EVALUATING REMOTE SENSING TECHNIQUES FOR MONITORING GRASSLAND DEGRADATION

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ABSTRACT

Ecosystem degradation is one of the most significant environmental challenges worldwide. In particular, grassland degradation poses serious threat to agricultural productivity, species diversity, and soil stability. This study aimed to compare the applicability of two remote sensing techniques – the Linear Spectral Mixture Model (LSM) and the Grassland Degradation Index (GDI) – in assessing and characterizing the degree of grassland degradation. The results revealed that the GDI exhibited higher overall accuracy than the LSM, with an accuracy rate of 73.4% compared to 63.1% for LSM. The GDI also yielded a higher Kappa coefficient (0.61), relative to the LSM (0.50). Furthermore, the GDI recorded higher F1 scores across all evaluated classes, indicating an enhanced capacity to identify true positives and minimize false positives and negatives. Both techniques demonstrated satisfactory performance and may serve as valuable tools to support grassland restoration and sustainable management studies.

Keywords: Grassland degradation. Spectral unmixing. Vegetation indices. Google Earth Engine. Sustainable grazing.

AVALIAÇÃO DE TÉCNICAS DE SENSORIAMENTO REMOTO PARA MONITORAMENTO DA DEGRADAÇÃO DE FORMAÇÕES CAMPESTRES

RESUMO

A degradação dos ecossistemas constitui um dos desafios ambientais mais relevantes enfrentados em escala global. Em particular, destaca-se o impacto da degradação das formações campestres sobre a produtividade agrícola, a diversidade de espécies e os processos de erosão do solo. Este estudo teve como objetivo comparar a aplicabilidade de duas técnicas de sensoriamento remoto, o Modelo de Mistura Espectral Linear (LSM) e o Índice de Degradação de Formações Campestres (GDI), na avaliação e na definição do grau de degradação dessas áreas. Os resultados indicaram que o GDI apresentou uma precisão geral superior à do LSM, com uma taxa de acurácia de 73,4%, em comparação a 63,1% para o LSM. O GDI também apresentou um coeficiente Kappa maior, de 0,61, enquanto o LSM atingiu 0,50. Ademais, o GDI demonstrou maior desempenho em termos de F1-score em todas as classes avaliadas, evidenciando maior capacidade de identificar verdadeiros positivos e reduzir falsos positivos e negativos. Ambas as técnicas demonstraram desempenho satisfatório e podem ser aplicadas para subsidiar estudos voltados à restauração e ao manejo sustentável.

Palavras-chave: Degradação de formações campestres. Mistura espectral. Índices de vegetação. Google Earth Engine. Pastoreio sustentável.

INTRODUCTION

Ecosystem degradation is one of the most challenging environmental challenges currently faced worldwide (IPCC, 2019). Among its most significant impacts, grassland degradation leads to reduced yield and diversity of high-value forage species, increased proliferation of toxic and exotic species, and intensified soil erosion, all of which severely limit ecosystem functions and services (Sheng *et al.,* 2022).

The degradation of grasslands has long been associated with anthropogenic factors, including fire management practices and overgrazing (Zhou *et al.,* 2017). In southern Brazil, native grasslands – knowns as "Highland grasslands" – have historically been used for grazing, mainly by cattle and sheep. These areas are often managed with fire during the winter to remove dry biomass and accelerate vegetation regrowth (Boldrini, 1997).

Assessing the conservation status of these habitats and their relationship with management strategies is challenging for society. The implementation of sustainable agricultural practices – such as improved grassland management for farming and livestock – can increase productivity while enhancing the adaptability and conservation of these ecosystems (Castellanos *et al.,* 2022).

Studies focused on the degradation of non-forest ecosystems, such as grasslands, has considered the reintroduction of traditional practices of using fire to remove accumulated combustible material and stimulate regrowth (Overbeck *et al.,* 2015).

Remote sensing has become an indispensable tool for monitoring degradation at both regional and global scales. Numerous studies have used spectral responses and vegetation indices to define the degradation levels (Gao *et al.,* 2010; Liu *et al.,* 2019; Sun *et al.,* 2017).

Research based on the Grassland Degradation Index (GDI), such as that proposed by Gao *et al.* (2006), has been used to monitor degradation related to changes in land use and land cover (Yang *et al.,* 2019), interactions with climatic factors (Zhou *et al.,* 2017; An *et al.,* 2021), and advancing desertification (Kuang *et al.,* 2020).

Another widely adopted method for detecting and monitoring degradation is spectral mixture analysis, originally proposed by Shimabukuro and Smith (1991). This technique has been used to convert spectral data into physical information (fractional values of the components in the pixel), generating, for instance, soil, shadow/water, and vegetation fraction images (Dawelbait; Morari, 2011; Bullock; Woodcock; Olofsson, 2020; Lyu *et al.,* 2020).

Other authors have employed the regression-based unmixing approach to recover fractional cover time series of photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and soil from Sentinel-2 data (Kowalski; Okujeni; Hostert, 2023). While this technique focuses on the physical decomposition of pixel reflectance into predefined land cover fractions, recent advances in hyperspectral image classification have introduced alternative ways of combining spatial and spectral data. For instance, Wang et al. (2025) proposed the S2Mamba model, which employs spatial-spectral state space mechanisms and a mixture gate to adaptively integrate spatial and spectral features.

In Brazil, remote sensing is increasingly being used to support land cover monitoring and data verification. Marques and Montanher (2023), for example, employed the Normalized Difference Vegetation Index (NDVI) and decision trees for vegetation classification but did not include field validation – despite acknowledging its importance for accuracy. Brito, Palhares, and Nero (2024) used satellite imagery to assess the reliability of land use data from the Rural Environmental Registry (CAR), identifying inconsistencies with ground truth. Both studies underscore the role of remote sensing in validating land information and highlight the need for accuracy assessment in environmental applications.

The varying results found in the literature demonstrate the need for a direct comparison between different techniques for grasslands monitoring. While some studies highlight the superiority of NDVI in identifying subtle changes in vegetation (Silva *et al.,* 2020; Masenyama *et al.,* 2022), others suggest that alternative metrics may be more robust in scenarios of severe degradation (Xu *et al.,* 2020; Yousefi *et al.,* 2021).

This research is justified by the lack of a comprehensive comparative studies to guide the selection of more appropriate methodologies for different ecological contexts and degradation levels. By addressing this gap, this study contributes to academic literature and provides insights for practical conservation and management. In this context, the aim of this study was to compare the applicability of GDI techniques, and the approach using the linear spectral mixture (LSM) model to assess and define the degree of grassland degradation.

MATERIAL AND METHODS

This study employs a comparative methodology to assess the grassland degradation levels. The methodological approach is detailed in Figure 1.

Study area

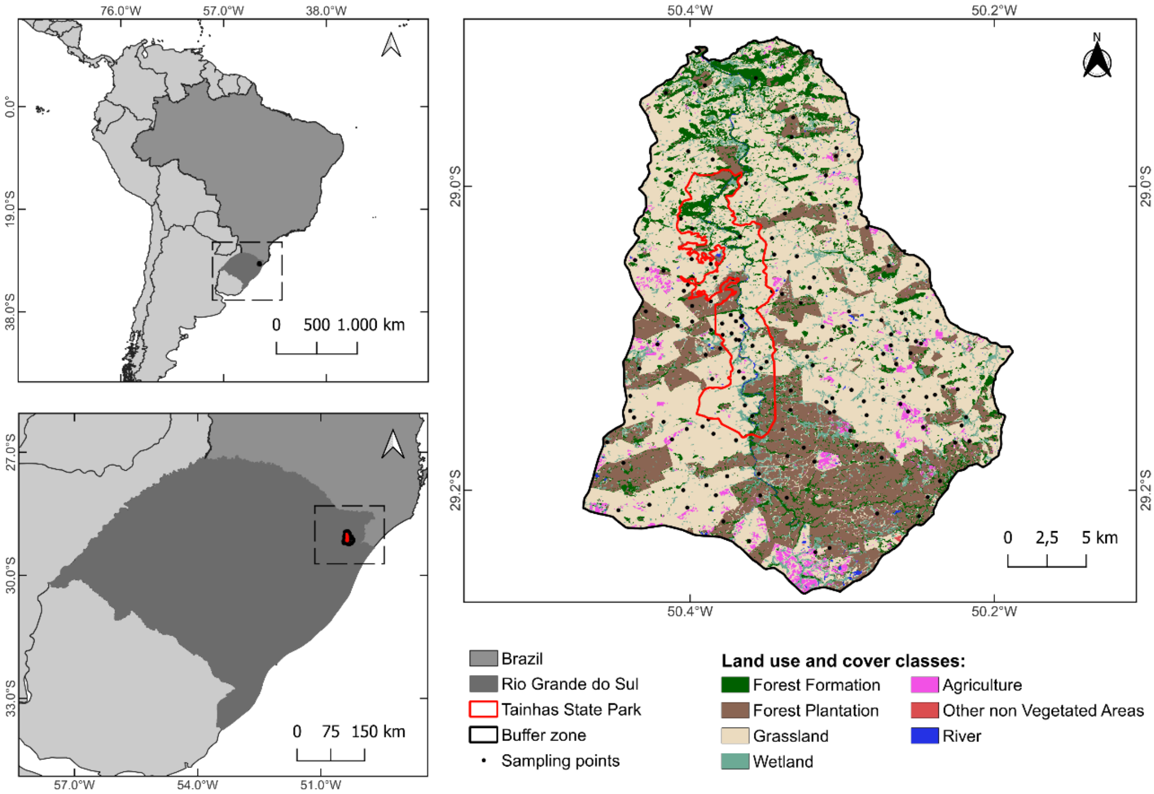
The "*Parque Estadual do Tainhas*" (PET), located in southern Brazil in a region known as "*Campos de Cima da Serra*" (CCS – Highland grasslands), is a State Conservation Area characterized by the predominance of grasslands in contact with the Atlantic Forest (SEMA, 2008) (Figure 2). The area is part of the *Serra Geral* Mountains, primarily located at elevations above 800 meters.

The region's cold climate, high rainfall, and elevated altitude contribute to a high level of endemism in the flora, with many plants adapted to this specific environment (Pillar *et al.,* 2009).

This vegetation is subjected to grazing and fire management – disturbances considered vital for maintaining grassland vegetation composed of plants from different groups, thus ensuring both biodiversity and conservation (Luza *et al.,* 2014). In the PET buffer zone (BZ), some communities depend on agriculture, forestry, and livestock, frequently using fire to manage rural areas (Bond-Buckup, 2008).

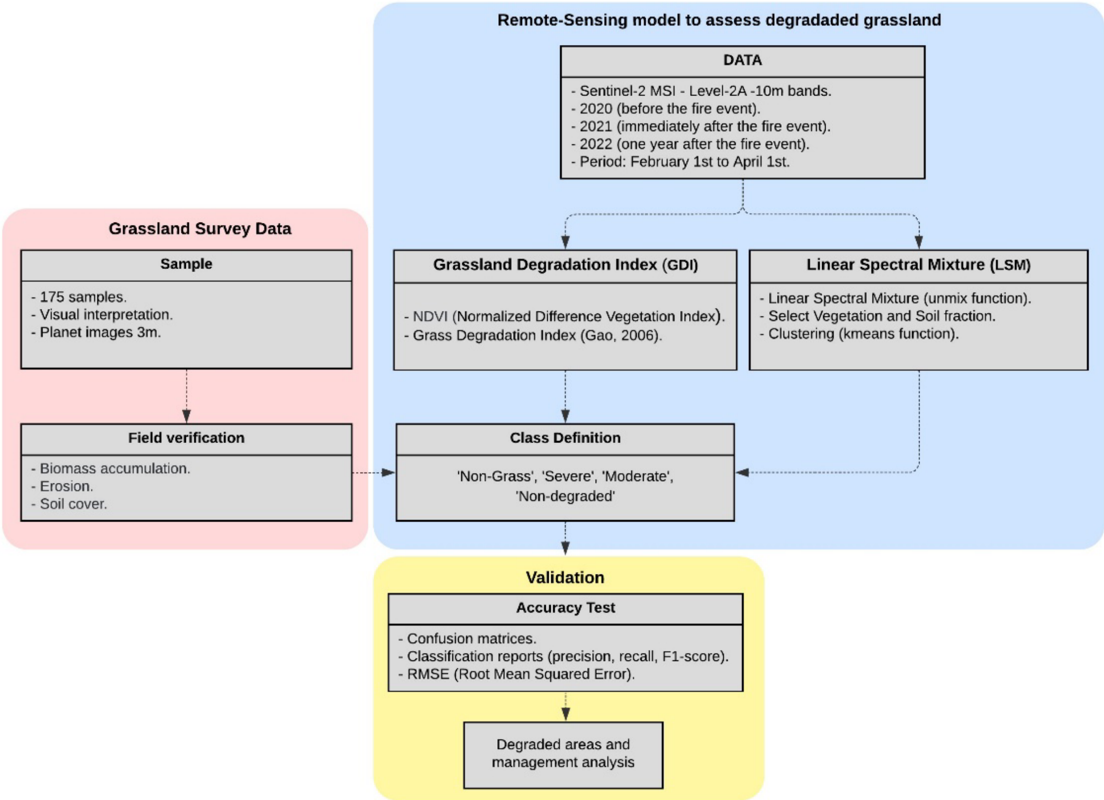
The PET includes areas acquired through land regularization, and many of these grasslands need to be assessed for their conservation level and to inform the development of restoration plans.

Figure 1 - Location and sampling points of the study area



Source: The authors, 2024.

Figure 2 - Methodological flowchart



Source: The authors, 2024.

Comparative models

This study employs a comparative methodology to assess the grassland degradation levels. The methodological approach is detailed in Figure 2. Images from the Sentinel-2 MSI Multispectral Instrument (Level-2A) were used (Table 1). This product provides bottom-of-atmosphere (BOA) images derived from Level 1C products. The images were selected for the years 2020 (before the known fire event), 2021 (immediately after the fire event), and 2022 (one year after the fire event), covering the period from February 1st to April 1st. This interval was chosen because the vegetation was not disturbed by fire and had already recovered from the previous winter's regrowth.

Table 1 - Dates of selected images by year.

Year	Image Acquisition
2020	04/02/2020; 24/02/2020; 29/02/2020; 29/02/2020; 05/03/2020; 10/03/2020; 10/03/2020; 15/03/2020; 15/03/2020; 20/03/2020; 25/03/2020
2021	08/02/2021; 08/02/2021; 20/03/2021; 20/03/2021; 25/03/2021
2022	03/02/2022; 03/02/2022; 05/03/2022; 05/03/2022

Source: The authors, 2024.

Grassland degradation index

The initial model was based on the GDI proposed by Gao (2008). The images were processed in Google Earth Engine (GEE), where the NDVI was initially calculated (Rouse *et. al*, 1973) as represented in Equation 1:

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (1)$$

NDVI is obtained by normalizing the reflectance in the near-infrared (NIR) and red (R) bands, with values ranging from -1 to +1. However, as far as vegetation is concerned, typical values range between 0 and +1.

To assess the level of grassland degradation, the NDVI results for each year was used to calculate Vegetation Cover (VC), following the methodology proposed by Gao et al. (2006), as defined in Equation 2.

$$VC = \frac{NDVI-NDVIs}{NDVIv-NDVIs}\ x\ 100 \quad (2)$$

where *NDVI* is Normalized Difference Vegetation Index, *NDVIs* is the lowest NDVI value found among pixels representing exposed soil, and *NDVIv* is the highest NDVI value grassland pixels.

Degradation levels were classified into three groups, according to the values described in (Table 2).

Table 2 - Degradation Levels

Level	**Cover**
Non-degraded	GDI>75%
Moderate	75% ≥ GDI > 50%
Severe	GDI ≤ 50%

Source: The authors, 2024.

Linear spectral mixture model

The second model used the LSM proposed by Shimabukuro (1991). The unmix function, available on GEE, was applied to generate fraction images for vegetation, soil, and shadow/water. This was based on pixels whose spectral response most closely matched the theoretical curve expected for pure pixels.

LSM assumes that pixel values are linear combinations of the reflectance of different components, called endmembers. The resulting images represent the proportion of each endmember within a pixel. Generating these fraction images serves as an alternative to reduce the dimensionality of image data and highlight the target features for digital classification (Shimabukuro; Smith, 1991). The fractions are generated according to Equation 3.

$$R_i = \sum_j^n f_i r_{i,j} + \varepsilon_i \quad (3)$$

where: Ri represents the spectral reflectance in the i spectral band; ri, j is the spectral reflectance of component j in band i (endmember); fi is the proportion of the component j within the pixel; and εi is the residual of band i.

In this research, vegetation and soil fractions were subjected to an unsupervised classification to identify degraded areas using the K-means algorithm. The process begins with K initial centroids, randomly chosen and proceeds with iterative refinement to improve the assignment of points to clusters by minimizing the within-cluster sum of squares (WCSS). This process continues until convergence is reached, when centroids do not change significantly between iterations (Ahmed; Seraj; Islam, 2020).

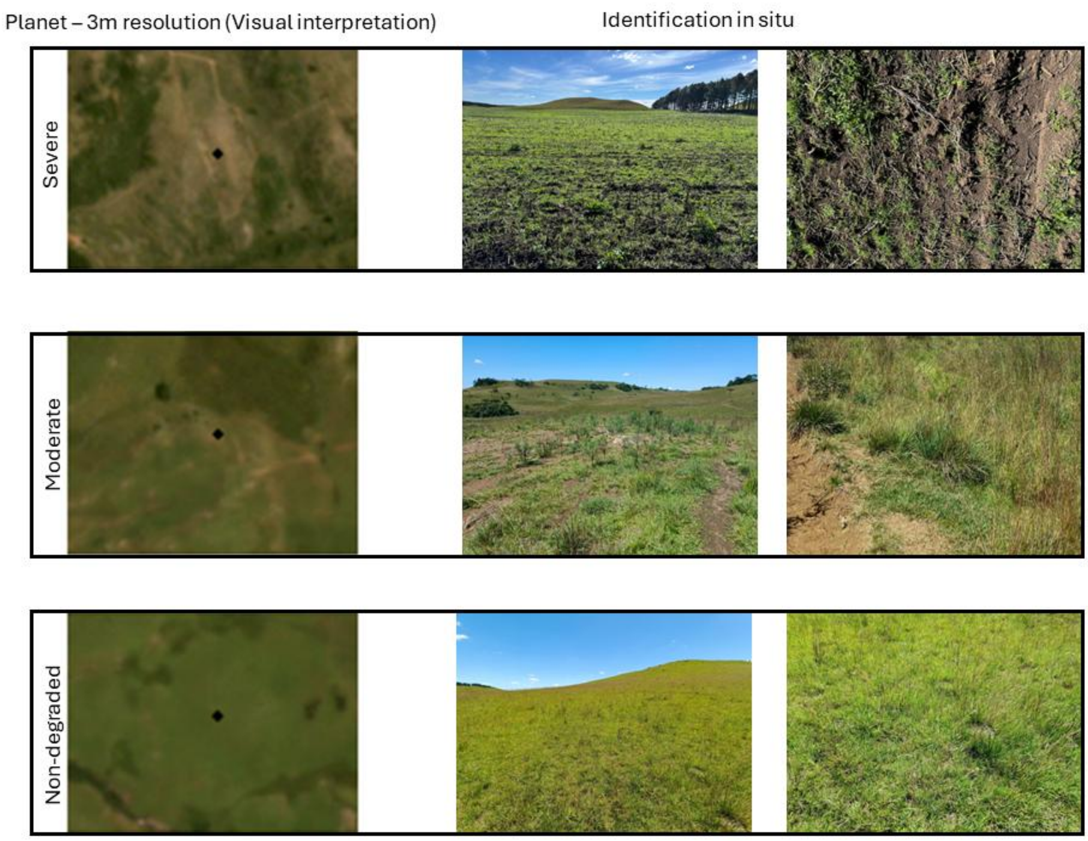
Grassland survey data

The total sample size was calculated for stratified random samples based on Equation 13 from Olofsson et al. (2014), aiming for a 10% error margin. Sample allocation across strata followed the "good practice" guidelines for area estimation (Olofsson *et al.,* 2014). The selection of training data was utterly independent of the design and reference sample selection (Bullock; Woodcock; Olofsson, 2020).

Therefore, with proportions Wi and assuming hypothetical standard deviations, the minimum required sample size n was determined to be 163 units.

Image mosaics from Planet, with a spatial resolution of 3 meters, were used for sample collection. These images were geometrically corrected and adjusted for surface reflectance. After sampling through visual interpretation, some were verified in the field by evaluating biomass accumulation, soil cover, and erosion characteristics (Figure 3).

Figure 3 - Degradation level with corresponding satellite imagery and ground truth visual interpretations



Source: The authors, 2024.

Accuracy test

To evaluate and compare the performance of the models generated, a comprehensive set of metrics was applied, including confusion matrices, classification reports (with precision, recall, and F1-score), and the Root Mean Squared Error (RMSE). The confusion matrix summarizes the model's predictions by comparing actual and predicted classes, providing a breakdown of correct and incorrect classifications by category, thereby revealing the types of errors made. The classification report complements this by quantifying, for each class, the precision (i.e., proportion of correctly predicted positive instances), recall (i.e., the proportion of actual positives correctly predicted), and the F1-score (i.e., harmonic mean of precision and recall), which are widely used to assess the effectiveness of classification models in supervised learning tasks (Han, Kamber & Pei, 2012; Powers, 2011).

Furthermore, the Kappa coefficient was computed to evaluate the degree of agreement between predicted and actual labels, accounting for agreement occurring by chance. This metric is particularly relevant in multi-class settings and imbalanced datasets, as it offers a normalized accuracy measure beyond the simple proportion of correct predictions (Foody, 2020; Foody, 2021).

RESULTS

Accuracy

The accuracy assessment and area estimation results are shown in Figure 4 and Table 3. The confusion matrix analysis reveals significant performance differences between the GDI and SLM models.

The GDI model demonstrated a superior ability to correctly classify instances of both non-grass and non-degraded levels. However, it still exhibited more classification errors, such as instances where the "Severe" class was incorrectly identified as "non-Grass." Conversely, although the SLM model achieved a lower overall accuracy (62.72% vs. 71.60%), it performed better in correctly identifying the Severe class, as indicated by its higher precision (87.18%) and F1-score (83.95%). Both models struggled with classifying the Moderate class, reflecting challenges distinguishing transitional degradation levels.

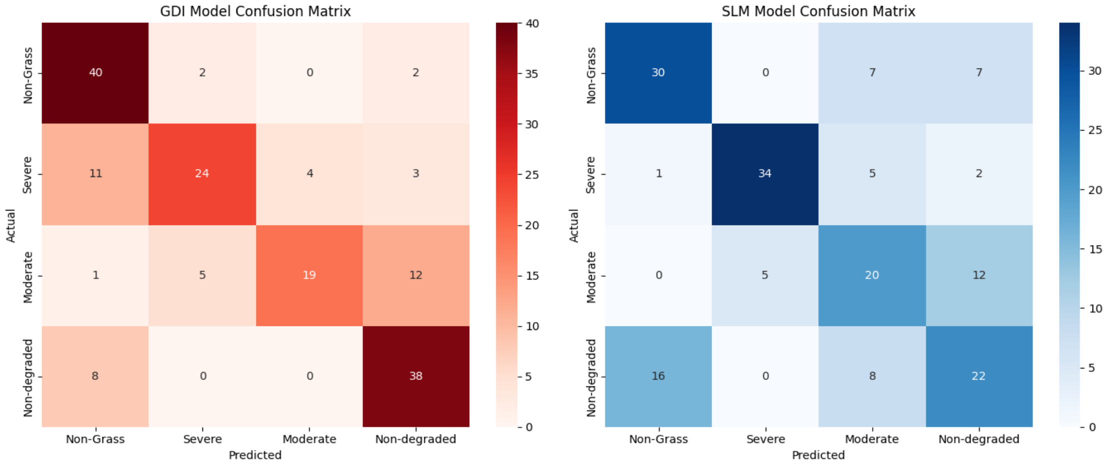
Table 3 - Performance Metrics Comparison between GDI and SLM Models

Class	Metric	GDI	SLM
Non-Grass	Precision	66.67%	63.83%
	Recall	90.91%	68.18%
	F1-Score	76.92%	65.93%
Severe	Precision	77.42%	87.18%
	Recall	57.14%	80.95%
	F1-Score	65.75%	83.95%
Moderate	Precision	82.61%	50.00%
	Recall	51.35%	54.05%
	F1-Score	63.33%	51.95%
Non-degraded	Precision	69.09%	51.16%
	Recall	82.61%	47.83%
	F1-Score	75.25%	49.44%
Macro Avg	Precision	73.95%	63.04%
	Recall	70.50%	62.75%
	F1-Score	70.31%	62.82%
Weighted Avg	Precision	73.49%	63.16%
	Recall	71.60%	62.72%
	F1-Score	70.72%	62.86%
Overall	Accuracy	71.60%	62.72%
Kappa		61,80%	50,02%
RMSE		0.91	1.27

Source: The authors, 2024.

The Kappa coefficient was also computed (GDI = 61.80%; SLM = 50.02%) to adjust for agreement expected by chance. However, as argued by Foody (2020), “the kappa coefficient is not an index of accuracy but a measure of the level of agreement observed beyond chance that is obtained using a model of chance that is inappropriate to the typical accuracy assessment scenario.” In remote sensing applications, where classification error sources are complex and sample independence is often violated, the routine use of the Kappa coefficient may be misleading. Instead, reporting overall and per-class accuracy, along with the confusion matrix and standard classification metrics, provides a more transparent and informative assessment (Olofsson et al., 2014; Stehman; Foody, 2019).

Figure 4 - Comparison of GDI and SLM Model Confusion Matrices

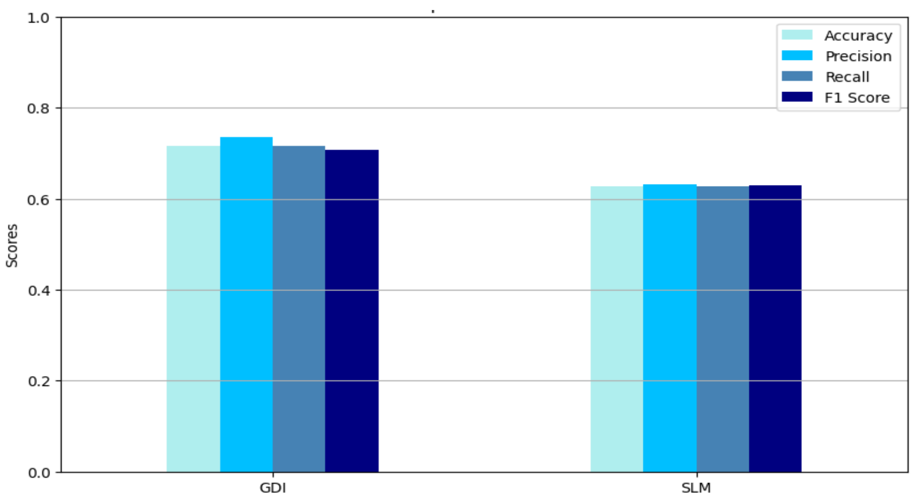


Source: The authors, 2024.

Therefore, the GDI model consistently outperforms the SLM model across all evaluated performance metrics, as seen in (Figure 5).

The enhanced accuracy of the GDI model suggests it is more effective at correctly predicting classes. Its higher precision and recall indicate that the GDI model is more effective at identifying true positives and has fewer false positives and negatives than the SLM model. Consequently, the GDI model's F1-score – representing the harmonic mean of precision and recall – is also higher, confirming its overall superior performance compared to the SLM model.

Figure 5 - Performance metrics comparing GDI and SLM models

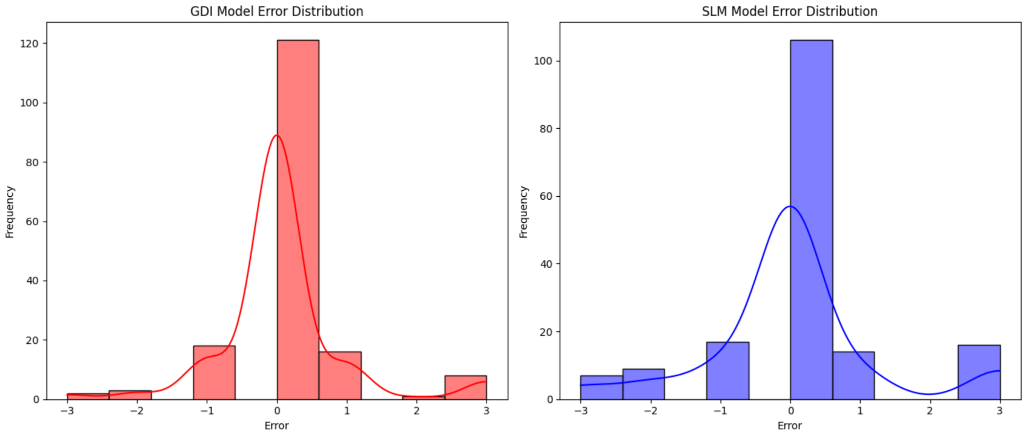


Source: The authors, 2024.

The error distributions from the GDI and SLM models (Figure 6) are depicted in a histogram plot with density curves. T

he bars represent the frequency of model errors, with most most values situated around zero, suggesting that a considerable proportion of the predictions are closely aligned with the actual values. The number of significant errors at both ends of the spectrum (i.e., at -3 and 3) is relatively low, indicating that the model is less prone to making highly inaccurate forecasts.

Figure 6 - Plot error Distribution Comparison between GDI and SLM Models



Source: The authors, 2024.

Nevertheless, the GDI model shows a slightly higher peak frequency and a narrower error spread, suggesting more precise predictions overall. By contrast, the SLM model exhibits a broader error distribution, indicating a more significant variability in prediction accuracy. The density plots provide further confirmation of these observations: the GDI's model displays a more normal distribution with a sharper peak, while the SLM model has a broader distribution with more pronounced tails.

Comparing the models

Figure 7 provides a visual representation of changes in degradation over time, allowing for an analysis of degradation and recovery trends within the study area.

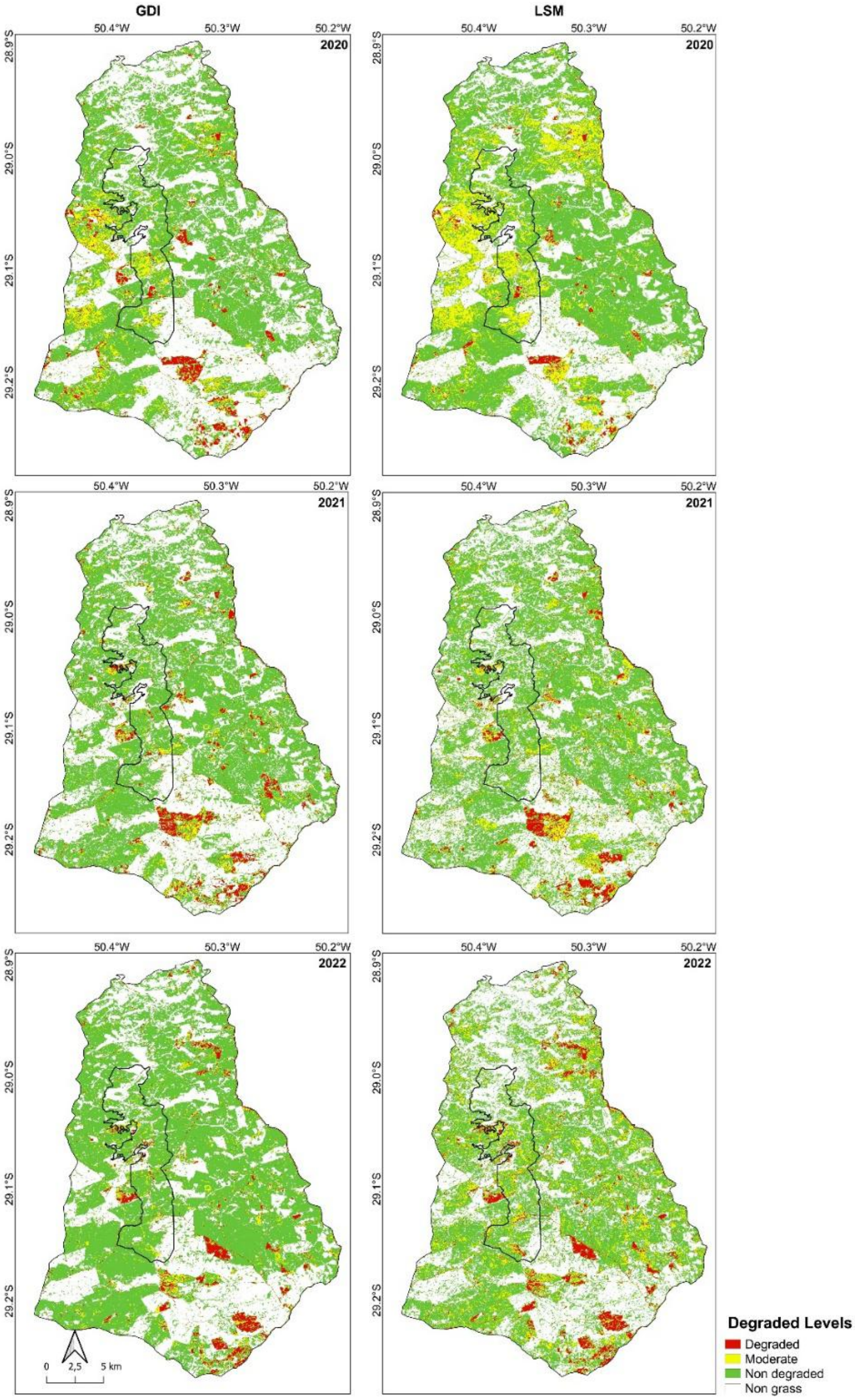
In both models, areas classified as severely degraded are concentrated near roads and regions where conversion of use has occurred. The "Severe" class exhibited no significant fluctuations throughout the period under analysis.

Figure 8 illustrates the area's evolution with different degradation levels in 2020, 2021, and 2022 for each model.

The "non-degraded" area increased overtime, particularly under the GDI method, demonstrating a notable rise from 55.04% in 2020 to 69.47% in 2022. The SLM method also reflects an increase, though with more subtle fluctuations. Meanwhile, non-grass areas remain relatively constant, with slight variations between the SLM and GDI methods – suggesting that the area without grass cover stays mostly unchanged yearly.

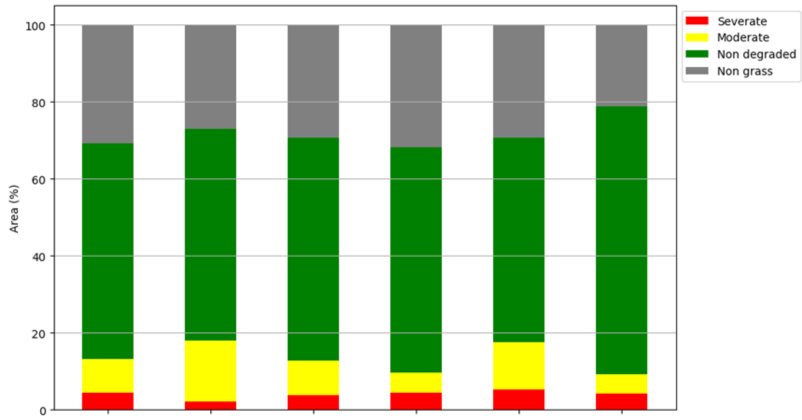
Moderately degraded areas exhibit the most significant variations, reflecting the accuracy of assessment results, and the class with the most confusion. In 2020, the GDI showed a more substantial area (12,491 hectares) than the SLM (6,324 hectares). In 2021 and 2022, these areas decreased considerably, especially in the GDI results. Finally, the GDI demonstrated greater variability in the moderate and severe classes, which may be attributed to this method's heightened sensitivity to detecting more nuanced alterations in degradation.

Figure 7 - Degradation Levels from 2020 to 2022



Source: The authors, 2024.

Figure 8 - Area of grassland categories over time using SLM and GDI



	2020		2021		2022	
	SLM	GDI	SLM	GDI	SLM	GDI
Non grass	22197,74	21208,16	21619,71	24240,11	21452,87	15308,15
Non degraded	40415,34	43176,81	42526,28	44403,01	38788,60	50066,84
Moderate	6324,63	12491,83	6627,14	3893,28	9002,90	3736,12
Severate	3115,00	1571,11	2780,49	3398,28	3850,01	2939,41

Source: The authors, 2024.

DISCUSSION

Degradation and the application of remote sensing techniques

Numerous grassland monitoring studies that consider grazing have also adopted some vegetation indices and estimated parameters, which are similar to the development of research on grassland degradation monitoring (Pereira *et al.,* 2018; Sheng *et al.,* 2022). However, studies have shown that vegetation indices can underestimate grassland degradation to a certain extent (Wang *et al.,* 2021; Wang *et al.,* 2022). This may explain the difficulty in defining the Moderate class in both models.

Assessing grassland degradation is challenging, requiring a definition of the characteristics that contribute to the degradation in such environments. Elements such as biomass accumulation and productivity (Zhang *et al.,* 2019; Wang *et al.,* 2023) and climate resilience (Zhang *et al.,* 2023) have been evaluated as aspects and used as indicative of degradation levels.

Previous studies have employed the GDI with biophysical data on toxic herbs and species richness, yielding an accuracy rate of 98.6% (Yang *et al.,* 2019). In contrast, authors have applied spectral mixing models to time series of Landsat data (Bullock, Woodcock, and Olofsson, 2020) and hyperspectral data (Lyu *et al.,* 2020) to address the degradation issue. In contrast, hyperspectral data yielded enhanced spectral separability, thereby facilitating more precise differentiation between cover classes. Nevertheless, the practical deployment of such data on a large scale is impeded by the expense and restricted accessibility of high-spatial-resolution hyperspectral imagery.

In Brazil, standardizing the elements for assessing and monitoring these areas remains a challenge, as there is no national classification system for grassland degradation, similar to the one used in China (Zhang *et al.,* 2019). Most remote sensing studies addressing grassland degradation focus on non-natural areas (Hott *et al.,* 2019; Valle Júnior *et al.,* 2019).

Given the area's history of fire disturbance, investigating vegetation recovery emerges as a strategic next step. This would support the restoration of essential ecosystem services, including forage production, pollination, soil processes, and habitat provision (Villarreal *et al.,* 2016; Alberton *et al.,* 2023). Furthermore, it would be possible to define various levels of grassland degradation in reverse, as grasslands are recovering.

A comparative analysis between NDVI techniques and other spectral mixing metrics demonstrates that, while NDVI remains a valuable tool for monitoring plant biomass changes, it has limitations in scenarios of extreme degradation, where spectral mixing models may provide more reliable results. This finding is particularly significant as it suggests the need for a more nuanced approach in selecting monitoring techniques, depending on the conservation status of the study area. Additionally, identifying regional variations in the response of the metrics underscores the importance of considering the ecological context when applying these techniques. Thus, this study not only contributes to methodological understanding but also offers practical implications for the sustainable management of grassland.

Limitations and further studies

This study may have limitations, as the model demonstrated a low ability to distinguish between grassland and other land uses. While mapping tools such as MapBiomas (Souza *et al.,* 2020), whose data were used as the basis for grassland cover definition, are effective for various applications and provide valuable insights into land cover, they also present some classification challenges. These include wetlands in the classification of grasslands and exclude more degraded areas from the class. This underscores the need to establish parameters to support the identification of degradation. Had a more precise grassland cover map been used, fewer model errors might have occurred.

Specifically, what is often treated as “ground truth” may lead to misclassification or conceptual ambiguity, particularly in transitional or degraded environments such as grasslands. The tendency of broad-scale products to mislabel wetlands as grasslands or to omit degraded patches reflects this issue. Furthermore, Foody (2022) and Foody (2024) highlight the importance of assessing classification quality even without ideal ground data, through uncertainty modelling and per-class reliability measures rather than oversimplified indices like the Kappa coefficient. Therefore, to improve the accuracy of degradation assessments, future work should incorporate multi-sensor and multi-temporal data, along with validation strategies that are robust to reference dataset limitations, and allow for more nuanced and context-aware interpretations of classification results.

It is recommended that additional studies be conducted using degradation levels established in the field, applying the proposed models. A further avenue for future research is the development and implementation of machine learning algorithms that can better manage the nuances of land cover classification, including identifying subtle degradation features.

Furthermore, integrating multi-temporal and multi-sensor remote sensing data could enhance the reliability of grassland degradation assessments. The combination of optical and radar imagery, such as Sentinel-2 and Sentinel-1 data, could help overcome limitations related to cloud cover and seasonal variations in vegetation reflectance, which often affect classification accuracy.

Future studies should explore these approaches to improve the accuracy and applicability of degradation monitoring frameworks, ultimately supporting better conservation and land management decisions.

CONCLUSIONS

This comparative study assessed the efficacy of two remote sensing techniques, LSM and GDI, in detecting grassland degradation. The GDI technique outperformed LSM in all evaluated metrics, exhibiting greater accuracy and the capacity to accurately identify non-degraded and severely degraded areas. In contrast, although LSM was less accurate overall, it proved more effective in classifying severely degraded areas.

The analysis indicated an increase in non-degraded areas between 2020 and 2022, highlighting the importance of sustainable management practices in recovering grassland ecosystems. These findings underscore the pivotal role of continuous monitoring and the implementation of effective restoration strategies to maintain and enhance the health of these vital landscapes.

Despite the effectiveness of both techniques, there are limitations in standardizing elements for assessing grassland degradation in Brazil. Future research should focus on vegetation recovery and the restoration of essential ecosystem services. Additionally, defining degradation parameters specific to the type of grassland and grazing use in the study region is essential.

In conclusion, while both LSM and GDI have their respective strengths, the continuous improvement and application of remote sensing techniques are crucial for effective grassland management and restoration efforts.

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