Land Degradation & Development

WILEY

RESEARCH ARTICLE OPEN ACCESS

Pasture Degradation Estimates Through Field Data in the State of Goiás, Brazil

Nathalia Teles[1] | Vinicius Mesquita[1] | Luis Baumann[2] | Wilton Ladeira da Silva[3] | Ana Andrade[2] | Laerte Ferreira[1]

[1]Remote Sensing and GIS Lab (LAPIG), Federal University of Goiás, Goiás, Brazil | [2]Institute of Mathematics and Statistics (IME), Federal University of Goiás, Goiás, Brazil | [3]Veterinary and Animal Science School (EVZ), Federal University of Goiás, Goiás, Brazil

Correspondence: Nathalia Teles (nathalia.teles@ufg.br)

Received: 3 February 2025 | **Revised:** 3 July 2025 | **Accepted:** 13 July 2025

Funding: This work was supported by MapBiomas and Coordenacao de Aperfeicoamento de Pessoal de Nivel Superior (CAPES).

Keywords: Cerrado | forage production | land degradation | pasturelands | pasture management | visual scores

ABSTRACT

Grasslands and pastures play a critical role in global food security, biodiversity, and ecosystem services, particularly in tropical regions where they serve as the primary base for livestock production. However, these areas are increasingly vulnerable to degradation due to poor management practices, as observed in the Cerrado biome. This study focuses on pastures in Goiás, a state located in central-western Brazil, which relies heavily on pastures for its agricultural economy. We present a comprehensive field-based assessment of pasture degradation in Goiás, aiming to estimate the area of degraded pasture according to three categories: non-degraded, in process of degradation, and severely degraded. A three-stage cluster sampling design was employed to evaluate 460 field points, incorporating visual assessments of key variables using the novel Pasture Assessment Score (PAS). The sample size was determined to achieve a maximum expected standard error of 4.47% for the estimated proportion of pasture area across the three degradation levels, calculated using the Monte Carlo method. The scores were analyzed using Multiple Correspondence Analysis (MCA) to reduce dimensionality and identify clusters corresponding to degradation levels, which were modeled using Decision Trees. The results revealed that 39.35% (SE = 3.92%) of the pasture area in Goiás was classified as non-degraded, 31.98% (SE = 2.66%) as being in process of degradation, and 28.67% (SE = 3.64%) as severely degraded. These findings underscore the need for targeted management strategies and enhanced monitoring frameworks integrating field-based assessments with remote sensing data to support sustainable pasture management.

1 | Introduction

Land use dynamics in tropical savannas have become increasingly relevant in global discussions on biodiversity conservation, food security, and climate resilience, particularly due to the essential role of grasslands and pastures in sustaining livestock production and providing ecosystem services. In Brazil, the Cerrado biome is the second largest in terms of land area, and it stands out for its ecological importance and extensive pasture areas (Sano et al. 2019). It is characterized by a predominance of acidic and dystrophic soils with high levels of aluminum and iron and low phosphorus availability (Lopes et al. 2024). The Cerrado remains a biodiversity hotspot and vital water source (Sano et al. 2019; Myers et al. 2000) and spans central Brazil, including Goiás, a key region in the country's agricultural sector.

Goiás heavily relies on pasture-based livestock production, contributing significantly to national beef output (IBGE 2024; CEPEA 2024). However, improper management and low soil fertility have heightened pasture degradation, posing ecological and economic risks (Dias-Filho 2023). Regions such as the Brazilian Cerrado face increasing demands for livestock grazing

(Dias et al. 2016), and understanding and mitigating degradation processes is essential to ensuring long-term sustainability (Bustamante et al. 2019).

Pasture degradation in Goiás is primarily driven by a combination of overgrazing, inadequate nutrient replenishment, and dominance of invasive plant species, which compete with forage grasses, reducing pasture productivity and livestock performance, as well as poor soil management. These processes lead to soil compaction, reduced forage productivity, biodiversity loss, and increased vulnerability to erosion. Over time, degraded pastures exhibit lower carrying capacity (Dias-Filho 2023), directly impacting livestock production and the region's economy.

However, how can we effectively identify the degradation process in pastures, given that characterizing this process is crucial for guiding appropriate management strategies that foster sustainable production systems, preserve environmental resources, and mitigate pasture degradation? This is a complex issue, and as such, a multifaceted approach is required to account for the various causes of degradation. These drivers include factors such as overgrazing, documented in pastures across Europe (Kairis et al. 2015), Brazil (Sattler et al. 2018), and Asia (Tuvshintogtokh and Ariungerel 2013), inadequate soil nutrient replenishment (Lima et al. 2022), as well as a consequence of the accentuated climate change in recent years (Li et al. 2025).

According to Dias-Filho (2023), pasture degradation typically occurs through two main pathways: agronomic degradation, indicated by shifts in the botanical composition either through the reappearance of native vegetation species or an increase in invasive species (e.g., *Sporobolus* spp.), and biological degradation, resulting from soil impoverishment due to insufficient nutrient replacement or improper grazing pressure. Thus, the employment of direct evaluation methodologies, including the assessment of forage productivity over time and monitoring of bare soil exposure, can provide accurate identification of degradation processes. However, these assessments are resource-intensive, requiring significant time, labor, and financial investment.

Recent methodologies have been developed to overcome the limitations of traditional approaches for assessing pasture degradation. These novel methods have the potential to streamline assessments by reducing the time required for collection of forage and soil samples, facilitating large-scale assessments, and offering real-time data analysis. Pasture Assessment Scores (PAS) have emerged as a practical and accessible tool to support pasture monitoring (Teles 2021). This standardized visual scoring system enables rapid, in situ evaluations by trained observers who assign scores (1–7) across multiple parameters, including plant development stage, weed/termite presence, ground cover, and forage availability.

Building on the hypothesis that PAS is an effective tool for classifying pasture degradation, this study applied a detailed, field-based assessment using the PAS system. The main objectives of this study were: (a) to present the results of the PAS; and (b) based on the classification of the level of pasture degradation in the state of Goiás, to estimate the areas of each level using the PAS.

2 | Methods

2.1 | Study Area

The study covers the entire state of Goiás, in central-western Brazil, covering 340,242.860 km^2 (IBGE 2024). Goiás lies predominantly within the Cerrado biome, accounting for approximately 17% of the biome's total extent (IBGE 2024). The target population included all pasture areas in Goiás, which occupy around 40.27% (over 13.7 million hectares) of the state's territory (Lapig 2024).

2.2 | Sampling Design

To obtain the final set of points that were visited and evaluated in the field, a cluster sampling approach was employed, structured into three distinct stages. The first stage involved a proportional and ordered systematic selection of primary units, defined as 100 × 100 km grids covering the state. The selection criteria was based on the proportion of pasture area within each grid.

In the second stage, a proportional and ordered systematic selection of secondary sampling units was conducted, represented by smaller grids of 10 × 10 km within the primary unit. The third stage involved a stratified, unbalanced selection of tertiary sampling units, defined by pixels (10 × 10 m) within the secondary unit. In this third stage, the tertiary units were randomly selected from two strata. The first stratum included pixels within a buffer of no more than 250 m from any paved or unpaved road (buffer in) to avoid overly distant collections that would complicate access. In the second stratum, a smaller number of pixels, sampling points (SP), was chosen outside the 250 m road buffer (buffer out) to reduce biases from sampling points too close to roads where pastures are typically better managed (Figure 1). Methods for determining sample size and precision are available in Appendix S2.

2.3 | Field Protocol

Fieldwork in Goiás was conducted under the MapBiomas initiative, coordinated by the Remote Sensing and Geoprocessing Laboratory at UFG (LAPIG/UFG), in partnership with the School of Veterinary and Animal Science (EVZ/UFG) and the Forage Study Group (GEFOR/UFG). Data collection for pasture evaluation and characterization occurred from January to May 2022.

Field teams were trained to systematically evaluate pastures following a standardized protocol that includes visual assessments of pastures using the PAS scoring system, collection of forage and soil samples, drone imagery, and ground-level photos. Each sampling area (SA), sized at 900 m^2 within the pasture, was marked with the sampling point (SP) at its center, located by GPS.

A total of 460 pasture sites were evaluated across Goiás. At each site, pasture productivity and degradation were assessed visually based on a set of predefined parameters. Additionally, forage samples were collected from 136 sites, and soil samples

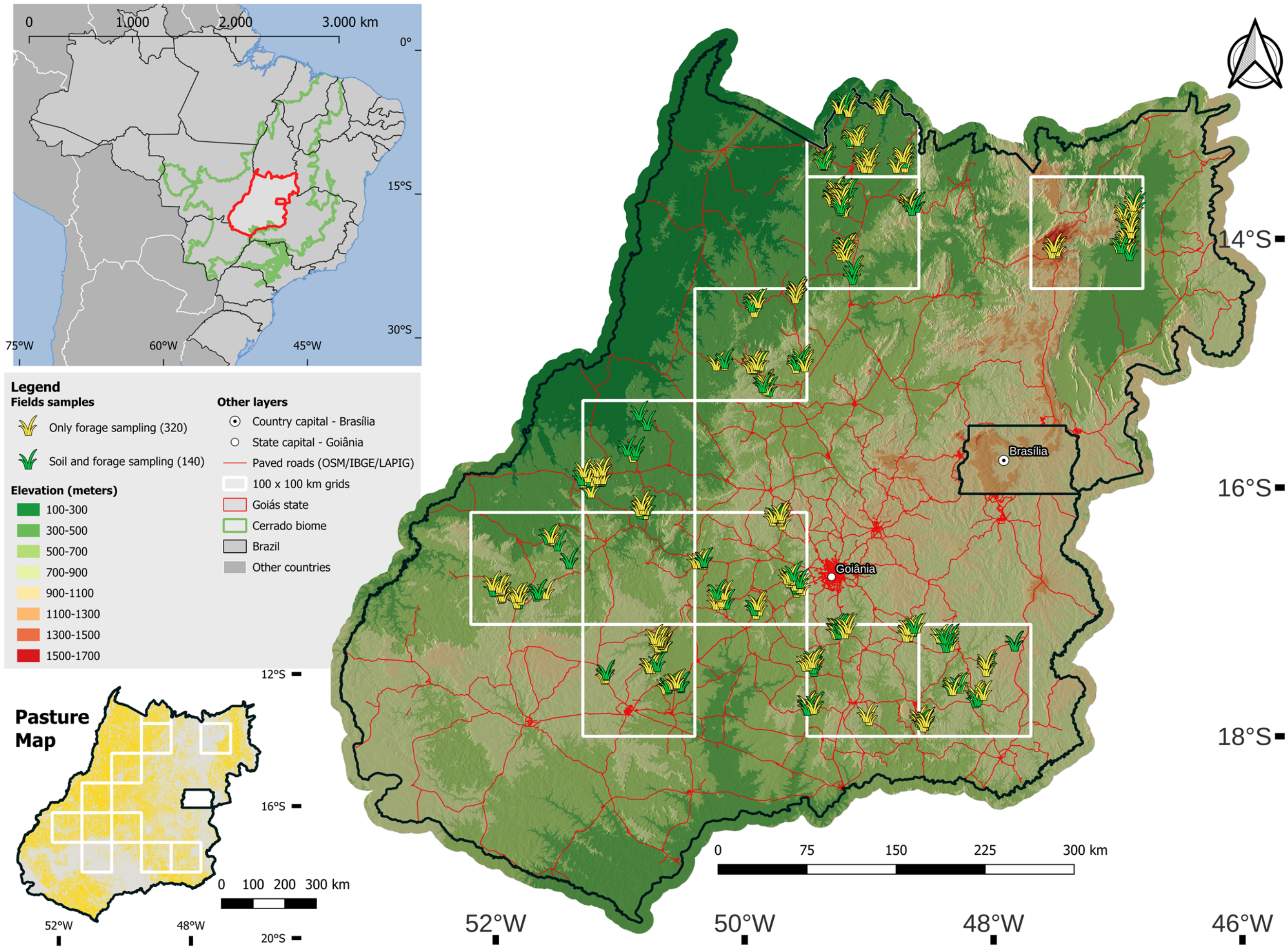

FIGURE 1 | Study area and sampling design in Goiás, Brazil, showing pixel locations. [Colour figure can be viewed at wileyonlinelibrary.com]

from 115 locations, which then underwent bromatological and physical–chemical analyses, respectively. The majority of the pastures evaluated in Goiás were composed of *Urochloa* spp. (67%); *Andropogon* spp. *and Panicum* spp. were also present, representing 23% and 6% of the sampled sites, respectively, while the remaining samples corresponded to other forage species. For this study, however, only the data obtained through visual field assessments were used.

2.3.1 | Pasture Assessment Scores—PAS

A variety of methods are employed to describe pasture degradation, including remote sensing data, forage and soil sampling, on-site assessments of invasive plants, soil cover, and monitoring of the stocking rate in the pasture (Kairis et al. 2015; Bardgett et al. 2021; Silva et al. 2019). These methods can be categorized as either direct or indirect. However, it should be noted that each method has its limitations, including assessment time, costs, and the use of trained and qualified labor, among others.

Pasture Assessment Scores (PAS) were specifically developed to provide a rapid visual evaluation of pasture conditions without requiring destructive sample collection. Inspired by earlier methods described by Morley et al. (1964) that were later adapted by Campbell and Arnold (1973), the scoring system applied here is novel, with unique parameters designed to address the specific challenges of assessing the condition and productivity of large areas of tropical pastures (Teles 2021; Silva et al. 2024).

Using a 1–7 scale (Norman 2010; Likert 1932), three to four independent observers assigned scores at each sampling point to evaluate key variables related to pasture productivity and degradation, including 1) plant development stage (DV), 2) weed coverage (WD), 3) termite incidence (TI), 4) soil coverage (SC), 5) forage availability (FA), 6) green leaves availability (GLA), 7) pasture current condition (PC), 8) productive potential (PP), 9) pasture degradation (PD), and 10) management effectiveness (MN).

This tailored scoring approach provides a comprehensive framework for identifying degradation severity and estimating pasture productivity over a 12-month period. Lower scores generally indicate degraded conditions (except for DV, WD, TI and PD), while higher scores reflect well-managed pastures with high productivity and minimal degradation.

Designed for consistent in situ application, this scoring system enables timely and reliable pasture assessments, independent of seasonality or specific management techniques. A detailed description of the parameters and scoring criteria is available in Appendix S1.

2.4 | Multiple Correspondence Analysis

Multiple correspondence analysis (MCA) was employed to examine associations among categorical variables, revealing structural patterns within the dataset. This method enables the projection of data points and variable categories into a lower-dimensional space (typically two or three dimensions), facilitating both visual interpretation and analytical insights (Figure 2). This analysis was chosen due to its suitability for handling categorical data, such as the scores assigned during field assessments. MCA reduces the dimensionality of the dataset by summarizing the information contained in multiple categorical variables into a few principal dimensions, which capture the major patterns of variation in the data (Greenacre 2017; Le Roux and Rouanet 2010).

2.5 | Area Estimates

The total pasture area (ha) corresponding to each parameter score was estimated for observations of the distributions of each score within each variable used in the PAS. In this way, we observed which score or scores are most representative within a PAS variable.

2.6 | Statistical Analysis

In the Multiple Correspondence Analysis, the input data consisted of individual evaluators' Pasture Assessment Scores (PAS) assigned at each SP for the various productivity parameters described earlier. A Burt matrix was generated to represent all pairwise cross-tabulations of these variables, which served as the basis for the MCA computation. The analysis was conducted using the *mjca()* function from the *ca* package in R. The results were visualized using the ggplot2 package to produce a biplot that displays the relationships between the

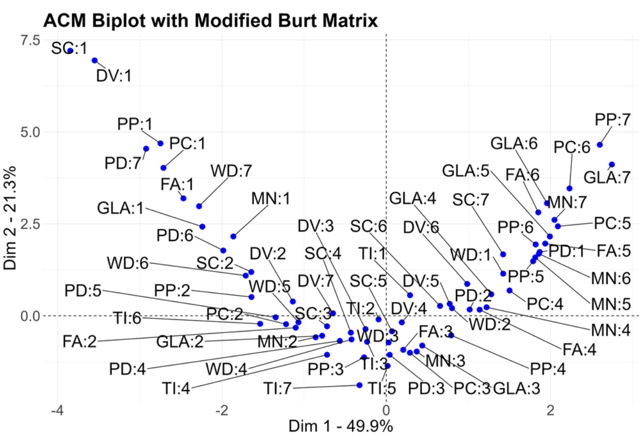

FIGURE 2 | MCA Biplot of PAS displaying the two main dimensions (Dim 1 and Dim 2). [Colour figure can be viewed at wileyonlinelibrary.com]

score variables, where each score category is represented as a separate variable in the principal dimensions. This method provides an intuitive approach for associating field data with degradation levels based on key dimensions of variation, offering clear insights for targeted pasture management and sustainable practices.

To calculate area estimates in Goiás as a function of PAS, we employed a robust statistical approach based on the Horvitz-Thompson estimator. This method calculates the mean or proportion of interest by assigning weights to each observation (), reflecting its inclusion probability across multiple stages of the sampling design (Olofsson et al. 2014; Stehman 2014). The hierarchical structure of the sampling process included P primary sampling units (100 km × 100 km grids), S secondary sampling units (10 km × 10 km grids), and K tertiary sampling units (10 m × 10 m pixels) distributed across H strata. Within each tertiary unit, repeated observations were conducted, with the final sample size n representing the total number of observed tertiary units across all strata.

The estimates of means and proportions, denoted by $\hat{\theta}$, were based on the Horvitz-Thompson estimator (Kish 1995; Cochran 1963):

$$\hat{\theta} = \frac{\sum_{s=1}^{n} w_s \ y_s}{\sum_{s=1}^{n} w_s}$$

where w_s is the weight of the sth observation and y_s is the value of the variable of interest for which the mean or proportion is being estimated. The initial weight w_{ijhk} is the inverse of the product of the inclusion probabilities of each sampling unit at each stage, given by:

$$w_{ijhk} = \frac{1}{p_{ijhk}} \text{ where } p_{ijhk} = p_i \times p_J \times p_{hk}$$

Here, p_i is the inclusion probability at the first stage for $i \in \{1, \ldots, P\}$, p_J is the inclusion probability at the second stage for $j \in \{1, \ldots, S\}$, and p_{hk} is the inclusion probability at the third stage for $h \in \{1, \ldots, H\}$ and $k \in \{1, \ldots, K\}$. The final weight w_s is obtained by dividing w_{ijhk} by the number of repeated observations (n_{ijhk}) in the tertiary sampling unit, as follows:

$$w_s = \frac{w_{ijhk}}{n_{ijhk}} \text{ for } l \ \epsilon \ \{1, \ldots, n_{ijhk}\}$$

where $s = s(i, j, h, k, l)$.

This method ensures that the sampling weights accurately reflect the probability of inclusion across all sampling stages, providing reliable and precise area estimates. The method for confidence interval calculation is available in Appendix S3.

3 | Results

3.1 | Pasture Degradation Classification

Building upon the field data collected and the methodological framework outlined in the previous section, this section presents the results for pasture degradation classification.

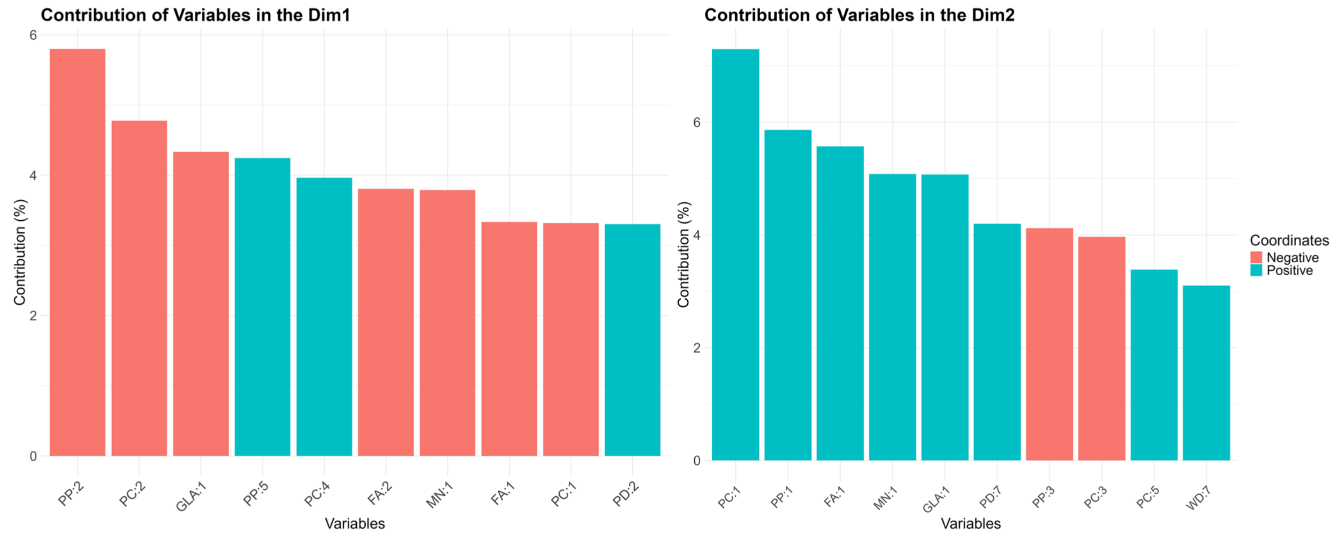

FIGURE 3 | Top 10 variables contributing to principal dimensions Dim1 (left) and Dim2 (right), with positive (green) and negative (red) weights. [Colour figure can be viewed at wileyonlinelibrary.com]

The first two principal dimensions of the variables, which combined explained 71.2% of the total inertia (49.9% by Dim 1% and 21.3% by Dim 2) (Figure 2), were retained for a hierarchical clustering analysis, which was used to synthesize and classify the field data. Figure 3 illustrates the 10 variables with the highest percentage-wise contribution to these principal dimensions, along with the direction of their influence.

Considering the first two main dimensions, the variables were grouped based on their proximity in the reduced-dimensional space, with closer variables indicating similar pasture conditions. A hierarchical cluster analysis was then performed using the two principal dimensions. The categories of the variables, represented as coordinate pairs in this space, were grouped using Ward's method to identify structural patterns in the data (Ward Jr. 1963). The resulting dendrogram illustrates the clustering process, identifying six distinct groups at a defined height threshold, as indicated by the dashed boxes (Figure 4). The six clusters identified in the hierarchical cluster analysis dendrogram were determined to be the optimal number of clusters according to the gap statistic method (Tibshirani et al. 2001).

The clusters exhibited clear patterns, with variables associated with better-managed pastures (e.g., high forage availability, low weed presence, and high soil cover) forming distinct groups, while indicators of severe degradation (e.g., high weed presence, low soil cover, and low forage productivity) characterized others.

These groups were subsequently classified into three main pasture degradation classes: (1) non-degraded (ND), (2) in process of degradation (PD), and (3) severely degraded (SD), based on their characteristics and distribution of variables within the six clusters identified. A decision tree was adjusted to model the relationship between degradation classes and the variables' principal dimension coordinates (Dim1 and Dim2). In the adjustment of the decision tree, only the first principal dimension (Dim1) was relevant to explain the classification of the three degradation categories. The resulting tree model, shown in Figure 5, highlights key decision splits based on thresholds in Dim1. The overall accuracy of the decision tree model was 97.05%, with only two misclassifications between the ND and PD categories.

Since the proximity between the main coordinates of the field evaluations at each sampling point and the principal coordinates of the variables in the biplot (Figure 2) indicates an association between them, the decision tree model was once again applied to the principal coordinates of each evaluation across all field points (individuals). This approach allowed for the classification of degradation levels for each assessment based on its position within the factorial space. As a result, the model classified 37.31% of the field evaluations as ND, 34.84% as PD, and 27.84% as SD. This classification was the basis for the degradation area estimates in Goiás.

3.2 | PAS Area Estimates

The total pasture area corresponding to each parameter score was estimated using a statistically robust approach that incorporated sampling weights and spatial information, ensuring accurate extrapolations across the state. Each parameter was assessed using a standardized scoring system, with area measurements derived from a representative sample of pasture sites.

The estimated pasture area in hectares for each PAS, along with the associated standard error $se(\hat{p})$, is presented in Table S1. These estimates provide a comprehensive quantification of pasture conditions across the state, highlighting variability in forage productivity, degradation status, and management effectiveness.

Figure 6 presents the distribution of estimated pasture area (in hectares) across different scores for the various pasture parameters assessed. Each subplot represents a specific parameter, with the x-axis indicating the score (ranging from 1 to 7) and the y-axis showing the corresponding pasture area in thousands of hectares (k ha).

For each parameter, the pasture area is highest at specific scores, indicating where most pastures fall in terms of condition.

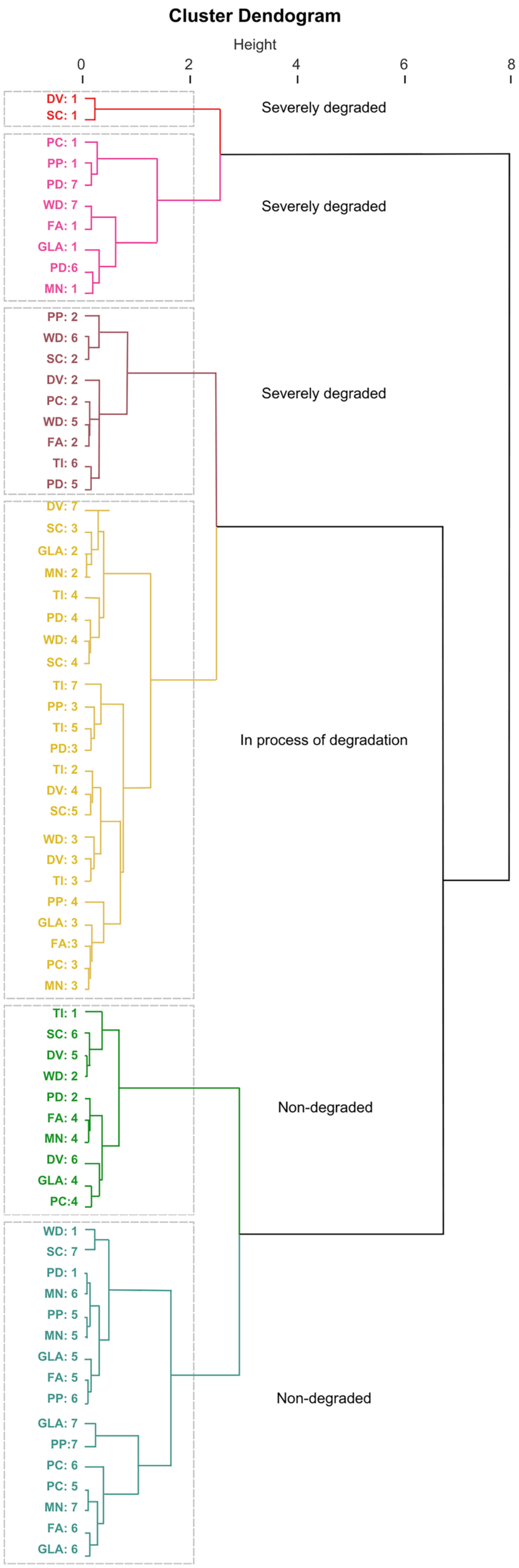

FIGURE 4 | Dendrogram illustrating the six distinct groupings of field variables. [Colour figure can be viewed at wileyonlinelibrary.com]

The results reveal distinct patterns across variables, highlighting the variability in pasture conditions. For instance, most pastures exhibit intermediate scores (2–4) for DV, indicating a predominance of pastures in active growth rather than those in early establishment or late senescence within the evaluation period (transition from wet to dry season). Weed coverage (WD) is highest at lower scores (2, 3), indicating that a significant portion of pastures experience low to moderate invasive species presence. Likewise, TI is most prominent at scores 1–2, indicating that termite distribution across Goiás pastures is generally low. It is important to note that the interpretation of these scores varies by parameter, as lower scores do not necessarily indicate poorer pasture conditions.

3.3 | Pasture Degradation Levels Estimates

Following the classification of sampling points into three degradation categories (ND, PD, and SD), pasture degradation estimates were statistically derived through spatial extrapolation using sampling distribution and weights. The area estimates for each class, along with their respective percentages, standard errors, and confidence intervals, are summarized in Table 1. These estimates provide a comprehensive assessment of pasture degradation across Goiás, offering valuable insights into its spatial distribution and extent.

An estimated 39.35% of the total pasture area in Goiás, approximately 5.4 million hectares, was classified as ND, with a standard error of 539,608 ha. Pastures classified as PD accounted for 31.98%, covering 4.4 million hectares. Meanwhile, SD pastures represented 28.67% of the total area, corresponding to 3.9 million hectares.

4 | Discussion

The hierarchical clustering analysis of the pasture assessment scores reveals insightful relationships between key indicators of pasture productivity and degradation. The dendrogram (Figure 5) organizes these variables into six distinct clusters, indicating potential correlations and dependencies among them and reinforcing the complexity of degradation processes.

One of the key findings is the strong association between low soil coverage (SC score 1) and forage in the early vegetative stage (DV score 1). These pastures likely experience significant soil exposure, often indicative of biological degradation (Dias-Filho 2023) or the aftermath of disturbances such as fire; both scenarios can be linked to severe degradation. Additionally, more mature forage development stages (DV scores 6–7) are associated with intermediate levels of degradation (PD). Prolonged forage growth without proper grazing management can result in reduced forage quality and the accumulation of senescent material, diminishing pasture productivity and livestock performance. Additionally, extended growing seasons in warmer environments accelerate plant growth, leading to reduced soil nitrogen availability and further declines in forage quality (Kirkman et al. 2023; Morris et al. 2022).

Another notable observation is the clustering of termite incidence with intermediate degradation levels (PD). This suggests that termite presence alone may not necessarily indicate severe degradation (Lima et al. 2011), challenging the common perception that links termite activity to declining pasture

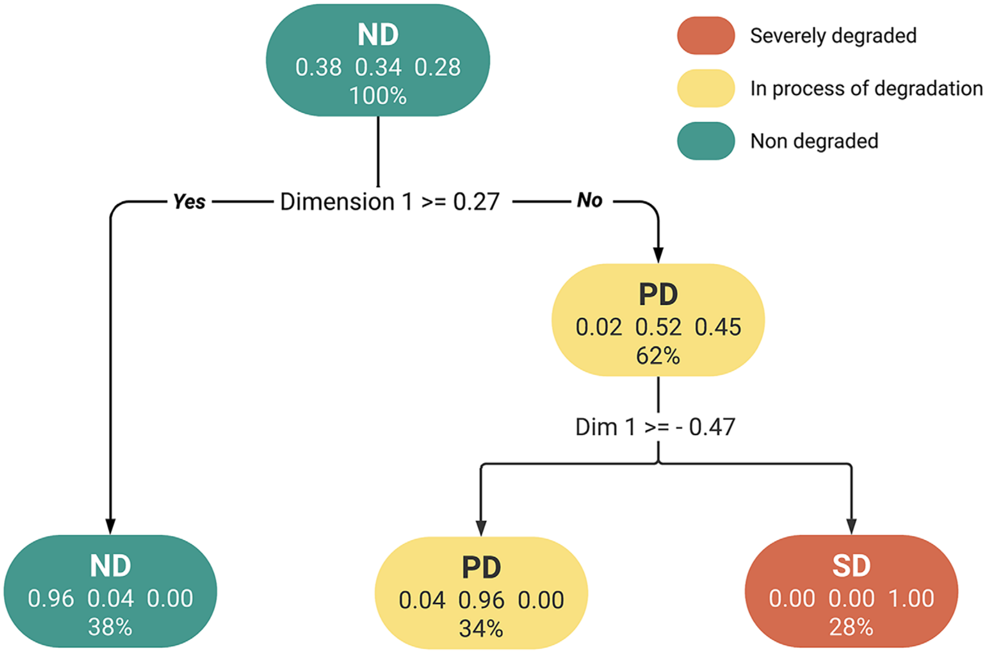

FIGURE 5 | Decision tree classification of pasture degradation levels. [Colour figure can be viewed at wileyonlinelibrary.com]

conditions. In contrast, some studies have shown that termites can positively contribute to soil health, improving organic matter content, aeration, and nutrient cycling (Chen et al. 2023). This pattern reinforces the idea that termite activity may serve as an ecological function rather than solely a degradation indicator, warranting further investigation into its role in pasture dynamics.

As for the area estimates for individual parameters, depicted in Table 1, it reveals that approximately 63.6% of pastures in Goiás, equating to 8.7 million hectares, fall within intermediate condition scores (PC). However, the distribution of productivity potential scores (PP) further highlights that a substantial portion of the assessed areas could achieve higher productivity levels with appropriate management and recovery practices. Implementing weed control, adjustments to stocking rates, and soil correction measures, such as liming and fertilization, can address nutrient deficiencies inherent in tropical soils, thereby enhancing forage growth and quality (Dias-Filho 2023; Lopes et al. 2024; Ortega Gastón et al. 2024). Effective pasture management is crucial for maximizing forage production and ensuring long-term sustainability (Cezimbra et al. 2021), particularly in tropical regions where soil fertility naturally declines over time without proper intervention (Rodelo-Torrente et al. 2022).

Although SC estimates suggest that a majority of pastures in Goiás maintain adequate biomass cover, FA scores reveal a concerning trend. Average scores range from 2 to 3, corresponding to approximately one to four tons of dry matter per hectare. This lower FA is likely linked to higher grazing pressure, which can hinder pasture recovery and reduce productivity over time (Lane 2020; Silva et al. 2019). Adjusting livestock stocking rates is essential to align forage production with animal demand, promoting a sustainable pasture-livestock balance and preventing further degradation. Effective grazing management, such as rotational grazing, allows for periods of rest and regrowth, preventing overgrazing and maintaining pasture quality, therefore supporting the economic viability of livestock production (Lane 2020).

Regarding the estimation of degraded areas in Goiás, our study revealed that around 28.67% of the pastures exhibit severe degradation, and another 31.98% are in the process of degrading. These categories combined represent over 8.2 million hectares, highlighting a critical challenge for pasture management within the state. The prevalence of degrading and severely degraded pastures underscores the necessity for targeted interventions to mitigate further deterioration and promote recovery. Recommended measures include enhanced soil management practices, rotational grazing systems, and restoration of forage productivity.

Previous studies based on remote sensing have consistently highlighted the widespread nature of pasture degradation in the Cerrado region. Pereira et al. (2018) estimated that approximately 46% of Cerrado pastures exhibited some level of degradation. Similarly, Santos et al. (2022) reported that over 3 million hectares (21.10%) of pastures in Goiás were classified as severely degraded, and 44.25% at intermediate degradation levels. However, these large-scale assessments rely primarily on indirect indicators such as vegetation vigor, which, despite being a valuable proxy, present important limitations. For instance, Pasture Vigor maps produced by LAPIG under the MapBiomas initiative (Lapig 2024) classify Goiás' pastures into three vigor levels: high (33.48%), medium (44.06%), and low vigor (22.45%). Yet, this classification may lead to misinterpretations, as vegetation vigor metrics primarily capture seasonal green-up and biomass accumulation and may not reflect agronomic degradation processes, such as increased dominance of invasive species. Additionally, these assessments do not distinguish between cultivated and native grasslands, which may result in the misclassification of native areas as degraded.

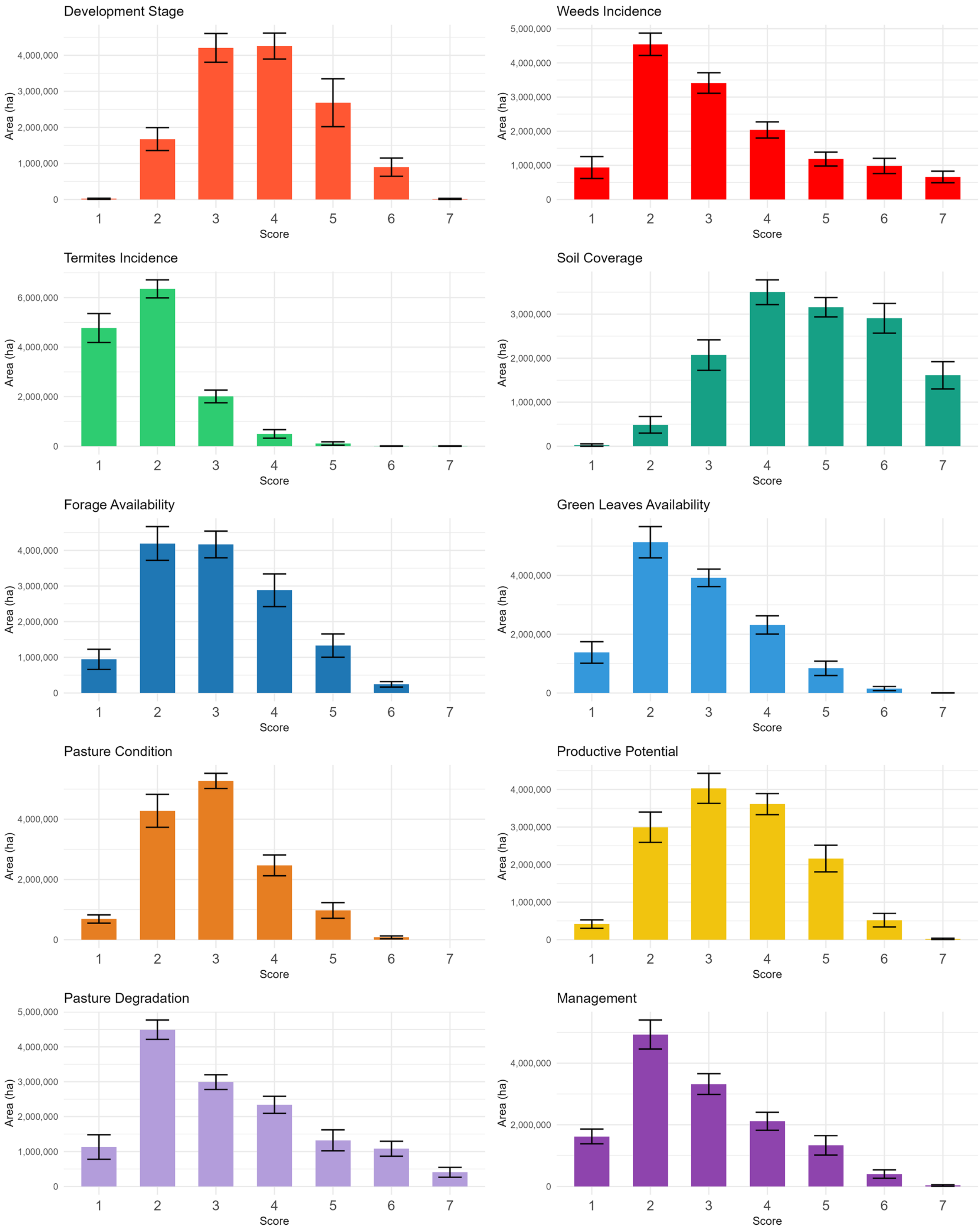

FIGURE 6 | Pasture area distribution and respective standard error across different scores in Goiás, Brazil. [Colour figure can be viewed at wileyonlinelibrary.com]

Integrating field data with remote sensing information can bridge the current gap in large-scale degradation monitoring. Recent efforts, such as those by Silva et al. (2024), have demonstrated the potential of combining high-resolution satellite data (e.g., PlanetScope SuperDove) with field observations to discriminate multiple degradation classes. However, their study

TABLE 1 | Area estimation for degradation class within Goiás, Brazil.

Classe	Percentage (%)	SE.Per (%)	LL.Per (%)	UL.Per (%)	Area (ha)	SE.Area (ha)	LL.Area (ha)	UL.Area (ha)
ND	39.35	3.92	31.66	47.04	5,412,294	539,608	4,354,682	6,469,906
PD	31.98	2.66	26.77	37.19	4,398,206	365,643	3,681,560	5,114,853
SD	28.67	3.64	21.54	35.79	3,942,569	500,095	2,962,401	4,922,738

Abbreviations: LL, lower limit; SE, standard error; UL, upper limit.

also highlighted significant classification uncertainties, particularly in distinguishing low-to-moderate degradation levels.

Effectively addressing pasture degradation requires targeted management strategies based on severity. For lightly or moderately degraded pastures, strategies include improving soil fertility, rotational grazing, invasive species control, and adjusting grazing pressure. Severely degraded areas may require intensive interventions, such as pasture renovation or establishing silvopastoral systems to restore productivity and ecosystem services (Macedo et al. 2000; Bustamante et al. 2019).

Ultimately, validating remote sensing-based assessments with ground-truth data is crucial to ensure the reliability of pasture condition monitoring. While satellite imagery enables large-scale, continuous monitoring, it may overlook localized degradation processes detectable only through field observations.

5 | Conclusions

This study presents a comprehensive field-based assessment of pasture degradation in Goiás, Brazil, using the Pasture Assessment Score (PAS) methodology combined with robust statistical analysis. By applying a scoring system specifically developed for tropical pastures, we classified pasture areas into three degradation levels: non-degraded (ND), in process of degradation (PD), and severely degraded (SD). Results indicate that 39.35% of the pasture areas presented low to no signs of degradation, 31.98% were undergoing degradation processes, and 28.67% were already severely degraded, highlighting the widespread impact of pasture degradation across Goiás.

The PAS approach offers valuable opportunities for broader application due to its adaptability and cost-effectiveness. Nonetheless, challenges remain regarding the resource-intensive nature of field data collection and the need for standardized protocols to ensure consistency across seasons and regions. Future work should focus on integrating field data with remote sensing products to enable large-scale, high frequency monitoring. Such combined approaches will help mitigate fieldwork constraints while improving the detection of early-stage degradation.

Acknowledgments

The authors gratefully acknowledge the financial support from MapBiomas initiative. We also thank the School of Veterinary and Animal Science (EVZ/UFG) for their collaboration during data collection and analysis. Finally, we appreciate the dedication of the field teams and the valuable contributions of all institutions and individuals involved in this study. The Article Processing Charge for the publication of this research was funded by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) (ROR identifier: 00x0ma614).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

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

References

Bardgett, R. D., J. M. Bullock, S. Lavorel, et al. 2021. "Combatting Global Grassland Degradation." *Nature Reviews Earth and Environment* 2: 720–735. https://doi.org/10.1038/s43017-021-00207-2.

Bustamante, M. M. C., J. S. Silva, A. Scariot, et al. 2019. "Ecological Restoration as a Strategy for Mitigating and Adapting to Climate Change: Lessons and Challenges From Brazil." *Mitigation and Adaptation Strategies for Global Change* 24: 1249–1270. https://doi.org/10.1007/s11027-018-9837-5.

Campbell, N. A., and G. W. Arnold. 1973. "The Visual Assessment of Pasture Yield." *Australian Journal of Experimental Agriculture and Animal Husbandry* 13, no. 1: 263–267. https://doi.org/10.1071/EA9730263.

Centro de Estudos Avançados em Economia Aplicada. 2024. *Indicadores do Agronegócio*. Universidade de São Paulo.

Cezimbra, I. M., P. A. de Albuquerque Nunes, W. de Souza Filho, et al. 2021. "Potential of Grazing Management to Improve Beef Cattle Production and Mitigate Methane Emissions in Native Grasslands of the Pampa Biome." *Science of the Total Environment* 780: 146582. https://doi.org/10.1016/j.scitotenv.2021.146582.

Chen, C., A. K. Singh, B. Yang, H. Wang, and W. Liu. 2023. "Effect of Termite Mounds on Soil Microbial Communities and Microbial Processes: Implications for Soil Carbon and Nitrogen Cycling." *Geoderma* 431: 116368. https://doi.org/10.1016/j.geoderma.2023.116368.

Cochran, W. G. 1963. *Sampling Techniques*. 2nd ed. John Wiley.

Dias, L. C. P., F. M. Pimenta, A. B. Santos, M. H. Costa, and R. J. Ladle. 2016. "Patterns of Land Use, Extensification, and Intensification of Brazilian Agriculture." *Global Change Biology* 22, no. 8: 2887–2903. https://doi.org/10.1111/gcb.13314.

Dias-Filho, M. B. 2023. *Degradação de Pastagens: Conceitos, Processos e Estratégias de Recuperação e de Prevenção*. Ed. do autor. Belém, PA.

Greenacre, M. 2017. *Correspondence Analysis in Practice*. 3rd ed. Chapman and Hall/CRC.

Instituto Brasileiro de Geografia e Estatística. 2024. Pesquisa da Pecuária Municipal. https://www.ibge.gov.br.

Kairis, O., C. Karavitis, L. Salvati, A. Kounalaki, and K. Kosmas. 2015. "Exploring the Impact of Overgrazing on Soil Erosion and Land

Degradation in a Dry Mediterranean Agro-Forest Landscape (Crete, Greece)." *Arid Land Research and Management* 29, no. 3: 360–374. https://doi.org/10.1080/15324982.2014.968691.

Kirkman, K. P., R. W. S. Fynn, D. McGranahan, P. J. O'Reagain, and T. Dugmore. 2023. "Future-Proofing Extensive Livestock Production in Subtropical Grasslands and Savannas." *Animal Frontiers* 13, no. 5: 23–32. https://doi.org/10.1093/af/vfad045.

Kish, L. 1995. *Survey Sampling*, 643. Wiley.

Lane, W. 2020. *Capturing Sunlight, Book 1: Skills & Ideas for Intensive Grazing, Sustainable Pastures, Healthy Soils, & Grassfed Livestock*. Lane Livestock Services.

LAPIG-Remote Sensing and GIS Lab. 2024. *Atlas Digital das Pastagens Brasileiras*. Universidade Federal de Goiás.

Le Roux, B., and H. Rouanet. 2010. *Multiple Correspondence Analysis*. SAGE Publications.

Li, T., L. Cui, Y. Wu, et al. 2025. "Unveiling and Advancing Grassland Degradation Research Using a BERTopic Modelling Approach." *Journal of Integrative Agriculture (JIA)* 24, no. 3: 949–965. https://doi.org/10.1016/j.jia.2024.11.008.

Likert, R. 1932. "A Technique for the Measurement of Attitudes." *Archives of Psychology* 22, no. 140: 155.

Lima, A. F. L., M. C. C. Campos, T. S. Martins, et al. 2022. "Soil Chemical Attributes in Areas Under Conversion From Forest to Pasture in Southern Brazilian Amazon." *Scientific Reports* 12: 22555. https://doi.org/10.1038/s41598-022-25406-9.

Lima, S. S., B. J. R. Alves, A. M. Aquino, et al. 2011. "Relation Between Termite Mounds and Pasture Degradation." *Pesquisa Agropecuária Brasileira* 46, no. 12: 1699–1706.

Lopes, A. D. R., N. M. Lage Filho, A. C. Do Rego, et al. 2024. "Effect of Nitrogen Fertilization and Shading on Morphogenesis, Structure, and Leaf Anatomy of *Megathyrsus maximus* Genotypes." *Frontiers in Plant Science* 15: 1411952. https://doi.org/10.3389/fpls.2024.1411952.

Macedo, M. C. M., A. H. Zimmer, and A. N. Kichel. 2000. *Degradação e Alternativas de Recuperação e Renovação de Pastagens*, 4. Embrapa Gado de Corte.

Morley, F. H. W., D. Bennett, and K. W. Clarke. 1964. *The Estimation of Pasture Yield in Large Grazing Experiments. CSIRO Division of Plant Industry, Field Station Record*. Vol. 3, 43–50. CSIRO.

Morris, C. D., K. P. Kirkman, and P. J. Zacharias. 2022. "Will the Grass Be Greener on the Other Side of Climate Change?" *South African Journal of Science* 118: 1–4. https://doi.org/10.2989/10220119.2024.2356674.

Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. Fonseca, and J. Kent. 2000. "Biodiversity Hotspots for Conservation Priorities." *Nature* 403: 853–858. https://doi.org/10.1038/35002501.

Norman, G. 2010. "Likert Scales, Levels of Measurement, and the "Laws" of Statistics." *Advances in Health Sciences Education: Theory and Practice* 15, no. 5: 625–632. https://doi.org/10.1007/s10459-010-9222-y.

Olofsson, P., G. M. Foody, M. Herold, S. V. Stehman, C. E. Woodcock, and M. A. Wulder. 2014. "Good Practices for Estimating Area and Assessing Accuracy of Land Change." *Remote Sensing of Environment* 148: 42–57. https://doi.org/10.1016/j.rse.2014.02.015.

Ortega Gastón, B., N. Berberian, and P. Chilibroste. 2024. "The Effects of Stocking Rate, Residual Sward Height, and Forage Supplementation on Forage Production, Feeding Strategies, and Productivity of Milking Dairy Cows." *Frontiers in Animal Science* 5: 1319150. https://doi.org/10.3389/fanim.2024.1319150.

Pereira, O. J. R., L. G. Ferreira, F. Pinto, and L. Baumgarten. 2018. "Assessing Pasture Degradation in the Brazilian Cerrado Based on the Analysis of MODIS NDVI Time-Series." *Remote Sensing* 10, no. 11: 1761. https://doi.org/10.3390/rs10111761.

Rodelo-Torrente, S., A. Torregroza-Espinosa, M. Moreno Pallares, D. Pinto Osorio, A. Corrales Paternina, and A. Echeverría-González. 2022. "Soil Fertility in Agricultural Production Units of Tropical Areas." *Global Journal of Environmental Science and Management* 8, no. 3: 403–418. https://doi.org/10.22034/gjesm.2022.03.08.

Sano, E. E., A. A. Rodrigues, E. S. Martins, et al. 2019. "Cerrado Ecoregions: A Spatial Framework to Assess and Prioritize Brazilian Savanna Environmental Diversity for Conservation." *Journal of Environmental Management* 232: 818–828. https://doi.org/10.1016/j.jenvman.2018.11.108.

Santos, C. O. d., V. V. Mesquita, L. L. Parente, A. d. S. Pinto, and L. G. Ferreira, Jr. 2022. "Assessing the Wall-to-Wall Spatial and Qualitative Dynamics of the Brazilian Pasturelands 2010–2018, Based on the Analysis of the Landsat Data Archive." *Remote Sensing* 14, no. 4: 1024. https://doi.org/10.3390/rs14041024.

Sattler, D., R. Seliger, U. Nehren, et al. 2018. "Pasture Degradation in South East Brazil: Status, Drivers and Options for Sustainable Land Use Under Climate Change." In *Climate Change Adaptation in Latin America. Climate Change Management*, edited by W. Leal Filho and L. Esteves de Freitas. Springer. https://doi.org/10.1007/978-3-319-56946-8_1.

Silva, A. G. P., L. S. Galvão, L. G. Ferreira Júnior, N. M. Teles, V. V. Mesquita, and I. Haddad. 2024. "Discrimination of Degraded Pastures in the Brazilian Cerrado Using the Planet Scope Super Dove Satellite Constellation." *Remote Sensing* 16, no. 13: 2256. https://doi.org/10.3390/rs16132256.

Silva, W. L., J. P. R. Costa, G. P. Caputti, N. M. Lage Filho, A. C. Ruggieri, and R. A. Reis. 2019. "Effects of Grazing Intensity and Supplementation Strategies on Tifton 85 Production and on Sheep Performance." *Small Ruminant Research* 174: 118–124. https://doi.org/10.1016/j.smallrumres.2019.03.015.

Stehman, S. V. 2014. "Estimating Area and Map Accuracy for Stratified Random Sampling When the Strata Are Different From the Map Classes." *International Journal of Remote Sensing* 35, no. 13: 4923–4939. https://doi.org/10.1080/01431161.2014.930207.

Teles, N. M. 2021. *Sensoriamento Remoto e Escore de Condição da Pastagem Para Avaliação da Qualidade e Produtividade de Pastagens. Master's Thesis*. Universidade Federal de Goiás, Escola de Veterinária e Zootecnia (EVZ).

Tibshirani, R., G. Walther, and T. Hastie. 2001. "Estimating the Number of Clusters in a Data Set via the Gap Statistic." *Journal of the Royal Statistical Society: Series B* 63, no. 2: 411–423. https://doi.org/10.1111/1467-9868.00293.

Tuvshintogtokh, I., and D. Ariungerel. 2013. "Degradation of Mongolian Grassland Vegetation Under Overgrazing by Livestock and Its Recovery by Protection From Livestock Grazing." In *The Mongolian Ecosystem Network. Ecological Research Monographs*, edited by N. Yamamura, N. Fujita, and A. Maekawa. Springer. https://doi.org/10.1007/978-4-431-54052-6_10.

Ward, J. H., Jr. 1963. "Hierarchical Grouping to Optimize an Objective Function." *Journal of the American Statistical Association* 58, no. 301: 236–244. https://doi.org/10.1080/01621459.1963.10500845.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1.** Supporting Information. **Appendix S2.** Supporting Information. **Appendix S3.** Supporting Information. **Table S1.** Estimated PAS area (hectare) with standard error *se* (*p*).