index < 0.75); average (0.60 ≤ c-index < 0.65); poor (0.50 ≤ c-index < 0.60); very poor (0.40 ≤ c-index < 0.50); and extremely poor (c-index < 0.40).

In the study, ANOVA was applied to the growth and yield parameters to evaluate differences among treatments The qualitative factor considered in the ANOVA was the nitrogen fertilization treatment, consisting of a control without N application and two N fertilizer sources: prilled urea® and Sulfammo®. Because the treatments combined the presence or absence of nitrogen fertilization with different fertilizer sources, treatment effects were interpreted as the overall response to N management. Therefore, no separate factorial interaction between N rate and fertilizer source was tested in this analysis.

Results

Climatic Conditions

During the cotton cycle (November 2014 to July 2015), total rainfall was 639.8 mm, higher than the minimum (500 mm) required by the crop (Reddy et al., 1991). However, the distribution was irregular, with higher monthly totals in December (226.6 mm) and April (155.6 mm), contrasting with periods of lower totals in January (23.8 mm) and mainly after May.

Average air temperatures remained within the ideal range (20–30 °C) for cotton for most of the cycle, according to Reddy et al. (1991) and Li et al. (2021), with averages of 31.1 ± 3.0 °C (maximum), 23.1 ± 1.8 °C (average), and 17.5 ± 2.3 °C (minimum). Extremes of 36.5 °C stood out in February and 10.7 °C in July. The average monthly maximum value was observed in January (34.1 ± 1.9 °C), while the average monthly minimum occurred in June (13.9 ± 1.4 °C) and July (13.9 ± 1.5 °C).

During the dry season, minimum air temperatures decreased, possibly due to increased atmospheric transmissivity (R_s/R_a) (Fig. 1), which intensified nocturnal heat loss. Maximum air temperatures remained high, likely due to intense incidents of solar radiation. Soil temperatures exceeded air temperatures, averaging 31.9 ± 4.1 °C (maximum), 27.6 ± 2.5 °C (average), and 24.6 ± 1.6 °C (minimum). The maximum (43.4 °C) occurred in January, the month with the highest atmospheric transmissivity, while the minimum (22.0 °C) was recorded in December, coinciding with the highest daily rainfall.

In January (31–60 DAS), the cotton plant went from the advanced vegetative stage (up to V5) to the beginning of flowering, with the appearance of the first flower buds (B) at 41 DAS and the first fertilized white and pink flowers at 55 DAS. Thermal accumulation was 410 °ADD until 41 DAS, and 559 °ADD until 55 DAS.

The accumulated global solar radiation (R_s) during the cycle was 4712 MJ m^{-2}, with a daily average of 19.5 MJ m^{-2}. The highest monthly accumulated value occurred in January (737 MJ m^{-2}), while the lowest was observed in June (546 MJ m^{-2}). The reference evapotranspiration (ET_o), estimated using Penman-Monteith FAO-56 (Allen et al., 1998), was intensified by high solar radiation and air temperature, especially in January and at the beginning of the dry season, increasing the vapor pressure deficit and reducing relative humidity.

Regarding the region's typical climate, which is a tropical savanna with a rainy season in summer and a dry season in winter (Alvares et al., 2013), data from 2014/2015 indicate a dry spell in January and a transition to the dry season from May onwards. In April (between 120 and 150 DAS), the crop was in the boll formation stage (C), with the first boll observed at 130 DAS (1250.4°ADD). At this stage, vegetative structures, flowers, and ripening fruits coexisted, favored by the rainfall recorded during the month, which corresponded to 87.5% of the total rainfall recorded at this stage (C). The high rainfall during this period interfered with farm planning, which predicted that the chemical ripening and harvest would happen in June. Due to heavy rains, there were losses in the bolls of the first reproductive nodes, resulting in a delay in harvest of more than a month.

Calibration and Validation of the SWAP-WOFOST Model

Field data collected over the 232 days of the crop season were used to calibrate and validate the SWAP model. The main variables used in the calibration are shown in Tables 2 and 3. Table 2 presents the experimental data measured in the study area, while Table 3 presents the parameters from the standard set of the WOFOST model for cotton, supplemented by information available in scientific literature.

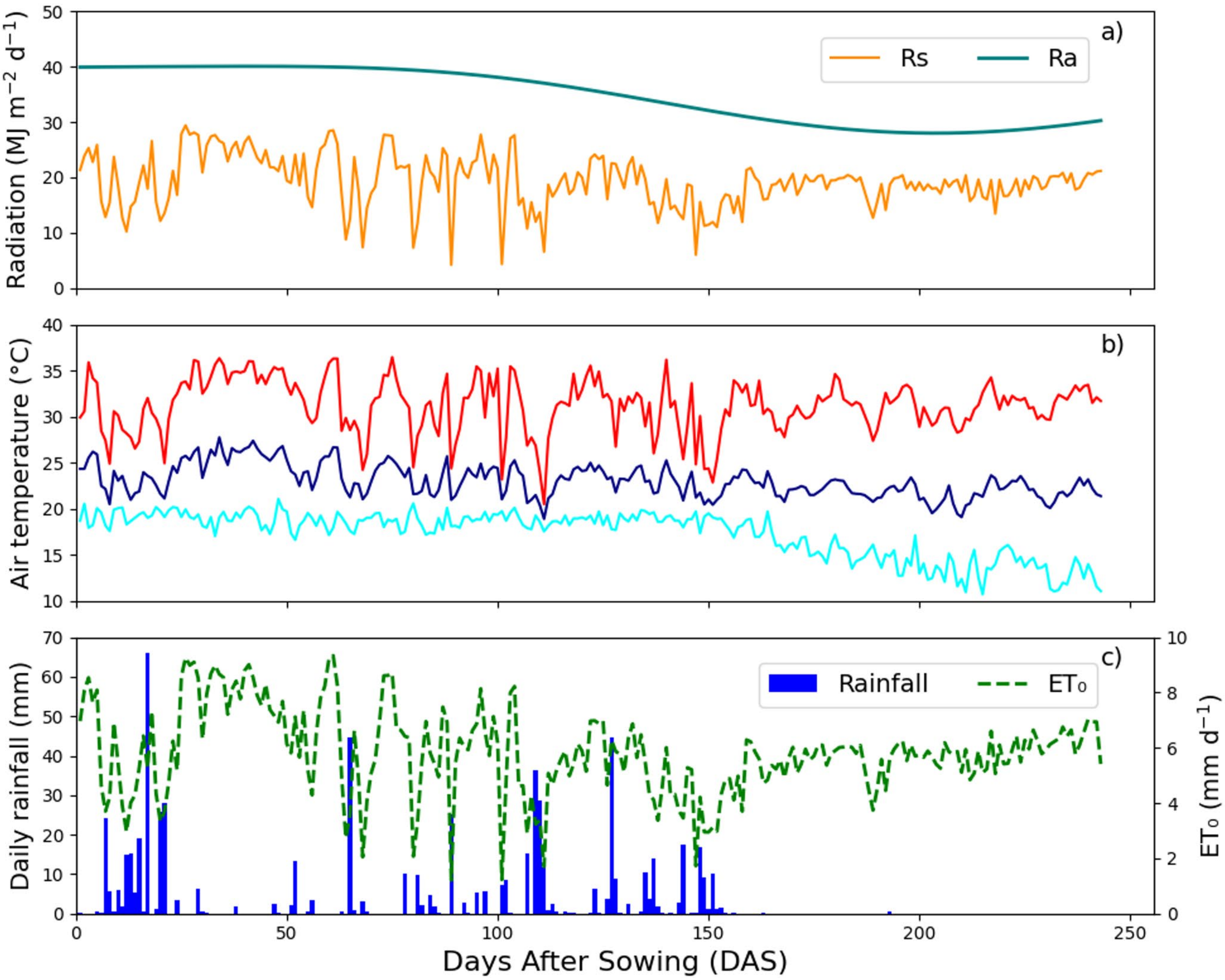

Fig. 1 Temporal evolution of weather variables in Luiz Eduardo Magalhães, BA, during the cotton crop cycle (Dec. 2014 – Jul. 2015), as a function of days after sowing: (**a**) global solar radiation (R_s, MJ m^{-2} d^{-1}, orange dots) and extraterrestrial solar radiation (R_a, MJ m^{-2} d^{-1}, dark blue line); (**b**) maximum (red), mean (blue), and minimum (cyan) air temperatures (°C); (**c**) daily rainfall (blue) and reference evapotranspiration (ET_o, green dashed line) (mm)

Table 2 van Genuchten-Mualem model parameters and hydraulic conductivity used in model calibration

Soil layer (cm)	θ_{res} (cm^3 cm^{-3})	θ_{sat} (cm^3 cm^{-3})	a (cm^{-1})	*n* (-)	K_{sat} (cm d^{-1})
0–10	0.037	0.214	0.0518	1.711	160.1
10–20	0.042	0.200	0.0578	1.688	107.8
20–30	0.057	0.239	0.0583	1.695	129.6
30–40	0.061	0.243	0.0487	1.801	157.2
40–50	0.071	0.226	0.0491	1.798	105.1
50–60	0.069	0.246	0.0424	1.913	105.4
60–70	0.067	0.236	0.0492	1.800	141.1
70–80	0.067	0.241	0.0485	1.812	211.0
80–90	0.074	0.273	0.0531	1.755	176.2
90–100	0.073	0.251	0.0678	1.636	105.8
100–110	0.077	0.276	0.0749	1.599	173.5

Soil Water Content

Simulations of soil volumetric water content (m^3 m^{-3}) with the SWAP model showed variable performance across treatments (Fig. 2). For soil water content values below 0.10 m^3m^{-3}, the model showed better agreement compared to higher soil water content values, where a tendency toward underestimation was observed (Fig. 2b). Despite the underestimation for values above 0.10 m^3m^{-3}, low dispersion was observed. The underestimation occurred on rainy days (Fig. 2a), indicating that the model did not adequately simulate water infiltration into the soil. This may be related to model calibration or parametrization used, since the low dispersion combined with the deviation from the 1:1 line suggests a systematic error. This, in turn, indicated that the model needs improved calibration under these conditions,

Table 3 Main cotton crop parameters specified to SWAP-WOFOST

Parameter	Value	Source
Basal temperature, Tb (C°)	15.5	Beltrão et al. (2008)
Critical matrix pressure, h (cm)		
h1	-0.1	Default
h2	-30.0	Default
h3h	-1200.0	Default
h3l	-7500.0	Default
h4	-16,000	Default
Direct light extinction coefficient, kdir (-)	0.60	Default
Diffuse light extinction coefficient, kdif (-)	0.75	Default
Light use efficiency, LUE (kg CO_2 J^{-1})	0.40	Default
Maximum CO_2 assimilation rate, Amax (kg ha^{-1} h^{-1})	50.0	Default
Efficiency of conversion into leaves, CVL (kg kg^{-1})	0.7200	Default
Efficiency on the conversion of reproductive structures, CVO (kg kg^{-1})	0.6100	Default
Efficiency of conversion into stems, CVS (kg kg^{-1})	0.6900	Default
Relative increase in respiration rate per 10 °C temp increase, Q10 (C°)	2.0000	Default
Maintenance respiration rate of leaves (kg CH_2O kg^{-1} d^{-1})	0.0300	Default
Maintenance respiration rate of reproductive structures (kg CH2O kg^{-1} d^{-1})	0.0100	Default
Maintenance respiration rate of stems (kg CH2O kg^{-1} d^{-1})	0.0150	Default

or that, for this soil type and parametrization used, infiltration is not being properly represented by the simulation.

Overall, the simulated data reported low soil water content. All treatments based on the c-index that were classified as *extremely poor*, which indicated low precision and agreement in the simulations. Although the precision and, RMSE/NRMSE indicated some ability of the model to represent soil water dynamics, the results revealed limitations in the efficiency (NSE) of the simulations (Table 4).

Leaf Area Index (LAI)

The SWAP-WOFOST model showed excellent performance in simulating the cotton leaf area index (LAI). The maximum simulated values were greater than 2.00 in the UP and Sulf treatments, and 1.53 m^2 m^{-2} in the control treatment. All maximum IAF simulated were observed between 150 and 155 DAE.

The LAI simulations showed a high degree of agreement with the observed data for all treatments evaluated (Fig. 3). Overall, the R^2 and the agreement d-index, and, c-index indicated performance classified as *excellent* (Table 5). The low mean RMSE/NRMSE, and the high Nash–Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970) reinforce the robustness and efficiency of the SWAP/WOFOST model in simulating cotton growth, regardless of the nitrogen source used.

Reproductive Structures Biomass

The reproductive structures biomass (RSB) was estimated based on the average number of harvested structures and the plant stand (63,962 plants ha^{-1}). The average values were 7,212.7 kg ha^{-1} (Sulf), 6,889.8 kg ha^{-1} (UP), and 5,674.8 kg ha^{-1} (T). For reproductive biomass, no significant differences were detected among treatments by ANOVA ($p < 0.05$). Nevertheless, the observed final reproductive biomass was numerically higher in the fertilized treatments, with increases of 21.4% for Sulf and 17.6% for UP relative to the control (Bender et al., 2020). These results indicated that, although nitrogen fertilization increased reproductive biomass in relative terms, the variability among experimental units prevented the detection of significant treatment effects at the $p < 0.05$.

The SWAP-WOFOST model showed robust performance in simulating reproductive structure biomass (RSB) across all treatments evaluated (Fig. 4 and Table 6). The Sulf treatment showed the lowest precision (R^2), accuracy (d-index), and c-index. The UP treatment showed highest d-index and NSE and, lowest NRMSE between observed and simulated values, with strong precision, accuracy, and efficiency. The Control treatment also demonstrated excellent performance, with performance indices comparable to or slightly higher (R^2) than those observed for the fertilized treatments. Overall, the performance metrics indicate that the model adequately represented RSB dynamics across treatments. Nevertheless, despite the excellent general performance, the observations recorded between 150 and 200 DAE showed larger deviations from the simulated values compared with the other evaluation dates.

The results show that the WOFOST model coupled with SWAP demonstrated high performance in simulating cotton RSB under different nitrogen fertilization strategies. The high R^2, d-index, NSE values, low NRMSE and, the *excellent* c-index rating in all simulations, demonstrate the model's confidence. These results reinforce the robustness and applicability of SWAP-WOFOST in simulating cotton reproductive growth.

Total Biomass

Total biomass (TB) was estimated by multiplying the average biomass per plant by the observed population density (63,962.0 ± 11,446.1 plants ha^{-1}). Dry matter production gradually increased throughout the crop cycle, until 175 DAS (Fig. 5), regardless of the nitrogen fertilization

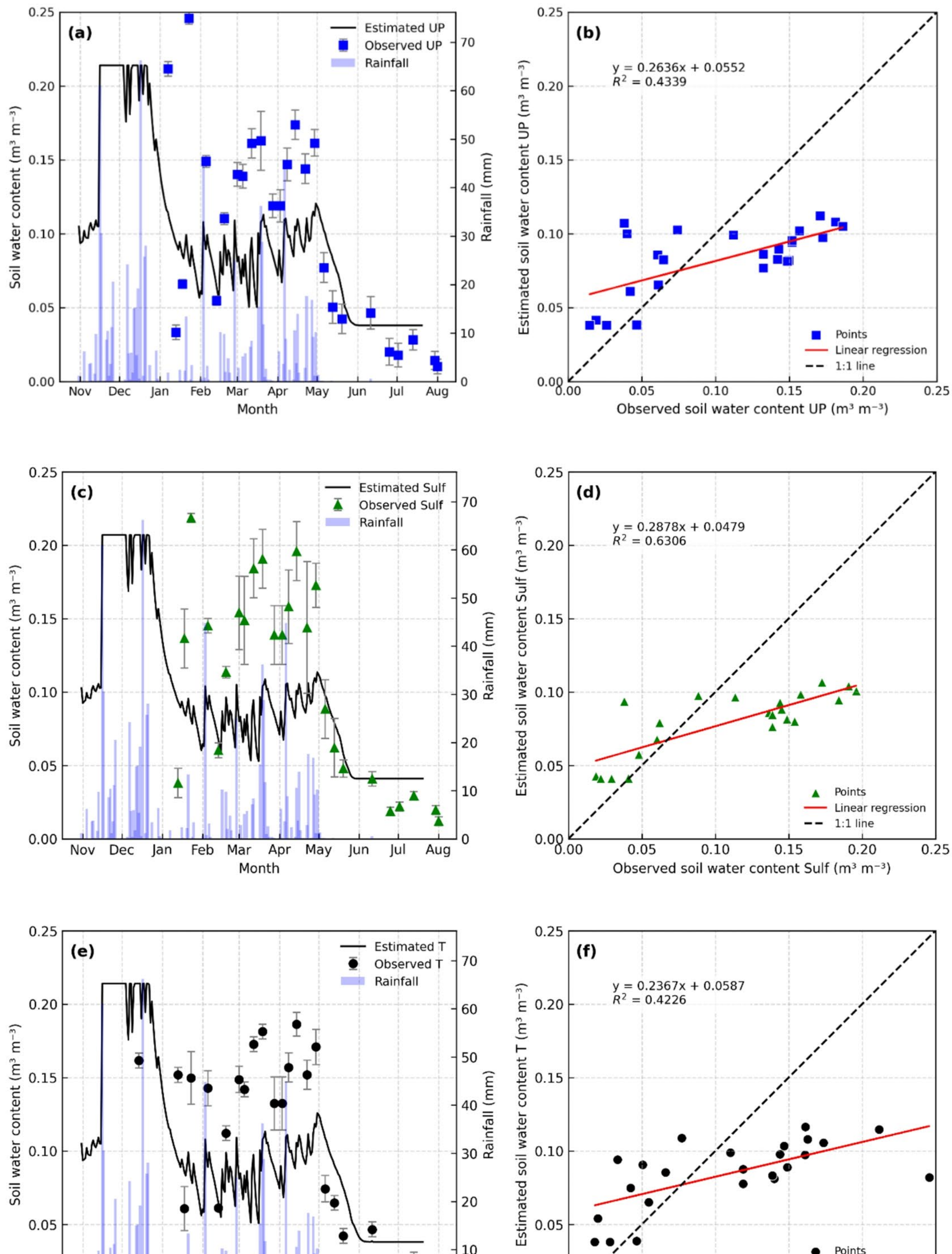

Fig. 2 Soil volumetric water content (0–10 cm, $m^3\ m^{-3}$) observed and simulated by the SWAP model throughout the experimental period (**a, c, e**) and scatterplot of observed versus simulated soil water content values (**b, d, f**) for the Urea (**a, b**), Sulfammo® (**c, d**), and Control (**e, f**) treatments, including the 1:1 reference line (dashed) and the fitted linear regression line (solid red)

Table 4 Statistical indicators of the performance of the SWAP model in the simulation of the soil volumetric water content ($m^3\ m^{-3}$) of cotton plants in the different treatments with nitrogen sources: UP (urea), Sulf (sulfammo®), and T (control). Coefficient of determination (R^2); Willmott's agreement index (d-index); Performance index (c-index); Root Mean Square Error (RMSE); Nash–Sutcliffe efficiency index (NSE)

Treat.	R^2	d index	c index	RMSE ($m^3\ m^{-3}$)	NRMSE (%)	NSE
UP	0.492	0.399	0.280	0.0114	10.5	0.203
Sulf	0.560	0.352	0.263	0.0124	10.8	0.060
T	0.416	0.510	0.330	0.0100	8.9	0.221

treatment, and the evolution of RSB followed this growth. The TB values obtained were 11,314.8 ± 4,369.3 kg ha^{-1} in the UP treatment, 11053.2 ± 2548.3 kg ha^{-1} in the Sulf treatment, and 8556.6 ± 2542.5 kg ha^{-1} in the control treatment (T), 24.4% (UP) and 19.9% (Sulf) more than the treatment without fertilization.

The ANOVA indicated that total aboveground biomass was not significantly affected by nitrogen fertilization treatment at the $p < 0.05$. Although the final aboveground biomass was numerically higher in the fertilized treatments, these differences were not statistically significant.

The simulations performed by the SWAP-WOFOST model presented excellent performance in estimating total cotton biomass (TB) in the three treatments evaluated. However, toward the end of the crop cycle, a tendency to overestimate TB was observed across all treatments. The performance coefficients indicated high accuracy, precision and efficiency, with emphasis on the UP treatment, which presented the best indicators (Table 7). The Sulf and T treatments also showed satisfactory results, with values close to each other, with exception of NSE for T. Similar to RSB, and despite the excellent overall performance, the TB observations for all treatments also showed larger deviations from the simulations between 150 DAE and the end of the crop cycle.

In the present study, the SWAP-WOFOST model showed even smaller errors (NRMSE), even with different nitrogen sources: 6.8% in the UP treatment, 10.6% in the Sulf treatment, and 18.2% in the control. The high precision of the model is clear with the high R^2 values (above 0.97), the d-index values above 0.96, NSE above 0.796 and, the *excellent* classification of the c-index in all treatments, which confirms its reliability to simulate the TB of cotton under different nitrogen fertilization conditions.

Discussion

Soil Water Content

Although the R^2 values indicate only a moderate precision in all scenarios, the agreement d-index and c-index suggest a greater predictive capacity of the model in the T treatment. This performance may be associated with an improvement in soil physical structure and soil water retention, attributed to the application of Sul fertilizer, resulting in greater consistency between the simulated and observed data. The NSE indicated that, overall, SWAP had low efficiency in reproducing the variability of soil water content under the conditions of the present study and with the calibration and parameterization procedures used. Similar results were reported by Eitzinger et al. (2004) in a comparative study between the SWAP and CERES models in predicting soil water content under barley and wheat cultivation. Similarly, Crescimanno et al. (2012) found that SWAP accurately simulated soil water and solute transport in soil profiles cultivated with grapevines if the hydraulic parameters were well calibrated. More recently, Shin et al. (2023), in a multi-model study with soil discretization, reported that although SWAP performs well under general soil water conditions, it exhibits high sensitivity to rainfall events and increased uncertainty when calibration is based on limited datasets.

Consistent with these findings, the present study identified a systematic underestimation of soil water content at higher values, particularly during rainfall events, suggesting that the model does not adequately represent infiltration processes and rapid soil water dynamics. This behavior agrees with previous studies reporting abrupt variations in SWAP simulations in response to rainfall, as well as a strong dependence on the parameterization and calibration of soil hydraulic properties.

Furthermore, the moderate dispersion combined with deviation from the 1:1 line indicates the presence of systematic errors rather than random variability. This suggests that the discrepancies are likely associated with structural limitations of the model and/or an inadequate representation of site-specific soil conditions or parametrization, particularly under high soil water scenarios. In this context, previous studies have shown that hydraulic parameters calibrated under certain conditions may not be transferable to contrasting scenarios (e.g., from normal to saturated conditions), which may explain part of the observed deviations.

Therefore, the *extremely poor* performance observed across all treatments (c index < 0.33) reflects not only calibration limitations but also inherent constraints of the model in representing soil water dynamics under rainfall-dominated conditions. These results highlight the need to improve model calibration and incorporate a more detailed

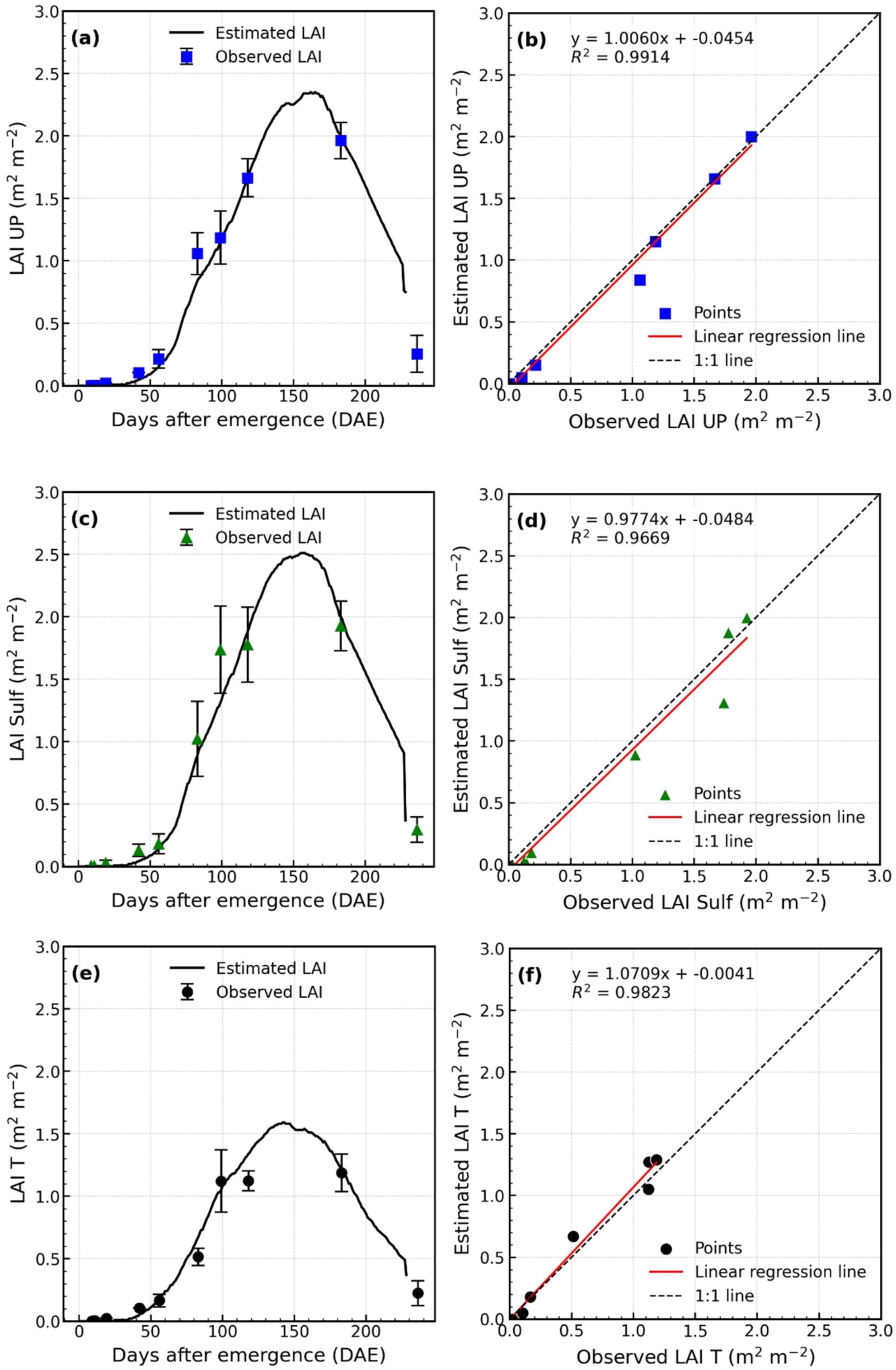

Fig. 3 Leaf area index (LAI) observed and estimated by the SWAP-WOFOST model throughout the experimental period (**a, c, e**) and scatter plot (**b, d, f**) of observed versus simulated (estimated) LAI values for the Urea (UP), Sulfammo® (Sulf), and Control (T) treatments, including the 1:1 reference line (dashed) and the fitted linear regression line (solid red)

characterization of soil hydraulic properties in order to enhance the reliability of SWAP simulations.

The suitability of SWAP–WOFOST as a decision-support tool should be interpreted considering the limitations observed in soil water simulations. Since soil water availability directly controls the water stress factor in WOFOST, uncertainties in soil water estimates may affect the reliability of crop growth simulations, particularly under conditions characterized by intense rainfall events or rapid infiltration processes. Therefore, model applications requiring accurate prediction of soil water dynamics should be accompanied

Table 5 Statistical indicators of the performance of the SWA-P WOFOST model in the simulation of the Leaf Area Index (LAI) of cotton in the different treatments with nitrogen sources: UP (urea), Sulf (sulfammo®), and T (control). Coefficient of determination (R^2); Willmott's agreement index (d-index); Performance index (c-index); Root Mean Square Error (RMSE); Nash–Sutcliffe efficiency index (NSE)

Treat.	R^2	d index	c index	RMSE ($m^2 m^{-2}$)	NRMSE (%)	NSE
UP	0.991	0.994	0.990	0.027	3.9	0.988
Sulf	0.967	0.980	0.964	0.053	7.0	0.961
T	0.976	0.983	0.971	0.032	6.7	0.964

by site-specific calibration and independent validation of soil hydraulic parameters.

Leaf Area Index (LAI)

The excellent performance of the SWAP-WOFOST model in simulating the cotton LAI suggests a good representation of the crop's vegetative growth under the conditions evaluated in this study. These results corroborate the findings of Zhuo et al. (2022), who observed good agreement between simulated and observed LAI in winter wheat ($R^2=0.94$; RMSE $=0.59$ m^2 m^{-2}), thus demonstrating the applicability of the model in different crops. However, Tang et al. (2023) observed greater uncertainty in the LAI simulation in *Capsicum annuum* L. under different nitrogen levels (RMSE $=0.76$ m^2 m^{-2}). In the present study, the high accuracy obtained can be attributed to the quality of the experimental data and the adequate calibration of the coefficients related to the vegetative growth of the crop.

Despite this overall excellent performance, it is important to recognize that WOFOST may present deviations in LAI simulation, particularly during early growth stages. Dewenam et al. (2021) reported that the model can overestimate or underestimate LAI due to biases in the estimation of thermal time (degree days) and uncertainties in the parameterization of the specific leaf area (SLATB), a key factor controlling canopy expansion. Similarly, Dlamini et al. (2025) identified residual errors during early canopy development, with relatively high uncertainty (NRMSE $\approx 41\%$), attributed to spatial variability in SLATB and heterogeneous field conditions. These findings suggest that LAI simulation is highly sensitive to parameter calibration and local variability, especially during the initial stages of crop establishment, when leaf expansion responds strongly to environmental conditions.

In addition, uncertainties in phenological estimation, such as errors in the determination of emergence timing, may propagate through the model and affect LAI dynamics and subsequent biomass accumulation. Variability in management practices and limited datasets can further constrain model calibration, contributing to systematic deviations rather than random errors. In this context, although such discrepancies were minimal in the present study, they should be considered when interpreting LAI simulations. These limitations are inherent to the model structure and highlight the importance of careful calibration and parameterization and the use of high-quality input data to improve simulation reliability.

Reproductive Structures Biomass

The similarity between the experimental results and those reported by Yang et al. (2012) indicates that the reproductive growth and development of cotton under tropical conditions follows a pattern comparable to that observed in other environments, despite differences in management and climate. In that study, reproductive structure biomass ranged from 80 to 100 g per plant at the end of the cycle, values consistent with those obtained in the present work. The slightly higher RSB observed in the fertilized treatments suggests that nitrogen availability enhanced assimilate partitioning toward reproductive organs, although the absence of statistical differences indicates that the crop maintained reproductive allocation even under limited nitrogen supply, possibly through compensatory mechanisms.

The strong agreement between observed and simulated values suggests that the SWAP-WOFOST model effectively captures the main physiological processes involved in reproductive biomass formation under the conditions evaluated in this study. These results are in line with previous studies demonstrating the model's ability to reproduce biomass dynamics and yield components under contrasting management conditions (Boogaard et al., 1998; van Dam et al., 2008; Confalonieri et al., 2016). Nevertheless, because the same dataset was used for both calibration and evaluation, part of the observed agreement may reflect adaptation to the specific experimental conditions. Thus, the present findings support the potential applicability of SWAP-WOFOST for evaluating nitrogen management strategies and their effects on cotton yield, although further validation using independent datasets is warranted.

The larger deviation observed between 150 and 200 DAE, despite the overall satisfactory performance of the SWAP–WOFOST simulations for RBS e TB, may reflect uncertainty in the phenological information used to parameterize the model, particularly anthesis and the transition to reproductive growth. In WOFOST, biomass accumulation, senescence, assimilate partitioning, and yield formation are

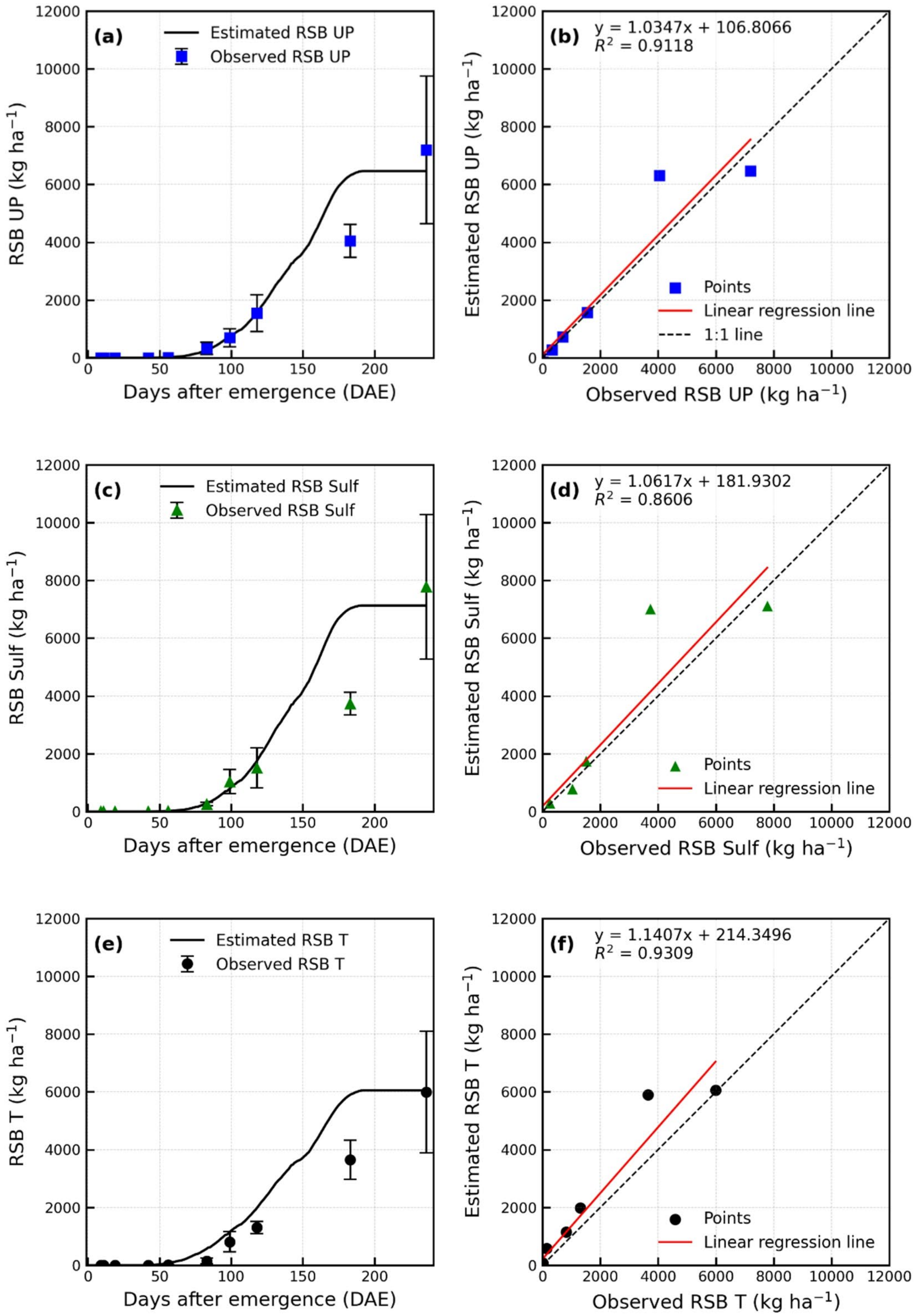

Fig. 4 Reproductive structures biomass (RSB) observed and estimated by the SWAP-WOFOST model throughout the experimental period (**a, d, e**) and scatter (**b, d, f**) plot of observed versus simulated (estimated) RSB values for the Urea (UP), Sulfammo® (Sulf), and Control (T) treatments, including the 1:1 reference line (dashed) and the fitted linear regression line (solid)

Table 6 Statistical indicators of the performance of the SWAP-WOFOST model in the simulation of the reproductive structure biomass (RSB) of cotton in the different treatments with nitrogen sources: UP (urea), Sulf (sulfammo®), and T (control). Coefficient of determination (R^2); Willmott's agreement index (d-index); Performance index (c-index); Root Mean Square Error (RMSE); Nash–Sutcliffe efficiency index (NSE)

Treat.	R^2	d index	c index	RMSE (kg ha^{-1})	NRMSE (%)	NSE
UP	0.912	0.950	0.907	238.4	17.2	0.891
Sulf	0.861	0.927	0.862	283.1	19.8	0.860
T	0.931	0.936	0.903	241.1	20.2	0.844

strongly driven by crop development stage, so small inconsistencies in the timing of reproductive development may result in larger deviations in simulated total and reproductive biomass (Ceglar et al., 2019; de Wit et al., 2020). This effect is especially relevant for cotton because of its indeterminate growth habit, in which vegetative growth, flowering, boll development, boll retention, and senescence overlap during the reproductive phase; therefore, the deviation between 150 and 200 DAE may also reflect field variability in destructive biomass sampling and limitations of generic crop models in representing cotton reproductive dynamics under rainfed Cerrado conditions (Bange & Milroy, 2000; Thorp et al., 2014).

Total Biomass

The results indicate that nitrogen availability played a decisive role in determining total biomass accumulation. Comparable findings were reported by Mao et al. (2014) in the Yellow River region, China, where biomass production under the application of 225 kg N ha^{-1} and a density of 6 plants m^{-2} ranged between 800 and 1000 g m^{-2}, values lower than those obtained in the present study, particularly in the fertilized treatments. Similarly, Dai et al. (2015) observed biomass accumulation of up to 14,350 kg ha^{-1} under irrigated conditions at a density of 6.9 plants m^{-2}, comparable to the experimental setup used here. In that study, total biomass ranged from 9,469 kg ha^{-1} (with 1.5 plants m^{-2}) to 17,160 kg ha^{-1} (with 10.5 plants m^{-2}), depending on plant spacing.

Brodrick et al. (2012), evaluating high-yield cotton systems in Australia, reported total biomass accumulation between 2,213 and 2,500 g m^{-2}, with fruit biomass ranging from 1241 to 1925 g m^{-2}. Despite the high TB values observed in treatments with nitrogen fertilization, Bender et al. (2020) found that the Sulf treatment achieved the highest seed cotton yield (5,263.4 ± 1,891.1 kg ha^{-1}), surpassing UP and T, which recorded 4,547.6 ± 1,686.2 kg ha^{-1} and 3,891.5 ± 1,302.0 kg ha^{-1}, respectively. The harvest index (HI) was also highest in Sulf (0.48), followed by T (0.46) and UP (0.40), all above the 0.37 value reported by Dai et al. (2015).

However, as pointed out by Ali et al. (2009), increased total biomass resulting from higher nitrogen supply or plant density does not necessarily translate into higher yield, since it may reduce assimilate allocation to reproductive structures. Previous simulations using the CSM-CROP-GRO-Cotton model in semiarid regions of Pakistan also showed satisfactory accuracy, with relative errors ranging from −4.4 to 15% for yield and between 7.5 and 19% for biomass, depending on cultivar and phosphorus level (Amin et al., 2017). The performance metrics obtained in the present study with SWAP-WOFOST were even better than those reported by Amin et al. (2017), suggesting a strong agreement between simulated and observed biomass dynamics under the experimental conditions evaluated. However, because the same dataset was used for both calibration and evaluation, these results should not be interpreted as evidence of fully independent predictive performance.

Although LUE, Amax, kdir, and kdif were maintained at their default values, previous WOFOST sensitivity analyses have shown that the relative importance of these parameters depends on the crop, environmental conditions, and simulated output variable, whereas phenological and biomass partitioning parameters are frequently among the main drivers of variability in crop growth and yield simulations (Gilardelli et al., 2018). Therefore, the good agreement obtained for LAI and biomass suggests that the default parameterization provided a reasonable representation of canopy radiation interception and biomass accumulation under the conditions evaluated in this study. However, because the same dataset was used for both calibration and evaluation, these results should be interpreted with caution, as part of the observed agreement may reflect adaptation to the specific experimental conditions rather than fully independent predictive capability. Consequently, additional validation using independent datasets collected across multiple growing seasons and environmental conditions is required to confirm the robustness and transferability of this calibration.

Conclusions

The coupling of the SWAP and WOFOST models constitutes a robust tool for the integrated simulation of the soil–plant–atmosphere system under the conditions of the Bahian Cerrado, Northeastern Brazil, enabling a comprehensive

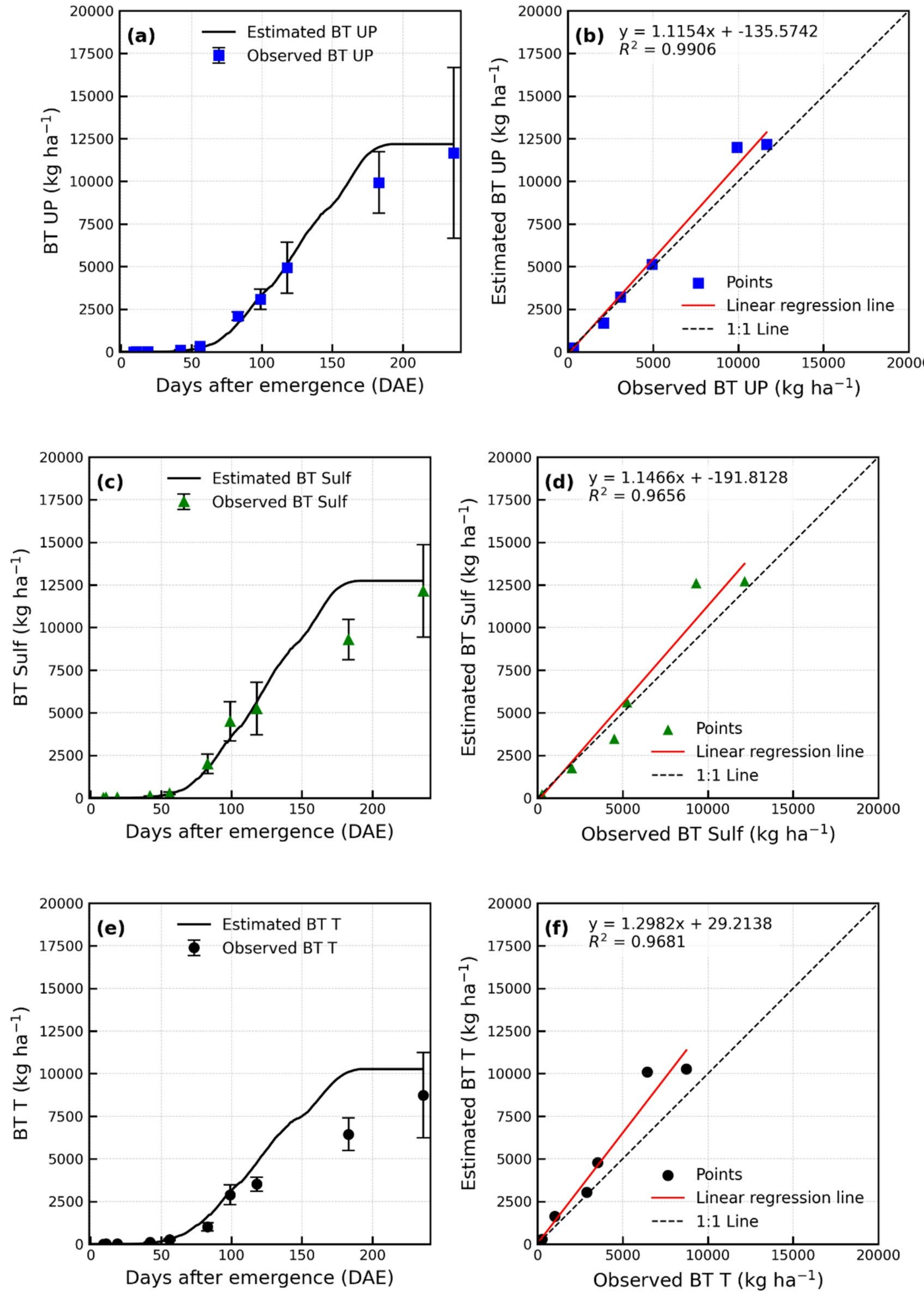

Fig. 5 Total biomass (TB) observed and estimated by the SWAP-WOFOST model throughout the experimental period (**a, c, e**) and scatter plot (**b, d, f**) of observed versus simulated (esimated) TB values (**b**) for the Urea (UP), Sulfammo® (Sulf), and Control (T) treatments, including the 1:1 reference line (dashed) and the fitted linear regression line (solid)

Table 7 Statistical indicators of the performance of the SWAP/WOFOST model in the simulation of the total biomass (TB) of cotton in the different treatments with nitrogen sources: UP (urea), Sulf (sulfammo®), and T (control). Coefficient of determination (R^2); Willmott's agreement index (d-index); Performance index (c-index); Root Mean Square Error (RMSE); Nash–Sutcliffe efficiency index (NSE)

Treat.	R^2	d index	c index	RMSE (kg ha^{-1})	NRMSE (%)	NSE
UP	0.991	0.987	0.983	219.2	6.8	0.972
Sulf	0.966	0.969	0.952	356.4	10.6	0.927
T	0.968	0.927	0.912	420.2	18.2	0.796

assessment of cotton growth and yield under different nitrogen sources and rates. The simulation of leaf area index, total biomass, and reproductive structure biomass was satisfactory across all treatments, demonstrating the model's ability and efficiency to adequately represent crop growth and yield under local edaphoclimatic conditions.

However, soil water dynamics remain a key limitation of the model, particularly under rainfall-dominated conditions, where systematic deviations were observed. These discrepancies are likely associated with the representation of infiltration processes, the calibration, and/or parameterization of soil hydraulic properties.

From an applied perspective, the SWAP-WOFOST model shows strong potential as a decision-support tool for nitrogen fertilization management in Cerrado agricultural systems, allowing the evaluation of management scenarios and optimization of input use. Nevertheless, its practical application requires site-specific calibration, especially regarding crop physiological parameters and soil hydraulic characteristics.

To improve model performance and applicability, future research should: (i) incorporate multi-season datasets to enable more robust independent validation; (ii) refine the calibration of key parameters such as SLATB, LUE, and soil hydraulic functions; (iii) evaluate alternative parameterizations and boundary conditions for the soil hydraulic relationships and the Richards equation to simulate soil water dynamics.; iv) integrate high temporal resolution data, such as remote sensing and continuous soil water content monitoring; v) evaluate inverse-problem algorithms for the automatic calibration of the SWAP and WOFOST models; and (vi) explore data assimilation approaches to reduce uncertainties, particularly during early crop stages and rainfall events.

Overall, these improvements will enhance model reliability and support its use as a strategic tool for sustainable nitrogen management in tropical agricultural systems.

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Data Availability The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Code Availability Not applicable.

Declarations

Ethical Approval Not applicable.

Consent to Participate All authors agree to participate in any survey or feedback task.

Consent for Publication All authors agree to provide manuscript for publication to the publisher of the journal.

Competing Interests The authors declare no competing interests.

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