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Article

Soybean yield potencial in petric plinthosols: climate and economic interactions

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ABSTRACT: Soybean production in central Brazil predominantly occurs on ferralsols. However, increasing global demand has driven expansion into marginal areas with less suitable soils, particularly petric plinthosols. These soils present significant agronomic challenges, especially their heightened vulnerability to climatic variability. Nevertheless, some regions with petric plinthosols, such as parts of Tocantins state, have achieved surprisingly high soybean yields. Despite this production potential, research on soybean cultivation in petric plinthosols are still limited. Our study addresses this knowledge gap by evaluating how environmental conditions and management practices, particularly sowing dates, affect soybean yields in petric plinthosols compared to ferralsols. We also developed economic indicators to support sustainable production decisions. The results demonstrated that while high yields are achievable in petric plinthosols, these soils exhibit greater climate sensitivity than ferralsols. Environmental factor such as air humidity, mainly in the reproductive phase, is a limiting factor for higher yields. Notably, our economic analysis revealed that cost management impacts profitability more substantially than yield improvements, even under unfavourable conditions. This finding suggests that strategic farm management could make petric plinthosol cultivation economically viable despite their agronomic constraints.

Key words: Tocantins, Goiás, machine learning, decision tree classification, gravel.

INTRODUCTION

Nowadays, Brazil is one of the world's leading producers and exporters of cereals. Much of this contribution is due to agricultural production in central Brazil, the Cerrado region, based mainly on soybean production. Due to its particular characteristics (high concentration of protein and oil) and high adaptability, this crop is still expanding, establishing itself mainly on degraded pastures, using sustainable cropping systems, with cover crops biomass inputs to increase soil carbon levels and grain yield (Almeida et al. 2017, Souza et al. 2024, Bortolo et al. 2025, Souza et al. 2025) and favouring the recovery of areas previously considered unproductive or of low yield (Budziak 2024, Loayza et al. 2023, Matos et al. 2022).

Much of the soybean production in central Brazil occurs on ferralsols, which, despite their low natural fertility, possess favorable physical characteristics for crop cultivation, such as deep soil profiles, balanced clay content and flat relief features, common in many regions of the Goiás and Tocantins savanna (Almeida et al. 2024).

Driven by rising global demand for soybeans (Martignone et al. 2024), Brazil is expanding cultivation into previously unsuitable areas, including petric plinthosols (Campos et al. 2025). These soils present significant challenges due to their low fertility and high gravel content (plinthites and petroplinthites), which hinder water infiltration, reduce soil moisture availability, restrict root growth, and complicate mechanization (Nikkel and Lima 2019, Almeida et al. 2023).

Currently, no official guidelines or studies exist on soybean production in petric plinthosols in Brazil. However, farmers, particularly in Tocantins, where petric plinthosols cover approximately 35% of the state's area (Ramos 2022), are increasingly cultivating soybeans on these soils.

One of the main challenges of cultivating crops in petric plinthosols is their susceptibility to climatic events, which can further constrain agricultural viability and increase production risks. Despite these challenges, some petric plinthosol areas in Tocantins state have demonstrated high soybean yield (Almeida et al. 2023, Campos et al. 2025).

However, studies on soybean cultivation in petric plinthosols are still limited, lacking well-established recommendations for productive systems in these soils, leading to yield variability.

Recommendations for sowing date, crop varieties, fertilization, and other agricultural practices rely on a thorough understanding of plant-environment interactions. In this context, this study aimed to assess the impact of environmental and management factors (sowing date and cultivars cycles) on soybean yield in petric plinthosol compared to ferralsol. By analyzing these interactions, the study developed scenarios highlighting the influence of management practices and environmental conditions. Furthermore, economic indicators were established to support informed decision-making and optimize agricultural sustainability of soybean production in petric plinthosols.

MATERIAL AND METHODS

Study area

The study area includes two Brazilian states, Goiás and Tocantins (Fig. 1a). These states are significant contributors to soybean production in Brazil, accounting for 11 and 3% of the national output, respectively (Conab 2024). Both states feature a predominant Aw climate (Fig. 1b). The distribution of soil types in these states is shown in Fig. 1c.

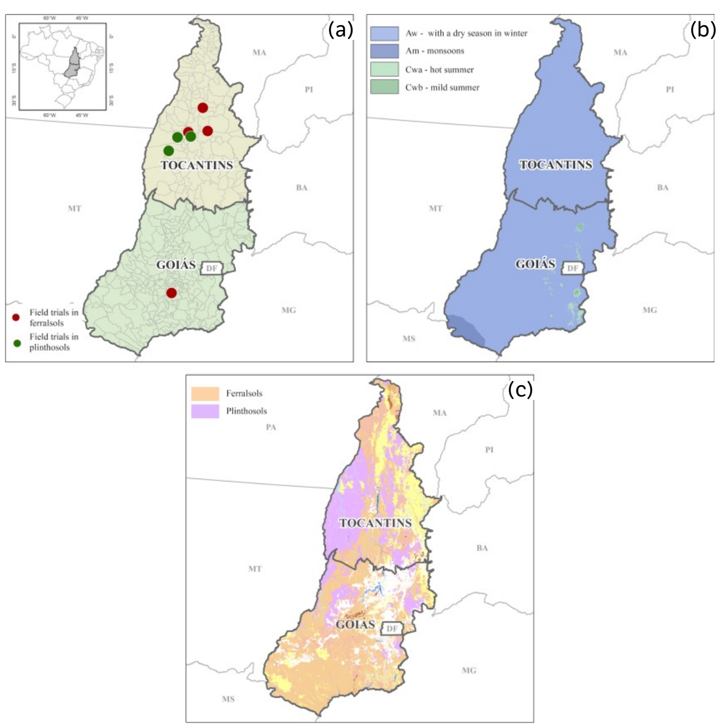


Figure 1. (a) Geographic localization of field trials, (b) climatic distribution on the study region and (c) soil class distribution along of Goiás and Tocantins states, Brazil.

Experimental dataset

Agronomic features

This study utilized a comprehensive dataset from a large field experiment consisting of 10 trials conducted between 2018 and 2023. These trials focused on commonly grown and well-adapted soybean varieties as part of Brazilian Agricultural Research Corporation (Embrapa) soybean breeding program, designed to evaluate candidate varieties under multi-environment trial conditions.

The trials took place in two Brazilian states: Goiás (one trial) and Tocantins (nine trials), spanning six municipalities (Fig. 1a). The trials in ferralsols were carried out in Goiânia-GO (2021/2022 growing season), Paraíso do Tocantins-TO (2020/2021 and 2022/2023), Pedro Afonso-TO (2017/2018), and Aparecida do Rio Negro-TO (2017/2018). Trials in petric plinthosols were carried out in Lagoa da Confusão-TO (2017/2018), Paraíso do Tocantins-TO (2019/2020; 2020/2021 and 2021/2022) and Pium-TO (2022/2023) (Fig. 1a).

All plinthosols used in the study were classified as petric plinthosol dystric soil (IUSS Working Group WRB 2006) or Plintossolo Pétrico Concrecionário típico according to the Brazilian Soil Classification System (*apud* Santos et al. 2018). The petric plinthosol of Paraíso do Tocantins contains 51% gravel in the surface layer, it is located in the Tocantins River basin and originates from sedimentary rocks such as siltstones and claystones. On their turn, the petric plinthosols of Lagoa da Confusão (80% gravel content) and Pium (75% gravel content) are in the Araguaia River basin and originate from metamorphic rocks such as schists with quartzite inclusions.

All farms received fertilization above 90 $kg \cdot ha^{-1}$ of K_2O and P_2O_5, in addition to periodic micronutrient applications, aiming for maximum productivity at each location.

According to Embrapa's standards, each trial featured an average of 25 genotypes, which varied over the years, arranged in randomized blocks with four replicates each. The genotypes included late, medium, early, and super-early cycles, and all trials were conducted under rainfed conditions. Local agronomic management recommendations were adhered to the field experiments, with sowing occurring between November and December. The 11 trials were categorized into two soil groups: ferralsol (five trials) and petric plinthosol (five trials) (Fig. 1a). Key agronomic features recorded included sowing and harvesting dates, yield, genotype, cycle, latitude, and longitude.

Environmental features

For each trial, climate features were collected from NASAPOWER (2024) for each genotype across three distinct crop phases: the vegetative phase (from sowing to 45 days after sowing—DAS), the reproductive phase (from 46 to 70 DAS), and the grain filling phase (from 70 DAS to harvest). The following climatic variables were extracted for each phase: mean, maximum, and minimum temperatures; dew point; wind speed; relative air humidity; rainfall; global solar radiation; mean evapotranspiration; the impact of temperature on radiation use efficiency; degree days; atmospheric water deficit; and the slope of the saturation vapor pressure curve. These features were obtained using the EnvRtype R package (Costa-Neto et al. 2024).

The climatic data were then integrated with agronomic information (as detailed in the previous section) and will be referred to as environmental features (EF) hereafter.

Clusters from soybean yield data

Using the soybean yield data described in the section "Agronomic Features", we identified independent yield classes using an unsupervised learning approach. Specifically, we employed the K-means algorithm, a widely used unsupervised machine learning (ML) method for pattern recognition and classification tasks. The optimal number of clusters, representing soybean yield classes, was determined using the Elbow method (Campos 2025), which evaluates within-cluster sums of squares to identify the point of diminishing returns. To measure similarity between data points, we utilized Euclidean distance, following Hartigan and Wong's (1979) approach.

Decision tree classification analysis

Given the complexity of the observed field data, which challenges the validation of assumptions underlying many parametric techniques, we employed a non-parametric approach decision tree classification (DTC). This method supports scenario development and enables robust and consistent modeling to meet the study's objectives. DTC, a supervised learning technique, was used to relate agronomic outcomes specifically, grain yield (GY) classes (see section "Clusters from soybean yield data") to EF, resulting in Eq. 1:

$$GY \sim f(EF) + r \tag{1}$$

where: r: residual variation not explained by EF, including measurement error.

For the optimization of the DTC, the following steps were implemented:

- Hyperparameter optimization through cross-validation;
- Grid search to find the best values for complexity parameter (CP), maxdepth, and minsplit;
- Analysis of the complexity curve to identify the optimal pruning point.

DTC was selected for its computational efficiency, insensitivity to redundant features, and lack of distributional assumptions about EF (Beucher et al. 2019). For that, we use the rpart package (Therneau and Atkinson 2025). The model's target variable was the GY class (genotype yield performance), while EF served as the explanatory variables. The primary goal was to identify environmental factors that best differentiate grain yield classes and estimate their transition probabilities.

Modeling was conducted using the rpart function from the rpart package (Therneau and Atkinson 2025) in R (version 4.2.1). Similar methodologies have been recently adopted by Costa-Neto et al. (2024), Justino et al. (2025), and Heinemann et al. (2024). To facilitate the interpretation, all continuous EF were categorized using the K-means algorithm. The number of clusters was based on the Elbow method (Campos 2025).

Economic analysis

To better understand the risks associated with soybean cultivation in petric plinthosols, we analyzed the profitability in soybean production scenarios, derived from decision tree classification analysis. These scenarios considering the interplay between soybean yield, profitability (P), total production costs (TPC), and market conditions—these variables provide critical insights for developing risk-mitigation strategies in soybean farming in petric plinthosols.

Profitability (P) was calculated by subtracting the gross revenue per hectare (GR; or the total value of the production obtained, in $kg{\cdot}ha^{-1}$) from the total production cost (TPC; fixed cost plus variable cost in $R\${\cdot}ha^{-1}$) of the agricultural activity in the 2024/2025 harvest, according to Eq. 2:

$$P = GR - TPC \tag{2}$$

The total value of production (or GR) was calculated by multiplying the yield (in 60 kg bag per hectare) by the average price of a soybag (R$ 135.58 per bag). The soybean price per 60-kg bag was calculated using the average of soybean price per 60-kg bag over the last 12 months (from March 2024 to February 2025; data from the Centro de Estudos Avançados em Economia Aplicada—CEPEA 2025).

The TPC encompasses all expenses incurred by the producer throughout the production process, from the acquisition of inputs and soil preparation to harvesting, transportation, and product commercialization. The cost, expressed in $R\${\cdot}ha^{-1}$, includes both fixed costs—which remain constant regardless of production scale (*e.g.*, depreciation, capital investments, labor and lodging)—and variable costs, which fluctuate with the volume and intensity of production (*e.g.*, machinery use, fuel, inputs, lubricants, maintenance, and repairs). For the 2024/2025 season, the reference production cost was estimated at R$ 5,998.05, according to APROSOJA/MS (2024). To account for cost variability, production costs were also projected at 10 and 20% above and below this reference value, allowing for a range of economic scenarios to be considered.

The soybean price per 60-kg bag was estimated at R$ 135.58, according to CEPEA (2025). To account for potential market fluctuations, two projections were considered: a decrease and an increase of 20% of the soybean price per 60-kg bag, allowing for an analysis of both downside risk and upside potential in market conditions. Then, the economic analysis explored the interaction between soybean selling prices and production costs, highlighting profitability across low, medium, and high yield levels, as defined in the section "Clusters from soybean yield data".

RESULTS AND DISCUSSION

Grain yield variation among trials

The soybean yields in experiments conducted in petric plinthosols showed greater variability and lower yield compared to those observed on ferralsols (Fig. 2). Additionally, the soybean cycle impacts yield in both soil classes. In ferralsol, soybean genotypes from early, medium, and late cycles exhibit yields highest than super-early one. In contrast, in petric plinthosols, the highest yield is observed for the late cycle, followed by the medium, early, and super-early cycles.

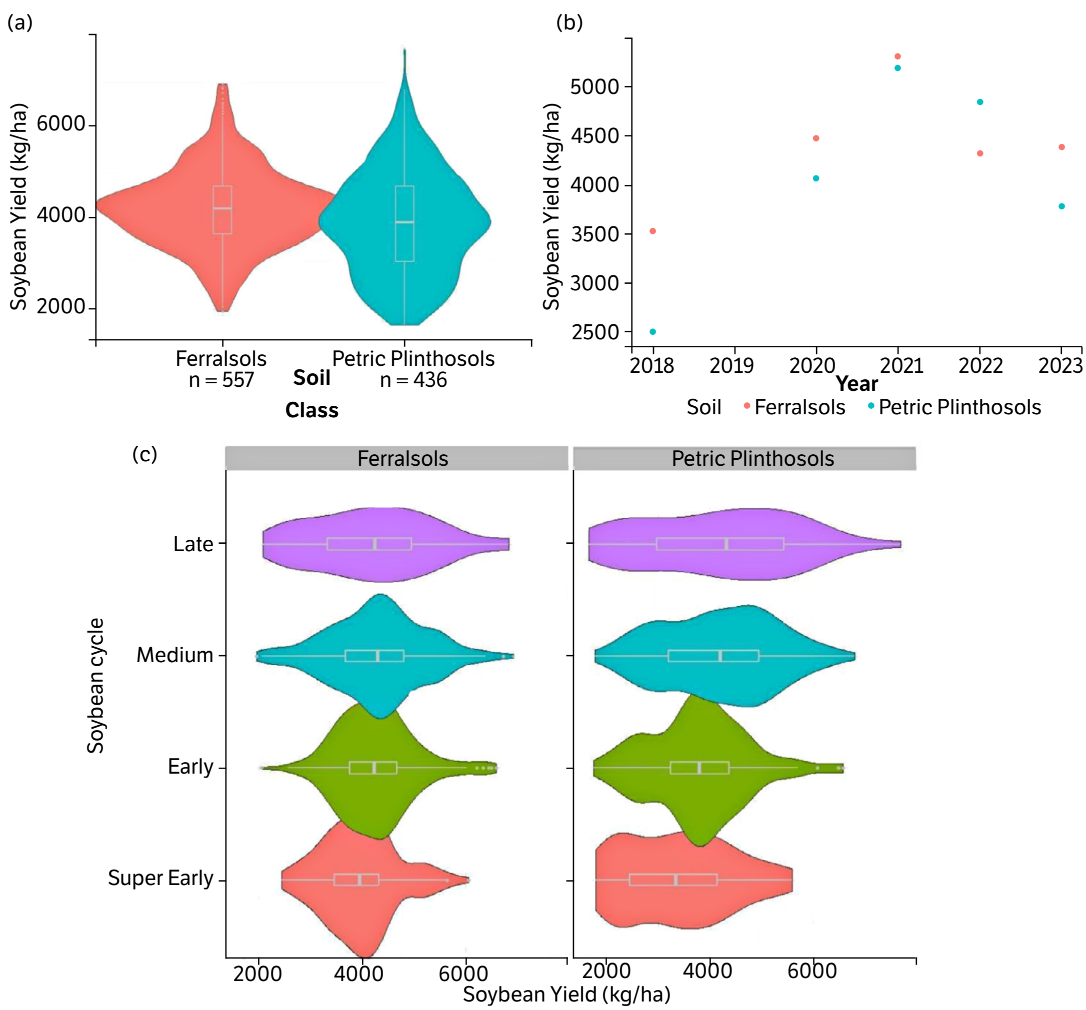


Figure 2. Soybean grain yield distribution considers (a) soil classes ferralsol and petric plinthosol across (b) annual yield and (c) soybean cycle.

Yields exceeding 6,000 kg·ha^{-1} were recorded in both ferralsols and petric plinthosols, although these cases were more specific. This indicates a good productive potential for both soil types, provided by the favorable climatic conditions occurrence (Fig. 2). Previous studies have also reported good yields in petric plinthosols (Almeida et al. 2023, Campos et al. 2025).

In petric plinthosols, yield was more dispersed than in ferralsols (Figs. 2a and 2c), reflecting the greater influence of environmental conditions on this soil type. This dispersion occurs regardless of the soybean cycle, but it is more pronounced when late-cycle cultivars are used (Fig. 2c).

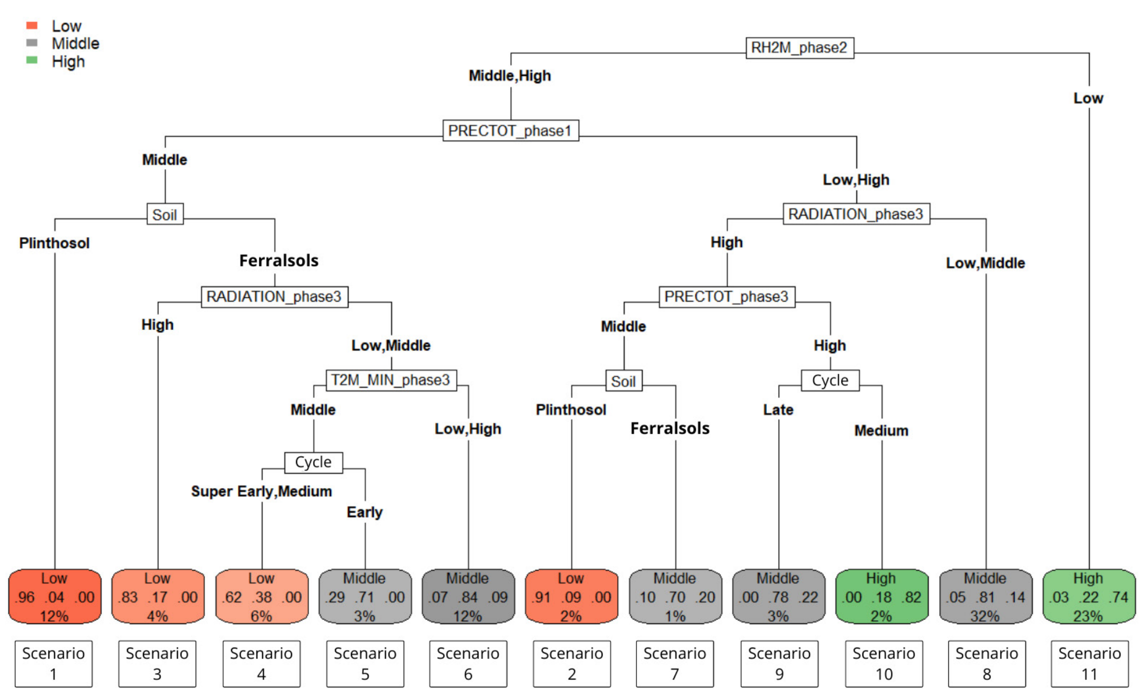
In 2022, soybean yield in petric plinthosol surpassed that in ferralsol (Fig. 2b). This difference may be attributed to the physical composition affecting soil chemistry. Fertilization management for petric plinthosol is still based on recommendations assuming 100% of the soil is available for fertilizer distribution and reaction (Almeida et al. 2024). However, petric plinthosol typically contains more than 50% gravel, resulting in a reduced volume for soil (sand silt and clay). Consequently, all fertilizer applied to petric plinthosols reacts in a smaller volume of soil, and promotes a more significant increase in soil fertility, with the capacity to supply plants even with high gravel contents (Almeida et al. 2024).

When comparing the yields of cultivars by growth cycle, no overall yield superiority was observed for ferralsol over petric plinthosol, except for super-early cycle cultivars (Fig. 2).

Although classified as fragile soils, proper management significantly contributes to maintaining plant productivity. The use of inputs such as lime, gypsum, balanced fertilization, and cover crops during the off-season to form mulch is essential for sustaining soybean yield in this soil type (Almeida et al. 2024). Cover crops play a crucial role in reducing surface temperature and improving water availability for plants in plinthosols (Anjos et al. 2017).

Recognition of patterns of the three main grain yield clusters

The unsupervised machine learning technique k-means was applied to identify yield classes based on field experiments conducted between 2018 and 2023. From the processed data, 11 scenarios were developed (Figs. 3 and 4), with yields ranging from 2,523 (scenario 1) to 5,188 kg·ha^{-1} (scenario 11).



RH2M: relative air humidity; RADIATION: solar radiation; PRECTOT: total precipitation in the crop cycle; Soil: soil type; T2M_MIN: minimum temperature; CYCLE: soybean maturity period; phase1: vegetative phase; phase2: reproductive phase; phase3: filling grain phase.

Figure 3. Decision tree illustrating different yield scenarios based on abiotic factors and crop phase, with corresponding classifications: low (red-orange), medium (gray), and high yield (green).

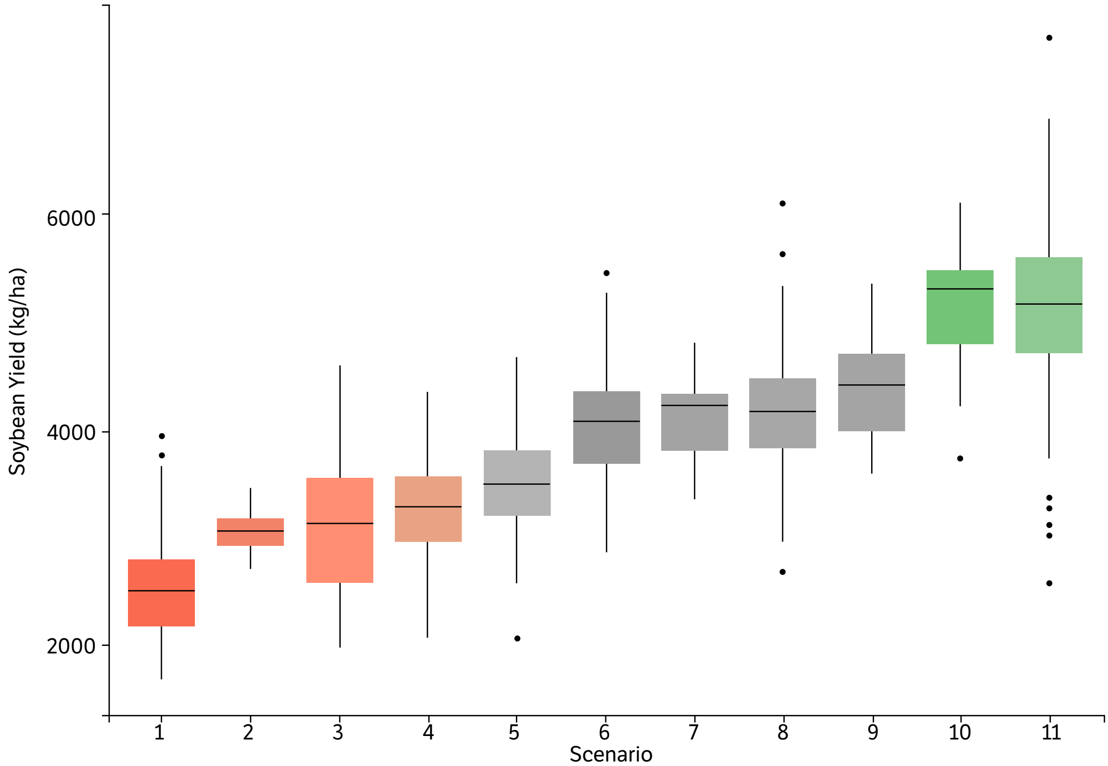


Figure 4. Box plot of soybean yield for each scenario defined by decision tree analysis (see Fig. 3).

Yield levels in these scenarios were further classified as low (1,658–3,406 kg·ha^{-1}), medium (3,407–4,713 kg·ha^{-1}), and high (4,714–7,671 kg·ha^{-1}), with the highest variability observed in the high-yields category.

Among the 993 observations, low yield was recorded in 23.3% of cases, while medium and high yield levels were observed in 53.7 and 23%, respectively.

Understanding the range of class intervals in a decision tree model facilitates interpretation and decision-making by allowing the identification of all relevant characteristics and their impact. To achieve this, the dataset was divided into a training set (695 samples), derived from soybean production system data collected in Goiás and Tocantins between 2018 and 2023, and a test set (298 samples) used to evaluate model accuracy.

As a result, the trained decision tree model achieved an overall accuracy of 78.5% for classifying new test samples, with individual classification accuracies of 74% for low, 79% for medium, and 80% for high soybean yield levels.

Key factors influencing yield scenarios

Relative humidity as the primary factor

In Fig. 3, the first root node of the DTC corresponds to relative air humidity during reproductive phase (RH2M_Phase 2, Fig. 3) in soybean, in which lower humidity levels are associated with higher yield (scenario 11; Fig. 3). Plantings that experienced low relative air humidity (74.4–76.1%) exhibited the highest yield levels (4,714–7,671 kg·ha^{-1}), representing 23% of the study examples.

Conversely, crops facing medium or high humidity require further analysis of the decision tree nodes to determine their yield classification. The increase in yield under low air relative humidity may be attributed to reduced incidence of fungal diseases, which thrive in high humidity (Beruski et al. 2019, Yadav et al. 2020), and enhanced transpiration, leading to greater nutrient uptake and lower leaf temperature, which optimizes photosynthesis (Wei et al. 2015, Adeboye et al. 2017).

Precipitation as the second factor

Total precipitation during vegetative phase (PRECTOT_Phase 1, Fig. 3) emerges as the second key factor shaping yield scenarios. Different precipitation levels influence yield outcomes as follows: low precipitation (156–242 mm) and high precipitation (367–451 mm) scenarios depend on solar radiation levels for their yield determination; and medium precipitation (243–366 mm) scenarios are shaped by the interaction between precipitation and soil type.

Precipitation in vegetative phase (PRECTOT_Phase 1, Fig. 3) directly affects: water availability for seed germination and nodule formation, crucial for biological nitrogen fixation, through soybean root associations with *Bradyrhizobium* (Sinclair et al. 2007), and nodule development, which may be impaired by low precipitation, reducing plant stand establishment.

On the other hand, excess rainfall can affect decrease oxygen availability for *Bradyrhizobium*, reducing nitrogen fixation (Scholles and Vargas 2004), and increase cloud cover, thereby reducing photosynthetic rates, which are essential for maintaining the plant-microbe symbiosis (Souza et al. 2016).

Within this factor, only a specific combination of environment conditions results in high yield (scenario 10, Fig. 3), in which high solar radiation (RADIATION_Phase3), high grain-filling precipitation (PRECTOT_Phase3), and medium-cycle cultivars (CYCLE) coincide (Fig. 3). In other scenarios, yield fluctuates between medium and low levels (Fig. 3).

Solar radiation and soil type as the third factor

Solar radiation in grain filled (RADIATION_Phase3; high and low/middle) and soil type (Soil; Ferralsol or petric plinthosol) form the third hierarchical factor (third node) influencing yield scenarios (Fig. 3).

Solar radiation, the fundamental driver of photosynthesis, enhances plant productivity only when sufficient water is available for plant transpiration. If water is limited or excess solar radiation can increase leaf temperature, photosynthetic efficiency is reduced (Ergo et al. 2018). High solar radiation levels (20.4–23.9 $MJ/m^2 \cdot day$, third node, Fig. 3) combined with moderate total precipitation (326–454 mm, fourth node, Fig. 3), lead to yield being determined by soil type (fifth node, Fig. 3).

Yield averages based on soil type were 4,124 (scenario 7; Fig. 4) and 3,055 $kg \cdot ha^{-1}$ (scenario 2; Fig. 4) for ferralsol and petric plinthosol, respectively. The medium yield observed in scenario 7 accounted for just 1%, while low yield in scenario 2 represented 2% of the dataset (Fig. 3). The soil type directly affects water infiltration and retention, and chemical variability (as previously explained, and corroborated by Almeida et al. 2024), which significantly influences yield.

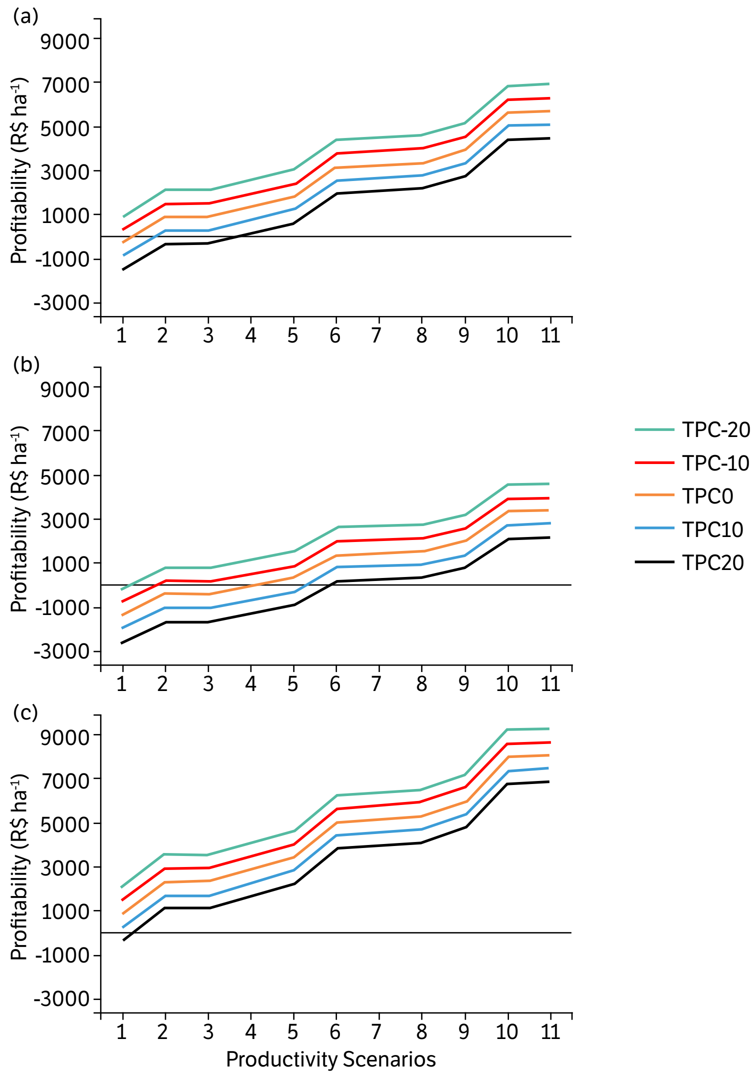
In the decision tree model, the presence of petric plinthosol consistently leads to lower yield scenarios compared to ferralsol (Fig. 3). However, good yield levels can still be achieved in petric plinthosols, particularly when medium and late-cycle soybean cultivars are used (Fig. 2).

The impact of soil type (ferralsol *versus* petric plinthosol) only emerges at the third and fifth level of stratification (third and fifth node, soil) in the decision tree (Fig. 3). After features about relative humidity, precipitation, and radiation, soil type differences lead to lower yield scenarios (scenario 1, Fig. 3) for soybean cultivation in petric plinthosol.

Economic analysis among scenarios

Agricultural activity involves significant risk as it depends on a favorable interaction between climate and crops. In environments particularly sensitive to climate variations, such as petric plinthosols, this risk is even greater (Mutegi et al. 2018).

Based on the total production cost and the soybean selling price per 60-kg bag (section "Economic analysis"), the producer's profit was estimated across 11 different yield scenarios (Figs. 3 and 4). The soybean selling price per 60-kg bag was also adjusted to reflect optimistic and pessimistic market conditions (section "Economic analysis"; Fig. 5). This approach allows us to assess producer profitability under low, medium, and high yield scenarios (Fig. 5).



TPC: total production cost.

Figure 5. Producer profit across different yield scenarios (from 1 to 11) in response to variations in total production cost [ranging from -20% (TPC-20), -10% (TPC-10), 0% (TPC0), 10% (TPC10), to 20% (TPC20) of the production cost; Aprosoja/MS 2024], and soybean price per 60-kg bag [(a) average of soybean price per 60-kg bag (CEPEA 2025) recorded between March 2024 and February 2025, (b) average price 20% lower than the current price, and (c) average price 20% higher than the current price].

Production profitability could be considered an indicator of the technical and economic efficiency of agricultural activity, as it shows the relationship between production and total production costs (Artuzo et al. 2018). In other words, the higher the profitability, the higher the production or the lower the cost.

Assuming no market fluctuations and an average of soybean selling price per 60-kg bag of R$ 135.58, positive profitability across all TCP levels (20, 10, 0, -10, and -20%) was observed only in scenarios equal to or greater than scenario 4 (Fig. 5a). The expected yield required to ensure positive profitability under these conditions is at least 3,600 kg·ha^{-1} (Fig. 4, scenario 4). In contrast, scenario 1, which presents the lowest average yield (2,500 kg·ha^{-1}, Fig. 4), along with moderate to high relative humidity during the reproductive phase (RH2M_phase2) and middle precipitation during the vegetative phase (PRECTOT_phase1) showed positive profitability only when production costs were reduced by 10 or 20% (TCP = -10 or -20%, Fig. 5a). Scenarios 2 and 3, both with an average yield of 3,000 kg·ha^{-1} (Fig. 4), also demonstrated positive profitability across most cost levels, except when production costs were reduced by 20% (TCP = -20%).

Assuming a negative market fluctuation, a decrease in 20% on the average of soybean selling price per 60-kg bag (R$ 108.46; Fig. 5b), profitability becomes positive for all estimated TCP only for scenarios equal to or greater than scenario 6

(Fig. 5b). The expected yield required to ensure positive profitability under these conditions is at least 4,000 kg·ha^{-1} (Fig. 4, scenario 6). In contrast, scenario 1, even with a 20% reduction in TCP, a negative profitability persists (Fig. 5b).

Assuming a positive market fluctuation, an increase in 20% on the average of soybean selling price per 60-kg bag (R$ 162.69, Fig. 5c), only an increase of 20% in the TCP makes the scenario 1 no profitable. The other scenarios (2 to 11) are all profitable. No considering the scenario 1, the expected yield required to ensure positive profitability under these conditions is at least 3,000 kg·ha^{-1} (Fig. 4, scenario 2).

Based on the economic results, to avoid negative profitability under any market fluctuations, farmers should be operating in scenarios equal to or greater than scenario 6, with an expected yield of at least 4,000 kg·ha^{-1}. However, scenarios 6 and 7—defined respectively by the following conditions: scenario 6: RH2M_phase2 = Middle or High; PRECTOT_phase1 = Middle; Soil = Ferralsols; RADIATION_phase3 = Low or Middle; T2M_MIN_phase3 = Low or High; and scenario 7: RH2M_phase2 = Middle or High; PRECTOT_phase1 = Low or High; RADIATION_phase3 = High; PRECTOT_phase3 = Middle; Soil = ferralsols—occur exclusively in ferralsol (Fig. 3). Therefore, for soybean cultivation in petric plinthosols, only scenarios 8, 9, 10, and 11 remain viable. Scenario 8 (RH2M_phase2 = Middle or High; PRECTOT_phase1 = Low or High; RADIATION_phase3 = Low or Middle) has a frequency of occurrence of 32% (Fig. 3). Scenario 9 (RH2M_phase2 = Middle or High; PRECTOT_phase1 = Low or High; RADIATION_phase3 = High; PRECTOT_phase3 = Middle; Cycle = Late) occurs in only 3% of cases and requires the use of a late-cycle cultivar. Scenario 10 (RH2M_phase2 = Middle or High; PRECTOT_phase1 = Low or High; RADIATION_phase3 = High; PRECTOT_phase3 = Middle; Cycle = Medium) occurs in just 2%. Scenario 11, characterized by low RH2M_phase2, occurs in 23% of cases. Together, scenarios 8 and 11 represent more than 50% of all occurrences, highlighting their relevance for soybean production in petric plinthosols. Based on both scenarios, cultivar cycle is not a limiting factor for higher soybean yield in petric plinthosols. Air humidity, mainly in the reproductive phase, is a limiting factor for higher yields.

CONCLUSION

This study demonstrated the possibility of achieving high yields in petric plinthosols, as observed across multiple growing seasons. However, studies on soil physics (gravel percentage, water retention, and soil water balance) are still underway to fine-tune and refine the modeling.

It is also noted that cost reduction can be a key factor in producer profitability, and this aspect is more decisive than plant productivity itself. Even in the worst-case scenarios, profit can still be achieved by lowering production costs.

Although good yields are attainable, petric plinthosols showed greater sensitivity to climatic factors compared to ferralsols, as indicated by the decision tree, which identifies the worst-case scenario when comparing the two soil types.

Therefore, it is strongly recommended to adopt management practices that enhance water infiltration and soil moisture retention (such as no-till farming and cover crops), as well as root growth (such as building a fertility profile in the soil and using bio-inputs and exogenous substances) to improve the yield stability of soybean crops in petric plinthosols.

CONFLICT OF INTEREST

Nothing to declare.

AUTHORS' CONTRIBUTION

Conceptualization: Campos, L. J. M., Heinemann, A. B. and Matta, D. H.; **Data curation:** Campos, L. J. M., Costa, R. V., Evaristo, A. B. and Almeida, R. E. M.; **Formal analysis:** Heinemann, A. B., Matta, D. H., Viotto, G. S. and Justino, L. F.; **Investigation:** Viotto, G. S., Justino, L. F., Feliciano, J. D. C. and Almeida, R. E. M.; **Methodology:** Heinemann, A. B., Matta, D. H., Viotto, G. S., Justino, L. F. and Feliciano, J. D. C.; **Writing – first draft:** Campos, L. J. M., Costa, R. V. and Almeida, R. E. M.; **Writing – review & editing:** Campos, L. J. M., Heinemann, A. B., Matta D. H., Evaristo, A. B. and Almeida, R. E. M.; **Final approval:** Campos, L. J. M., Costa, R. V. and Almeida, R. E. M.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author.

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DECLARATION OF USE OF ARTIFICIAL INTELLIGENCE TOOLS

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