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Applications, challenges and perspectives for monitoring agricultural dynamics in the Brazilian savanna with multispectral remote sensing

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A R T I C L E I N F O

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A B S T R A C T

Land use and cover changes significantly impact landscape configuration, climate change, and society. The processes of expansion, conversion, intensification, diversification, and reduction materialize these changes in the agricultural environment. The Cerrado, or Brazilian Savanna, is a biodiversity hotspot, extremely important for water production, and one of the most important biomes for global food production. In this sense, monitoring agricultural dynamics in this environment plays a crucial role in sustainable planning, assessment of environmental impacts, and food security. In this study, we propose to analyze the evolution of the role of multispectral orbital remote sensing in mapping and monitoring agricultural dynamics processes in the Cerrado. Therefore, a narrative review of the literature based on studies developed in the biome was carried out to identify advances in tools, processes, and resources, as well as evaluate the challenges and perspectives for the future. Among other relevant results, monitoring these processes has become faster, more frequent, and more accurate, mainly through the combined use of high temporal resolution time series of spectral data and machine learning algorithms. Promising results have been obtained with Harmonized Landsat Sentinel-2 (HLS) data. The consolidation of deep neural networks has contributed substantially to detecting and delimitating complex intensification and diversification systems, such as central irrigation pivots and intercropping. However, there are challenges and obstacles to be faced, such as expanding the use of Sentinel-2 data, establishing means for sharing field data, and expanding studies to more fragmented landscapes, especially agricultural production on small properties.

1. Introduction

The Brazilian Savanna, or Cerrado (Fig. 1), Brazil's second-largest biome, encompasses about 24% of the country's territory and serves as a rich biodiversity hotspot, hosting numerous plant and animal species (Aquino and Oliveira, 2006). Despite its ecological significance, less than 5% of its area is exclusively dedicated to environmental protection (Sano et al., 2019b; Spera, 2017). Over the

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latter half of the 20th century, political and economic factors triggered extensive transformation of the Cerrados' landscape, turning it into one of the worlds' primary agricultural production regions (Contini et al., 2020). The conversion of natural landscapes into cultivated fields and pastures has long characterized the agricultural dynamics within the biome. However, in the early 21st century, facing land depletion, scarcity, and the burgeoning global commodities market amid accelerated climate change, the Cerrado agricultural scene undergoes a profound transformation. This shift is marked by the emergence of MATOPIBA, an expanding frontier covering parts of Maranhão, Tocantins, Piauí, and Bahia (Bolfe et al., 2016). Simultaneously, historically established areas witness accelerated vertical intensification, diversification, and reduction (Vieira et al., 2022; Kuchler et al., 2022; Spera, 2017). In this context, monitoring these transformative processes becomes imperative for sustainable planning and evaluating environmental impacts, where remote sensing emerges as a crucial tool. While expansion, conversion, intensification, diversification, and reduction can be conceptualized individually, they are intricately interlinked and influence one another as causes or consequences.

The concept of expansion is broad and may be related to increasing income and expanding activities and will be considered as the increase of agricultural areas, cultivated through the suppression of natural vegetation, but also through the conversion of agricultural areas, such as degraded pastures (Vieira et al., 2022; Spera et al., 2014). Although the concept of conversion is also treated in the literature as the suppression of native environments for agricultural introduction (Vieira et al., 2022), in this study, we chose to address all concepts from an agricultural perspective. Thus, the conversion processes considered involve the dynamics of replacements between crops and pasturelands. These land use changes can indicate economic reconfiguration, are linked to environmental aptitudes, quality, and availability of resources, and are also relevant to climate change understanding (Cohn et al., 2016; Huang et al., 2023). Furthermore, the expansion concept contemplates expanding agricultural areas by suppressing natural environments.

Agricultural intensification is linked to maximizing the use of consolidated cropland, with an increase in production per unit of area and time, and differs from the so-called horizontal intensification, which refers to expansion over forests and savannas. Here, intensification will be analyzed by initiatives of mapping and monitoring temporary crops carried out in a succession of first and second crops/year, or double cropping (DC), and crops produced under irrigation systems. From an agronomic point of view and, specifically from anthropic agricultural areas, within production units, agricultural diversification involves simultaneous or successive production, in a simple, associated, or intercropped manner, of more than one variety of crops or even the combination of agricultural and livestock activities (Piedra-Bonilla et al., 2020). Here, diversification is analyzed based on approaches to map these diversified production systems, such as Crop-Livestock-Forest Integration (iCFL) and Agroforestry Systems (AFS). Thus, there is a direct relationship between agricultural intensification and diversification since intensive systems can increase the level of diversity in agriculture, and diversification leads to more intensive land-use, often linked to more sustainable production strategies (Arvor et al., 2011). Finally, reduction is a concept associated with the reduction of 'anthropogenic agricultural areas' due to legal, environmental, agronomic, social, economic, or infrastructure issues. In literature, reduction is a concept acknowledged as the abandonment of farmland or its conversion into other types of use or coverage, such as the regeneration of areas of natural vegetation. However, the reversion of intensive systems (e.g., DC to single cropping) has also been considered agricultural reduction (Spera et al., 2014; Vieira et al., 2022).

Therefore, this study aims to analyze the trajectory of optical orbital remote sensing in monitoring agricultural spatial dynamics in the Brazilian Savanna. It considers processes of expansion, conversion, intensification, diversification, and reduction to identify perspectives, advances, and challenges. As a strategy, we use a narrative review of the literature. We also show examples of the

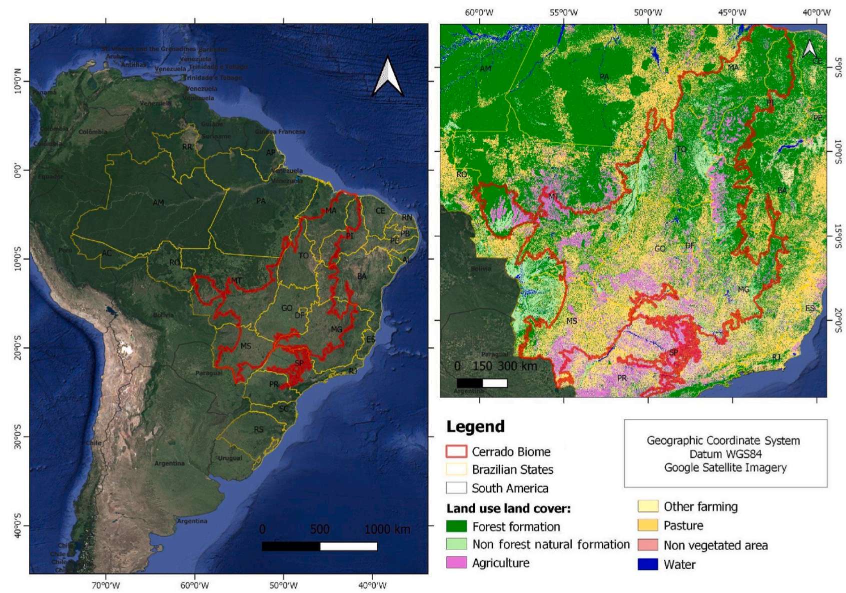

Fig. 1. Borders and main classes of land use and cover in the Brazilian Savanna, Brazil. Sources: Brazil's political map (https://www.ibge.gov.br/geociencias/downloads-geociencias.html); Cerrado borders (http://terrabrasilis.dpi.inpe.br/downloads/); land use land classes (MapBiomas, 2022).

application at different scales.

2. Environmental characteristics

Studies estimate that around 45% of Cerrado has already been allocated to human activities, mainly cultivated pastures and crops (Sano et al., 2019b; Scaramuzza et al., 2017; Grecchi et al., 2014). Due to the heterogeneous geographic aspects, Cerrado was subdivided into 19 ecoregions with different natural (geomorphological, pedological, climatic, and vegetation) and agricultural characteristics (Sano et al., 2019a,b). The biome is influenced by the Amazon to the north and northwest, the Caatinga to the northeast, the Atlantic Forest to the south and southeast, and the Pantanal to the southwest (Sano et al., 2000). In the transition zone with the Caatinga, the annual accumulated precipitation ranges from 800–1000 mm to over 1800 mm in the Cerrado-Amazonia transition The average annual temperature varies between 15.6 °C and 28.1 °C, strongly influenced by latitude, increasing from South to North (Sano et al., 2019b). From a floristic point of view, the Cerrado is a savanna, a landscape intermediate between forests and grasslands, with a predominance of grasses and a varied occurrence of trees and shrubs (Walter et al., 2008). The relief is characterized by plateaus in the central-eastern portions, with an elevation between 528 and 1045 m and a slope between 4.8% and 9.6%, and depressions that occupy the areas to the west and north, with an average elevation between 85 and 415 m, and slope between 3.8% and 4.7%. The most abundant soil types are Oxisols (44%), Plintisols (10%), Cambisols (10%), and Argisols (~8.8%) (Sano et al., 2019b).

3. Monitoring Cerrado's agricultural dynamics by multispectral remote sensing

Since the 1970s, orbital optical remote sensing has been fundamental for monitoring land-use land-cover (LULC) dynamics in the Brazilian Savanna (Skole, 1994). The launch of the ERTS (Earth Resources Technology Satellite) program in 1972, renamed Landsat in 1975, revolutionized agricultural mapping worldwide, with numerous advances in spatial, spectral, temporal, and radiometric resolution achieved since then. Moreover, Landsat historical data became free of charge to the public in 2008 (Wulder et al., 2019). New sensor systems placed in orbit by other space programs of Earth's natural resources observation, such as the Moderate-Resolution Imaging Spectroradiometer (MODIS), launched by the National Aeronautics and Space Administration (NASA), and the Multispectral Instrument (MSI) from the European Spatial Agency (ESA), also play an essential role. Data from the Landsat program, MODIS, and MSI are the most used in studies aiming to map and monitor agricultural dynamics in the Cerrado, although not exclusively.

At the end of the 20th century, multispectral remote sensing was the principal way of monitoring LULC changes (Skole, 1994; Sano and Ferreira, 2005). However, even in the 1990s, there was a significant lack of information on trends in land use and occupation in the Cerrado. The monitoring of agricultural expansion was based on analysis of census data collected by the Brazilian Institute of Geography and Statistics (IBGE) and deforestation maps generated mainly through visual interpretation of Landsat 5 TM and Advanced Very High-Resolution Radiometer (AVHRR) images. Such frameworks often resulted in uncertain and incongruous estimates (Nepstad et al., 1997). Some factors contributed to the scarcity of detailed mapping in the Cerrado, such as the greater attention given to the Amazon, the vast extension of the biome, the similar spectral response of several targets, and the high occurrence of cloud cover harming optical images. In addition to hindering the monitoring of agricultural dynamics, this lack of information affected the delimitation of priority areas for conservation and planning for the rational use of soil and water resources (Nepstad et al., 1997; Carreiras et al., 2005; Sano and Ferreira, 2005).

Between 2000 and 2020, studies involving orbital remote sensing in global agriculture increased exponentially (Khanal et al., 2020). One key factor was the unprecedented data availability due to the new earth observation satellites launched by different space programs, which improved the spatial, spectral, temporal, and radiometric resolution of available image datasets. However, to process

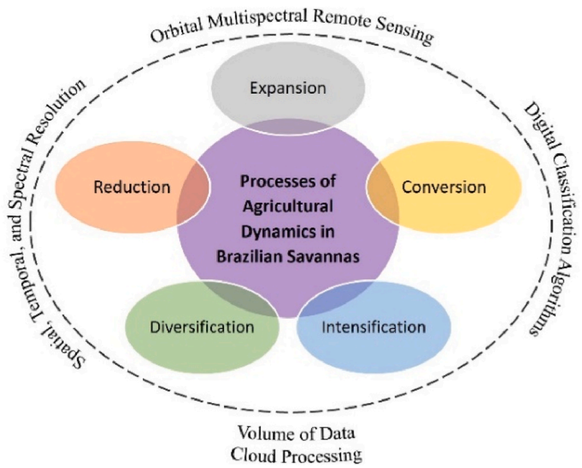

Fig. 2. Processes of agricultural dynamics in the Brazilian Savanna and drivers of growth in the role of remote sensing in their monitoring. Source: Authors.

and analyze such an amount of data, the expansion of computational capacity, the development of free and commercial software for geospatial analysis, the advancements in cloud computing, and the consolidation of machine learning algorithms in remote sensing were also essential elements for this growth (Khanal et al., 2020; Weiss et al., 2020). In the further sections, we aim to analyze and discuss how remote sensing has been used to map and monitor agricultural dynamics in the Cerrado biome through expansion, conversion, intensification, diversification, and reduction processes (Fig. 2).

3.1. Agricultural expansion

Data from the Landsat program have been essential for monitoring agricultural dynamics in Brazil since its launch in the 1970s. The Landsat Global Archive Consolidation (LGAC) initiative ensured cross-calibration between the different sensors of the program (MSS, TM, ETM+, and OLI), which favored the execution of historical analyses based on surface reflectance data (Wulder et al., 2019). Additionally, the pre-processing with geometric and atmospheric corrections was significantly reduced, making it easier for users. Brannstrom et al. (2008), Cunha et al. (2020), Grecchi et al. (2014), Jepson et al. (2010), and Kraeski et al. (2023) employed historical multispectral data from the Landsat program aiming to map and monitor agricultural expansion in the Brazilian Savanna using digital classification and detection of LULC changes under different approaches (Table 1).

Brannstrom et al. (2008) revealed that agriculture expanded 300% in western BA and 88% in eastern MT between 1986 and 2002. The occupation rate of agriculture in those study areas went from 11% to 44% and 25% to 47%, respectively. Considering the total expansion area, the conversion of the natural vegetation of the Brazilian Savanna represented 66% in MT and 55% in BA. The authors associated the expansion and conversion processes with topographic, political, and economic factors. In eastern MT, they found a scenario of higher fragmentation of the remaining native vegetation due to the more irregular topography and longer-established agriculture. In the western BA, the flat relief and the context of the modern agricultural frontier expansion post-1979 led to high deforestation rates and clearings of larger sizes. Jepson et al. (2010), when reproducing the methodology of Brannstrom et al. (2008), found the same trend for eastern MT, analyzing the results with colonization processes in the region, including interviews with local producers.

Grecchi et al. (2014) identified an agricultural expansion rate of 62% in Primavera do Leste, Mato Grosso (MT) State, between 1985 and 2005. This expansion occurred mainly due to the conversion of native vegetation, including land of high fragility and little suitable for agricultural activity. Kraeski et al. (2023) revealed that 60% of the Cerrado in the Teles Pires river basin, MT, were transformed into annual crops and pastures, which grew by 643% and 250% between 1986 and 2020, respectively. The authors also revealed that 2.2 million hectares of pastures were converted into annual crops, especially after 2005, which led to smaller deforestation rates. In a study

Table 1
Methodological characteristics of studies that aimed monitoring agricultural expansion in the Brazilian Savanna using Landsat program's historical archive of images.

Reference	Location/Period	Classification type/ Method/Algorithm	Imagery/Sensor/Features	Mapped classes	Accuracy assessment
Brannstrom et al. (2008)	Western BA and Eastern MT/1986, 2002	Unsupervised/object-based/ISODATA	Annual cloud-free image[a]/ TM and ETM+/Spectral bands	Cerrado, agro-pastoral, dark object (burned areas + water)	84% and 0.74 of OA and K in BA; 72% OA and 0.56 K in MT
Jepson et al. (2010)	Eastern MT/1972, 1973, 1986, 1992, 2002	Unsupervised/object-based/ISODATA	Annual cloud-free image[a]/ MSS, TM and ETM+/ Spectral bands	Cerrado, agro-pastoral, dark object (burned areas + water)	Non-informed
Grecchi et al. (2014)	Primavera do Leste, MT/1985–2005	Supervised/object-based/NN	*n* images from dry period/ TM, MODIS/Spectral bands, vegetation indices, DEM	Annual crops, pasture, natural vegetation, water bodies, urban areas	Non-informed
Cunha et al. (2020)	Rio Prata RB, MS/ 1986, 1999, 2007, 2016	Supervised/object-based/NN/	Annual cloud-free image[a]/ TM and OLI/Spectral bands, spectral indices, geometry, and texture features	Pasture, agriculture, semideciduous forest, banhado, cerrado, riparian forest, swampy grasslands, eucalyptus, barren land, fallow agricultural land, water bodies	89.9, 93.6, 90.9, 93.4 (OA each year)
Ajadi et al. (2021)	BA, GO, MT, and MS States	Supervised/object-based + pixel-based/ Boundary Net + XGBoost	MSI (for segmentation), Annual metrics from MODIS + OLI + SAR (all 250 m) for pixel-based	Crop x non-crop; soybean in the summer growing season or corn in the 'safrinha'	87% recall and 91% f1 in MT; 86% recall for soybean in MT and GO; 95% recall for corn
Kraeski et al. (2023)	Rio Teles Pires RB, MT-PA/1986, 1991, 1996, 2000, 2005, 2011, 2015,2020	Supervised/pixel-based/MLC	5 cloud-free images from dry period/TM and OLI/ Spectral bands	Water, forest, cerrado, pasture, crops, burned area, other areas	89.4% OA and 0.85 K

[a] Images from similar dates among the years. Abbreviations are: MT – Mato Grosso State; PA – Pará State; MS – Mato Grosso do Sul State; RB – river basin; NN – Nearest Neighbor, a machine learning algorithm; MLC – Maximum Likelihood Classifier, a parametric algorithm; MSS – Multispectral Scanner, sensor from Landsat −3; TM – Thematic Mapper, sensor from Landsat 4–5; ETM + - Enhanced Thematic Mapper, sensor from Landsat 7; OLI – Operational Land Imager, sensor from Landsat8-9; MODIS - Moderate-Resolution Imaging Spectroradiometer, sensor from Terra and Aqua satellites; DEM – Digital Elevation Model; OA – Overall Accuracy; K – kappa coefficient.

carried out in a river basin in Mato Grosso do Sul (MS), a state of long livestock culture, Cunha et al. (2020) identified an expansion of cultivated pastures by 37% between 1986 and 2016, mainly by the conversion of Cerrado and riparian forest. Crops expanded on a smaller scale by converting natural environments with suitable soils, occupying areas of ecosystem relevance.

Multi-institutional approaches of official and unofficial mapping have also provided relevant products for understanding the Cerrado LULC dynamics. In 2002, the Project for Conservation and Sustainable Use of Brazilian Biological Diversity (Probio), coordinated by the Ministry of the Environment, carried out the first semi-detailed mapping of the entire Cerrado Biome. Therefore, images of 121 ETM + orbits/points and a semi-automated classification approach were used, with segmentation followed by visual interpretation of colored compositions of multiple scenes according to predetermined interpretation keys (Sano et al., 2007). In 2013, 2018, 2020, and 2022, maps of land uses in deforested sites detected by the Cerrado Monitoring Project, or PRODES Cerrado, were made available by the TerraClass, a project coordinated by the Ministry of the Environment and executed in partnership with institutions such as the National Institute for Space Research (INPE) and the Brazilian Agricultural Research Corporation (Embrapa). The Terraclass maps were based on medium-resolution images from sensors like ETM+, OLI, and MSI, using ML algorithms. TerraClass maps are accessible using the GeoPortal TerraClass platform, where it is possible to create transition matrices, diagrams, and evolution graphs at different scales (INPE. Instituto Brasileiro de Pesquisas Espaciais, 2024).

Another important multi-institutional initiative is the historical reconstruction of LULC made by the Mapbiomas Project (https://mapbiomas.org/), which provides annual mappings up to the level of some crops, such as soybeans and sugar cane, at 30 m resolution (Souza Jr. et al., 2020). MapBiomas has used the Landsat historical time series since 1985 to feed the ML Random Forest (RF) algorithm using a cloud computing environment, and these products are available via Google Earth Engine (GEE). Due to the regularity and easy access, MapBiomas' historical series of mappings are being used to rewrite the history of LULC changes in the Brazilian Savanna and monitor tthe agricultural frontier's expansion in MATOPIBA. Polizel et al. (2021), Moura Neto et al. (2022), and Silva et al. (2023) used data from the project in different study areas in the MATOPIBA, identifying an expansion rate of annual crops (soybeans, cotton, and corn) up to 2600%. The authors also noticed the expansion of cultivated pastures between 2000 and 2020, mainly via the conversion of Cerrado areas, which decreased by 27% in that period. Moreover, the historical mapping helped to estimate the impacts of agricultural expansion on evapotranspiration (Moura Neto et al., 2022), on the hydrological regime (Silva et al., 2023), and to simulate possible effects of adopting the Soy Moratorium in reducing deforestation rates in the region (Polizel et al., 2021).

In addition to Landsat, MODIS data has been widely used in monitoring agricultural expansion, mainly the vegetation indices (VIs) Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), which have become some of the most relevant covariates for LULC mapping in the Cerrado (Chen et al., 2018; Picoli et al., 2018). These VIs are 16-day composites generated from daily sensor observations, in which the best pixel is selected and provided in atmospheric-corrected surface reflectance of 250 m spatial resolution since 1999. These composites always consider the same days of the year, favoring the historical transferability of classification models, as was the case of Kastens et al. (2017), who used 14 years of NDVI data from MODIS to feed the RF algorithm and monitor the impact of the Soy Moratorium on Mato Grosso LULC dynamics. Thus, due to the regularity and quality of observations, these data become the first choice for studies relating to the dynamics of natural or cultivated vegetation on a regional or global scale. By employing regular VIs time series, it is possible to extract phenological indicators related to the agricultural calendar, such as the start date of photosynthetic activity (greenup), maturity, senescence, dormancy, number of cycles, and others. These indicators are extracted using mathematical functions that evaluate the rate of change in the VIs curvatures to identify possible transition dates and can be used as variables in the feature space of ML classification models to increase class separability (Zhang et al., 2003; Eklundh and Jönsson, 2016). Fig. 3 illustrates some seasonality indicators extracted from regular NDVI or EVI time series using the TIMESAT software (Eklundh and Jönsson, 2016), which is broadly used in studies of agricultural dynamics in the Brazilian Savanna.

Morton et al. (2006), Spera et al. (2014), and Morton et al. (2016) used seasonal metrics and phenology indicators extracted from NDVI and EVI time series to feed the ML algorithm Decision Tree (DT) to analyze land use changes and agricultural expansion in the MT in the first two decades of the 21st century. According to the authors, the conversion of natural environments was still the main

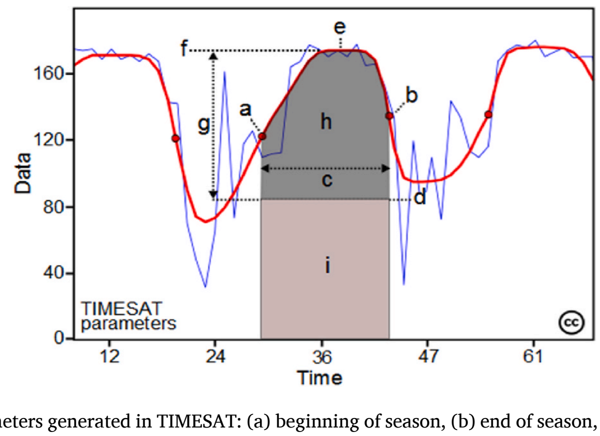

Fig. 3. Some of the seasonality parameters generated in TIMESAT: (a) beginning of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h + i) large integrated value.
Source: https://web.nateko.lu.se/timesat/timesat.asp.

form of crop expansion, although the pasture-to-crop conversion was growing. The authors also revealed that the expansion in MT slowed down from 2004 to 2005 and that new croplands were placed in areas of lower altitude, drier, steeper, and further away from established markets. These new croplands also present low or moderate suitability for agriculture, lower productivity, and use rate compared to those cleared at the beginning of the state's colonization. They also found that the expansion dynamics in the state are directly related to soybean prices on the international market and the logistics infrastructure, findings corroborated by Arvor et al. (2011) and Vieira et al. (2022) and illustrated in Fig. 4.

Although studies over more than a decade have demonstrated the efficiency of MODIS vegetation index time series in identifying the phenology of cultivated or natural vegetation, favoring the distinction between vegetation types and the consequent agricultural expansion over native areas, the spatial resolution (≥250 m) of this product limits its application in medium and small-scale production regions. In this context, integrating multiple sensors is a simple and effective solution, as Ajadi et al. (2021) demonstrated. These authors used neural networks (BoundaryNet) in Sentinel-2 mosaics with a resolution of 10 m to delimit field boundaries in several Brazilian states. They then performed a pixel-by-pixel classification with the Extreme Gradient Boosting (XGBoost) algorithm, combining vegetation index reduction metrics and surface reflectance from Landsat and MODIS, in addition to backscatter from Sentinel-1, to produce a crop mask, in addition to identifying summer soybean and second-crop corn production. The temporal and spatial transferability of the models was assessed, achieving recall rates consistently above 85%. The data and routines Ajadi et al. (2021) use are easily reproducible through Google Earth Engine (GEE) and Python resources in cloud computing. When employed in multitemporal analyses, it helps analyze agricultural expansion.

3.2. *Agricultural conversion*

Land use change (LUC) related to agriculture is among the main emitters of greenhouse gases (GHG). Crop and livestock expansion in the Brazilian Savanna directly stems from replacing forests and savannas, predominantly through suppression. With land scarcity and accelerated climate change, converting processes, such as turning degraded pastures into croplands, represent a strategy for expanding crop production without deforestation. This approach aligns with the ABC + Plan (Low Carbon Emission Agriculture), a national strategy promoting sustainable technologies in agriculture through planning and financing (Brasil, 2021). More recently, the Brazilian government launched the National Program for the Conversion of Degraded Pastures (PNCPD) through decree 11815 of 2023 (BRASIL, 2023) to encourage the implementation of temporary crops and integrated production systems in low-quality pastures. According to Victória et al. (2017), approximately 44 million hectares of cultivated pastures in the Cerrado share climatic and topographic similarities with crop areas, with roughly 50% displaying signs of degradation (Andrade et al., 2016).

In MT, cultivated pastures (CP) are up to seven times more likely to be converted into sugarcane than soybeans (Spera et al., 2017). Alkimim et al. (2015) suggest that approximately 50 million hectares of CP in the Cerrado region hold the potential for conversion into sugarcane. The increasing presence of sugarcane within food-producing regions has prompted concerns regarding environmental, social, and food security risks, such as loss of natural habitats, pollution of air and water, questionable labor practices (Souza et al., 2017), as well as increase of GHG emissions by the process of conversion and intensive management (Bento et al., 2018). In contrast, its expansion across pastures is a strategy to produce biofuels (Souza et al., 2017; Bento et al., 2018). Thus, monitoring conversion processes at the crop level becomes imperative to assess the impact of public policies, such as the ABC Plan and agricultural zoning. These efforts will help identify priority areas and ensure adherence to GHG goals (Souza et al., 2017).

Sano et al. (2019) analyzed data from Probio and TerraClass (2013) using transition matrices and revealed that, between 2002 and 2013, pasture expansion was the main reason for the suppression of native vegetation in the Cerrado. This trend was also found by Kraeski et al. (2023) and Vieira et al. (2022). Cohn et al. (2016) used data from PROBIO, Morton et al. (2006), and the TerraClass project to reveal that while only 15% of suitable crop-growing areas underwent conversion, logistical considerations had a more significant influence on these changes than agronomic attributes. Through intensity analysis using EVI time series data from MODIS collected in Pedro Afonso, Tocantins State, from 2008 to 2013, Souza et al. (2017) showed a predominant trend in sugarcane expansion. Their findings indicated that the expansion primarily involved the conversion of existing agricultural land rather than

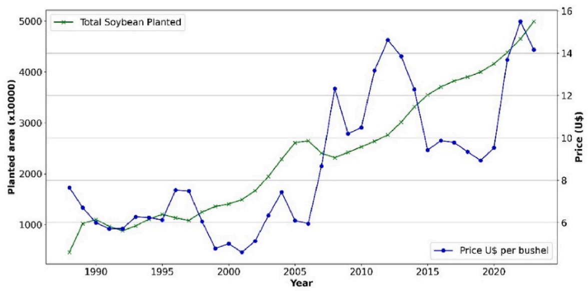

Fig. 4. The international soybean price in US dollars and the total area planted with soybeans, in hectares, in the Brazilian states of Mato Grosso (MT), Mato Grosso do Sul (MS), Goiás (GO), Minas Gerais (MG), São Paulo (SP), and Bahia (BA), that together cultivated around 58% of Brazil's total soybean area in 2023, boasting significant cultivation within the Cerrado biome.
Sources: IBGE (2022) and Macrotrends (www.macrotrends.net/2531/soybean-prices-historical-chart-data).

pasture.

This study also demonstrates the potential of shared knowledge and products by presenting an example of monitoring agricultural processes in Guia Lopes da Laguna, Mato Grosso do Sul. Using historical LULC mappings from the MapBiomas (2022), we mapped and monitored processes of expansion, conversion, and reduction in agriculture between 1990 and 2020 (Table 2). We accessed data via GEE and reclassified it using predetermined transition matrix rules, cloud computing resources and Python in Google Colab. Further methodology details for map preparation can be found in the supplementary material. The results are part of the Science Center for Development in Digital Agriculture (CCD-SemeAr) from Embrapa. Empresa Brasileira de Pesquisa Agropecuária (2023) and corroborate with results from other authors. The expansion process was relevant until 2005, when conversion between agricultural uses became the main process, especially in the southern part of the municipality. Currently, the main type of conversion observed in Guia Lopes da Laguna is the transformation of pastures into annual crops, especially soybean and corn.

Some pre-classification approaches are suitable for LULC change detection, such as enhancement, subtraction, or principal components analysis (PCA) (Singh, 1989; Souza et al., 2017). However, post-classification methods involving transition matrices have been a primary choice for conversion analysis. For conversion processes to be correctly identified and monitored, there is a demand for more accurate maps with reproducible classes and outputs shared with the scientific community (Brannstrom et al., 2008; Picoli et al., 2018; Parreiras et al., 2022). Due to the growing interest in crop-pasture conversions, crucial challenge lies in identifying resources and strategies capable of upgrading the quality of these maps and minimizing frequently observed classification errors, especially the confusion between areas of CP and sugarcane, savannah phytophysiognomies, and other temporary crops, as reported by Sano et al. (2010), Arvor et al. (2011), Müller et al. (2015), Chen et al. (2018), Picoli et al. (2018), Bolfe et al. (2023a,b).

3.3. *Agricultural intensification*

Agricultural intensification involves maximizing land use by increasing inputs and outputs per unit of area and time (Vieira et al., 2022), often linked to a land-sparing effect (Spera et al., 2017), as well diversification (Perosa et al., 2024). While various methods exist to intensify production, this discussion focuses on two primary strategies for the Cerrado region: intensification through successive cropping, notably double cropping (DC), and the utilization of irrigated systems, particularly center-pivot systems that facilitate up to three harvests per year.

3.3.1. *Intensification with double cropping (DC)*

To accurately map and monitor double crop (DC) systems, it is essential to distinguish between various crop types and their recurring patterns across multiple harvests within a year. Consequently, the primary approaches for this task have been dense and consistent time series analysis of VIs, coupled with machine learning algorithms for supervised pixel-by-pixel classification, as detailed in Table 3.

Arvor et al. (2012), Chen et al. (2018) and Picoli et al. (2018) revealed the consolidation of agricultural intensification through the adoption of double cropping (DC), mainly soybean-corn, in MT, one of the major producers of agricultural commodities in Brazil and the world. Using methodology developed by Arvor et al. (2012), Oliveira et al. (2014) observed a 266% increase in DC in the Rio Verde watershed in MT. Between 2001 and 2014, Kastens et al. (2017) revealed that the average value of crops in each pixel with soybean production went from 1.1 to 1.6, reinforcing the strong trend towards DC. Spera et al. (2014) showed that the scarcity of land suitable for agriculture in MT boosted the intensive use of consolidated areas, slowing the expansion of deforestation in the early 2010s. Thus, Spera (2017) argues that the lessons learned by MT and GO with DC can spare the Cerrado native vegetation in the last agricultural frontier, MATOPIBA, a region that encompasses part of the states of Maranhão (MA), Tocantins (TO), Piauí (PI) and Bahia (BA) (Bolfe et al., 2016). In the previous section, studies revealed a significant expansion of agriculture in natural environments at the beginning of the 21st century. However, GO and MT managed to increase crop productivity while reducing deforestation due to two main factors: converting of degraded pastures into crops and consolidating of double cropping (DC) (Spera et al., 2014).

The adoption of double cropping (DC) in MT rose from 6% of annual crops in 2000–2001 to approximately 8.43 million hectares, covering 35% of the state's total area by 2015–2016, marking a substantial 590% increase (Arvor et al., 2012; Chen et al., 2018; Picoli et al., 2018). In this process, biotechnological advances allowed the expansion of commercial crops in a second season, mainly corn, which began to be cultivated preferentially after the soybean harvest (Arvor et al., 2012; Picoli et al., 2018). Besides augmented land productivity and diversity, DC practices expanded vegetative cover over crop areas during the rainy season, shielding the soil against sunlight and water erosion and facilitating no-tillage practices (Arvor et al., 2012). Consequently, monitoring the intensification of cropping practices in the Brazilian Savanna, a biome renowned for its biodiversity and concurrent status as a hub for modern, high-yield agriculture, bears significant economic, social, and environmental implications at regional, national, and international levels.

Table 2
The total area (km^2) of agricultural expansion, conversion, and reduction in Guia Lopes da Laguna, Mato Grosso do Sul, Brazil, was analyzed for the period between 1990 and 2020. This monitoring was conducted using historical data provided by MapBiomas (2022).

Processes	1985–1990	1990–1995	1995–2000	2000–2005	2005–2010	2010–2015	2015–2020
Expansion	116	80.8	47.6	52.3	20.8	18.0	27.1
Conversion	151	177	144	124	104	152	211
Reduction/Abandonment	67.1	27.4	27.4	19.6	24.7	25.0	14.0

Table 3
Methods, covariates, and main results of studies whose objective was the mapping and/or monitoring of agricultural intensification with double cropping (DC) in the Brazilian Savanna.

Reference	Location/Period	Classification type/ Method/Algorithm	Imagery/Sensor/Covariates	Crop types and patterns mapped	Accuracy assessment
Arvor et al. (2011)	MT State/ 2000–2007	Hierarchic[a] - supervised/pixel-based/MLC	16-day time series/MODIS/ EVI, index metrics	Soybean, cotton, soybean + NCC, soybean + maize, soybean + cotton	74% OA, 0.67 K; 66%, 85%, 56%, 73%, 93% UA, respectively
Oliveira et al. (2014)	Rio Verde watershed/ 2000–2010	Hierarchic[a] - supervised/pixel-based/MLC	16-day time series/MODIS/ EVI, index metrics	Single crop, double crop, savanna	59%, 88%, 93% UA, respectively
Spera et al. (2014)	MT State/ 2001–2011	Supervised/pixel-based/DT	16-day time series/MODIS/ EVI, index and phenology metrics	Soybean, cotton, soy-cotton, soy-corn, irrigation	Non identified**
Spera et al. (2016)	MATOPIBA/ 2002–2013	Supervised/pixel-based/DT	16-day time series/MODIS/ EVI, index and phenology metrics	Single crop (soy, corn, or cotton), double crop (with corn), sugarcane, native vegetation, pasture	87 % accuracy (crop types)
Kastens et al. (2017)	MT State/ 2001–2014	Supervised/pixel-based/RF	16-day time series/MODIS/ NDVI	Pasture/cerrado, soy-single, cotton, soy-double, soy-cotton	85% OA and 0.78 K; 87%, 64%, 69%, 90%, 91% UA, respectively.
Bendini et al. (2019)	LEM – BA/	Hierarchic - supervised/pixel-based/RF	Time series/OLI/ Phenometrics from EVI	At Level 4, 16 classes with 13 rotation types, such as soy followed by maize, cotton, millet, sorghum etc.	0.96 OA in Level 4; f1-scores between 0.83 and 0.99
Picoli et al. (2018)	MT State/ 2001–2016	Supervised/pixel-based/SVM	16-day time series/MODIS/ EVI, NDVI, NIR, MIR	Cerrado, fallow-cotton, forest, pasture, soy-corn, soy-cotton, soy-fallow, soy-millet, soy-sunflower	94% OA, 092 K. 97%, 92%, 99%, 96%, 87%, 96%, 100%, 87%, 90% UA, respectively
Chen et al. (2018)	MT State/??	Hierarchic - supervised/pixel-based/DT	16-day time series/MODIS/ NDVI	Level-2: soy-maize, soy-cotton, fallow-cotton, soy-fallow, soy-pasture, single	78%, 88%, 78%, 30%, 81%, 87% UA, respectively
Chaves et al. (2021)	Industrial farms in MT/ 2008–2012	Supervised/pixel-based/TWDTW	8-day time series/MODIS/ NDVI, EVI, spectral bands	Cotton-fallow, forest, soybean-cotton, soybean-maize, soybean-millet	86%, 89%, 93%, 91% OA in 2008–2009, 2009–2010, 2010–2011, 2011–2012, respectively
Kuchler et al. (2022)	MT State/ 2012–2019	Supervised/pixel-based/RF	16-day time series/MODIS/ NDVI, EVI, spectral bands	Soybean-cotton, soybean-cereals, integrated systems	1.0, 0.79, 0.9 UA, respectively
Bolfe et al. (2023)	Sorriso-MT/ 2021–2022	Hierarchic - supervised/pixel-based/RF, XGboost, ANN	2-3-day time series/HLS/ NDVI, SAVI, NDWI	Single crop, double crop, triple crop (Level 2); corn, cotton, beans, and other crops (Level 3)	99% OA and 0.98 K (Level 2); 97% OA and 0.96 K (Level 3) with XGBoost e NDVI
Sano et al. (2023)	Goiatuaba-GO/ 2021–2022	Supervised/pixel-based/RF	Monthly mosaics/Planet Scope/Spectral bands, spectral indices, texture features	Single crop, double crop, native vegetation, pasture	90% OA; 0.91 f-score for DC

[a] In hierarchic approaches, authors isolated crop pixels from pastures and natural vegetation. ** Supporting online material was not available. OA – Overall Accuracy; K – Kappa coefficient; MT - Mato Grosso State; GO - Goiás State; LEM – Luis Eduardo Magalhães municipality; BA – Bahia State; MATOPIBA – agricultural frontier covering a portion of the Maranhão, Tocantins, Piauí and Bahia states; NDVI – Normalized Difference Vegetation Index; EVI – Enhanced Vegetation Index; SAVI – Soil Adjusted Vegetation Index; NDWI – Normalized Difference Water Index; NCC is non-commercial crops; UA – user's accuracy; MLC – Maximum Likelihood Classifier; RF – Random Forest; DT – Decision Tree; SVM – Support Vector Machines; XGBoost – Extreme Gradient Boost; ANN – Artificial Neural Network; TWDTW - Time-Weighted Dynamic Time Warping; MODIS - Moderate-Resolution Imaging Spectroradiometer, from Terra and Aqua satellites; MSI – Multispectral Instrument, from Sentinel-2 A and B satellites; OLI – Operational Land Imager, from Landsat 8 and 9 satellites.

Chaves et al. (2021) mapped crops and cultivation systems with accuracy greater than 85% in Sapezal, MT, using the Time-Weighted Dynamic Time Warping (TWDTW) algorithm that measures the dissimilarity of a given pixel regarding a pre-established temporal pattern, considering seasonality, associated with time series of spectral bands and indices. The algorithm is available in the R environment with the dtwSat package, and it is possible to evaluate its performance with ground data collected by Maus et al. (2016) between 2008-2009 and 2011–2012. TWDTW is an open method that allows the selection of temporal patterns and, therefore, is suitable for dealing with dynamic agricultural landscapes, although it is still underused.

Despite the findings, MODIS data reveals a significant limitation regarding spatial resolution. The landscape configuration notably influences the classifiers' performances (Chen et al., 2018; Lin et al., 2022), indicating that 250 m pixels may not be suitable for highly fragmented areas. In this context, Bendini et al. (2019) evaluated the performance of RF models fed with phenology metrics extracted from Landsat 7 ETM+ and 8 OLI EVI time series in a hierarchical classification approach to map multiple crop types and systems in western Bahia. The authors used the Radial Basis Function (RBF) convolutional neural network to interpolate and fill pixels contaminated by clouds and shadows, generating regular time series with 8-day resolution. TIMESAT was used to smooth the data with the Savitsky-Golay (SG) filter and extract 13 phenology metrics. The authors achieved accuracies (F-score) higher than 0.82 in a four-level classification scheme. At the third level, DC detection was performed, on average, with 0.98 accuracy. At the fourth level, 16 crop rotation configurations (soybean-corn, soybean-cotton, soybean-potato, soybean-brachiaria) presented accuracies between 0.82 (soybean-sorghum) and 0.99 (corn-carrot).

Bolfe et al. (2023) evaluated the potential of a multi-sensor dataset, the Harmonized Landsat Sentinel-2 or HLS (Claverie et al., 2018), to map crop intensification in Sorriso, MT, in the 2021–2022 season, using a three-level classification scheme. The authors evaluated the performance of ML algorithms with VIs time series to produce crop masks, count the number of crop seasons in each pixel (one, two, or three), and identify crop types in the second harvest season, as shown in Table 1. Sano et al. (2023) mapped crop intensification in Goiatuba, GO State, during 2021–2022, with an overall accuracy of 90% and an F-score for DC of 0.91. The authors used the RF algorithm, fed with multispectral bands, spectral indices, and textural attributes, obtained from six 4.77 m resolution monthly mosaics made available by PlanetScope and Norway's International Climate & Forest Initiative (NICFI). Results from Bolfe et al. (2023a,b) and Sano et al. (2023) corroborate what was argued by Spera (2017) about the consolidation of DC in the states of GO and MT and the lessons learned to preserve the Cerrado in the MATOPIBA. Bolfe et al. (2023a,b) and Sano et al. (2023) identified that DC was present in 99% and 63% of crop areas, respectively. Arvor et al. (2011) found that, in 2007, 50% of crop areas were intensified by DC in Sorriso. Therefore, a 98% increase was observed by Bolfe et al. (2023a,b). Regarding Sano et al. (2023), there was a high occurrence of sugarcane in Goiatuba, and considering only fields occupied with temporary crops, 100% were under a succession system, mainly with corn and sorghum succeeding soybeans.

3.3.2. *Intensification with irrigation*

Irrigation involves techniques for artificially applying water to crops, which is essential for arid and semi-arid regions, enabling production during droughts or dry seasons. When coupled with good management practices, irrigation reduces the risk of crop failure, increases productivity up to three times, and favors higher-quality products. Water availability enables the production of two or three harvest seasons, increasing crop diversity and regularizing the food supply (ANA. Agência Nacional de Águas, 2021). In Brazil, flood irrigation initially facilitated rice production in Rio Grande do Sul State (RS) between the late 19th and early 20th centuries. As agricultural expansion extended to the less favorable Cerrado region, irrigation practices grew during the 1970s and 1980s. In 1960, approximately 460,000 ha of crops were under irrigation. By 2017, this area had expanded to 7 million hectares - an annual growth averaging 216,000 ha/year (ANA. Agência Nacional de Águas, 2021).

The center pivot is the primary irrigation system in the Brazilian Savanna because it is highly effective and presents reduced losses (ANA. Agência Nacional de Águas, 2021). The biome concentrates approximately 80% of center pivots, raising concerns about the impact of irrigation on the capacity of surface and subsurface reservoirs to provide water in the long term (Althoff and Rodrigues, 2019; ANA. Agência Nacional de Águas, 2021). In Brazil, the National Water Agency (ANA. Agência Nacional de Águas, 2021) surveys central pivots and flood rice production throughout the national territory. However, the methodology is based on manual vectorization and visual interpretation of medium-resolution multispectral images, such as Landsat and Sentinel-2 (ANA. Agência Nacional de Águas, 2021). Although this is the most accurate way, it is highly demanding regarding time, resources, and specialized human work (Ozdogan et al., 2010). Therefore, the trend has been to search for strategies for automated detection of irrigation systems on different scales, mainly in the Brazilian Savanna (Albuquerque et al., 2020). In addition to the different sizes and shapes (which are not always complete circles), one of the main challenges in mapping central pivots is the internal variability caused by multiple cropping, making pixel-based classifications and spectral parameters challenging (Albuquerque et al., 2020; Carvalho et al., 2021).

Semantic or instance segmentation techniques based on convolutional neural networks (RNNs) from deep learning represent the most promising strategy for automatically detecting and delimiting center pivots in the Cerrado (Saraiva et al., 2020; Albuquerque et al., 2020; Carvalho et al., 2021; Liu et al., 2023). These algorithms have been evaluated with medium and high-resolution images, such as Landsat (Albuquerque et al., 2020; Carvalho et al., 2021; Liu et al., 2023) and Planet Scope (Saraiva et al., 2020), this last, with approximately 5 m resolution. Although mapping central pivots is more demanding in terms of spatial resolution, studies have shown that, in terms of temporality, a few images from the crops growing season are sufficient, mainly from the dry season, when they are active, as opposed to rainfed areas that remain fallow during this time of the year. Fig. 5 exhibits some results obtained with semantic and instance segmentation in the Cerrado.

The MapBiomas Project has leveraged the efficiency of these methodologies. Since its fifth collection, the methodology has undergone significant improvements. It now incorporates advanced tools such as deep neural networks, including U-Net, and Random

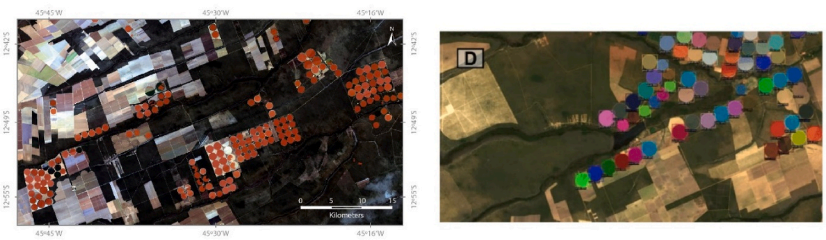

Fig. 5. On the left, center pivots mapped with semantic segmentation with the U-Net neural network in western Bahia, carried out by Saraiva et al. (2020). On the right, central pivots detected by instance segmentation with the Mask-RCNN algorithm, carried out by Carvalho et al. (2021).

Forest algorithms to map irrigation across the country using historical Landsat data (MapBiomas, 2022). Using the products generated by the MapBiomas initiative, Sano et al. (2024) examined the spatiotemporal dynamics of central pivot irrigation systems in the Cerrado, identifying that approximately 75% are in regions with low water availability. This finding underscores the importance of accurate analyses for understanding and managing this critical production system.

3.4. Agricultural diversification

The development of Brazilian agriculture in the second half of the 20th century was marked by the emergence of clusters specialized in producing commodities, mainly soybeans and corn, favored by natural, social, economic, and infrastructure conditions. This specialization increased the vulnerability of several regions due to their high dependence on these products. In the 21st century, however, economic and technological advances contributed to consolidating agricultural practices that increase the number of crops per area, reducing dependency and increasing diversity, such as double crop systems (Perosa et al., 2024).

Traditionally, diversification analysis has relied on census data like the Municipal Agricultural Production (PAM) survey (IBGE, 2022) and diversity indices such as the Shannon or Simpson Index (Piedra-Bonilla et al., 2020). However, advancements in satellite imaging databases, classification algorithms, computational capabilities, and accrued knowledge enable more detailed, precise, and frequent agricultural mappings. These methodologies are now suitable for monitoring diversification processes, as carried out by Kastens et al. (2017), who quantified the number of crops per pixel per year. However, such strategies become limited when more than one crop is cultivated simultaneously. Given the emergence of climate change, there is a need for production systems to combine economic gains while conserving ecosystem services (Perosa et al., 2024; Balbino et al., 2011). However, very little attention has been given to intercropping systems. Therefore, this topic will analyze strategies for mapping production systems that integrate crops, livestock, and forests, one of the most promising forms of agricultural diversification that present economic and environmental benefits. Intercropping systems intensify consolidated spaces and bolster resilience by increasing the variety of crops per area while intertwining cultivation with forests and pastures. These transformations lead to a more intricate agricultural landscape, presenting challenges for orbital SR (Bégué et al., 2018).

3.4.1. Intercropping systems

Intercropping systems involving crops, livestock, and forestry, simultaneously or successively, so-called iCLFs or agroforestry, meet four sustainability principles: they are technically efficient, environmentally adequate, economically viable, and socially accepted (Balbino et al., 2011). Agricultural production based on intercropping systems is one of the priority actions of the ABC + Plan. There are four configurations for these systems considering large-scale production: i) crop-livestock integration (iCL); ii) livestock-forest integration (iCF); iv) crop-forest integration (iCF); and vi) crop-livestock-forest (iCLF). According to the iCLF Network, in 2020, there were around 17,430,000 ha of integrated systems in Brazil, mainly in the states of Mato Grosso do Sul, Mato Grosso, Rio Grande do Sul, Minas Gerais and Goiás, which together accounted for 61% of the total area cultivated with these systems (Polidoro, 2020). However, these estimates were based on census data, so they cannot represent these systems' locations nor spatialize the implemented configurations. iCLFs are complex production systems from a spatial, temporal, and spectral point of view; since integration can be

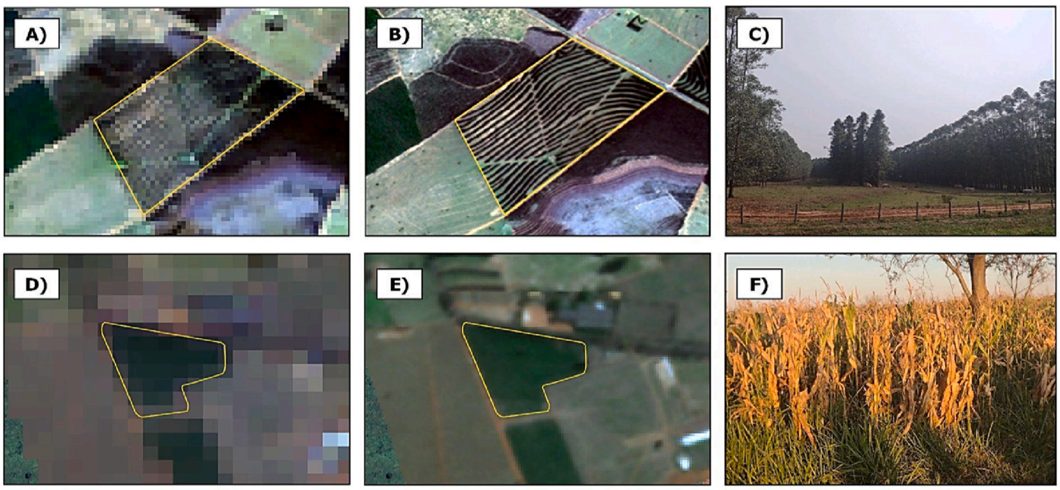

Fig. 6. Examples of intercropping systems observed by the authors during field activities in the Brazilian Savanna. In the top row, livestock-forest integration (iLF) from Campo Grande, Mato Grosso do Sul, is seen from: A) a Landsat 8 true-color composition, 30 m resolution, B) a monthly Planet Scope NICFI mosaic, ~5 m resolution, and C) a photograph taken in situ, all referring to September 2022. In the bottom row, a crop-livestock integration system (iCL) in Uberlândia, Minas Gerais, is seen by: D) a true color composite from Landsat 8 OLI at 30m resolution, E) a monthly Planet NICFI mosaic at ~5m resolution, and by F) a photograph taken in situ in May 2023. The satellite images are from August of the same year, illustrating the persistence of vegetation even in the dry period, contrasting with the surrounding pastures, with a dryer aspect.

done in consortium, succession, or rotation, with activities of similar calendars in the same area, the coexistence of plant canopies of different structures, various management practices, resulting in complex spectral response patterns of these targets, making their monitoring and mapping through orbital RS challenge (Bégué et al., 2018; Kuchler et al., 2022; Toro et al., 2023), as exemplified Fig. 6.

In a study carried out in three municipalities in MT, Manabe et al. (2018) developed a hierarchical framework to detect iCP systems using 9 years of smoothed MODIS EVI time series, between 2008 and 2016. The authors chose the TWDTW algorithm to perform the pixel-by-pixel supervised classification in three steps: first, identifying crop areas with double cropping (DC) and iCP systems and separating them from other LULC classes. Then, iCP was separated from DC and cotton areas in the second harvest, considering only images from the winter. In the last step, parameters based on change detection were established to identify interannual iCP. Despite the component of subjectivity involved in the operationalization of TWDTW, the validation of the models was carried out with field data and reported an overall accuracy of 92% in distinguishing iCLs from other classes, with user and producer accuracy of 86% and 91%, respectively. The authors estimated a rate of occupation of iCLs in 5% of the total study area.

Kuchler et al. (2020) analyzed data from interviews with rural producers in Mato Grosso to determine the most effective method of identifying agricultural production systems, including iCLs, during the 2014–2015 crop year. They used different methodological settings, such as RF and SVM models, phenological metrics, time series smoothing, and pixel-by-pixel supervised classification. The results indicated that the best approach to identify iCLs was to combine the unsmoothed NDVI and EVI values with both RF and SVM (with F-scores of 0.97 and 0.96, respectively). As observed by Manabe et al. (2018) and Bolfe et al. (2023), the research highlighted that NDVI values in intercropped systems are considerably higher than in areas with DC at the end of the dry season. The phenological indices extracted from NDVI MODIS by Chen et al. (2018) showed that the variable 'values at the end of the dry season' (VLDS) were crucial to distinguish the soybean-pasture class from the others (such as soybean-corn, soybean-cotton, soybean-fallow). The NDVI in the consortium area can be up to 60% higher at the end of the dry season.

Kuchler et al. (2022) mapped the occurrence of iCLs between 2012-2013 and 2018–2019 in the MT State, using cloud computing in GEE. The authors developed a methodological structure based on a hierarchical classification scheme with an RF algorithm, considering the smoothed and unsmoothed EVI and NDVI time series, along with near-infrared (NIR) and mid-infrared (MIR) bands of MODIS as explanatory variables, aiming to identify iCL areas in the different agroclimatic zones of the state. With this structure, the authors observed users' and producers' accuracies from 0.80 to 0.94 and 0.68 to 0.88, respectively. With these results, for the 2015–2016 harvest, for example, a total area of 1,370,000 ha of iLPs was estimated throughout the state, a very close estimate to that provided by the ILPF Network, which was 1,250,000 ha. Toro et al. (2023) explored the potential of multispectral data from the Sentinel-2 MSI and different polarizations from the Sentinel-1 Synthetic Aperture Radar (SAR) to identify iCLs in various contexts in the states of São Paulo (SP) and MT between 2019 and 2021. The authors aimed to determine whether detecting intercropping systems in different areas is possible using the same methodology and distinct time windows. The authors used the RF and Deep Learning (DL) algorithms, the long short-term memory (LSTM) neural network, and the transformer (TF) network, whose classification was object-oriented after a segmentation step with a simple non-iterative clustering algorithm (SNIC) performed on GEE. Optical data produced better results than SAR images, and the detection of iCLs can be performed with a seven or nine-month time series. RF was superior in the MT and presented performance similar to the Transformer neural network (TF) in SP. All models created with MSI images achieved accuracies higher than 0.83 for iCLs. Bueno et al. (2023) also used a deep neural network, the fully convolutional

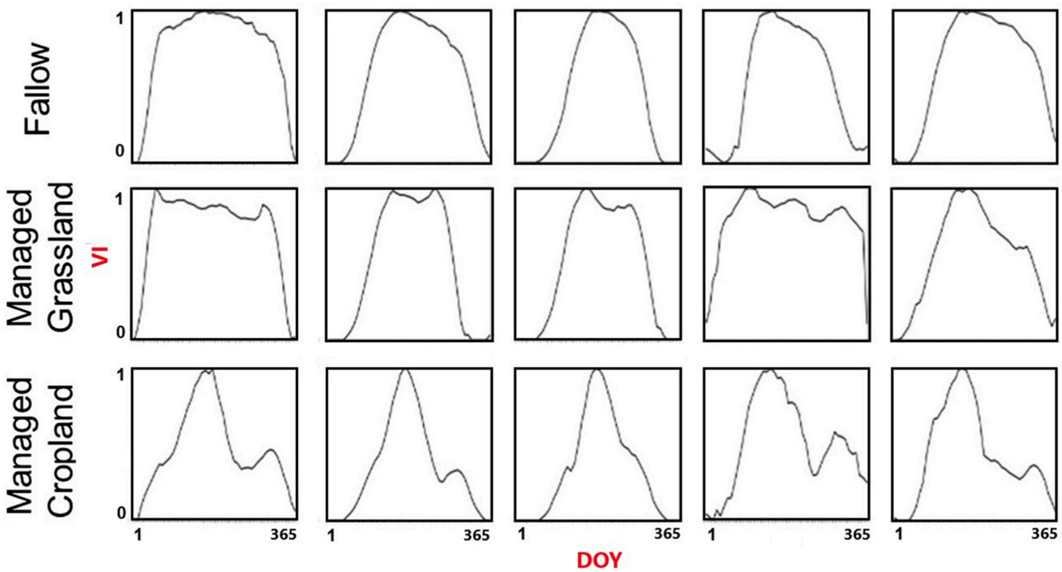

Fig. 7. Examples of land surface phenology from fallow lands, managed grasslands and croplands used to identify farmland abandonment. The idea is that an area with five or more years without signs of management in dense time series of vegetation indices, or fallow, is possibly abandoned. Non-parametric classifiers can be used to perform spatial predictions outside training areas. Source: Estel et al. (2015).

network (LSTM -FCN), coupled with spectral bands and indices from high-resolution Planet Scope images to map iCLs in various study sites in SP and MT. The authors identified ICLs among several other LULC classes, such as pastures, forestry, forests, and DC, with users' accuracy of 96.5% and 97%.

3.5. Farmland abandonment and crop reduction

3.5.1. Farmland abandonment

Croplands have been abandoned since the mid XX century due to social, economic, and environmental factors (Crowford et al., 2022). Considering the economic relevance and growing apprehensions regarding environmental impacts surrounding land use changes, more attention should be given to farmland abandonment and cropland reduction (Wuyun et al., 2024; Castro et al., 2022; Yin et al., 2020; Estel et al., 2015). Recovery of biodiversity and carbon stocking are presented as opportunities from farmland abandonment, but assessing such impacts depends on the knowledge of where those lands are, when they were abandoned, and what happened after desertion (Crowford et al., 2022). Mapping farmland abandonment faces some non-trivial challenges. For starters, there is a conceptual issue. The Food and Agriculture Organization of the United Nations (FAO) establishes that the abandonment is consolidated after five years without cultivation. However, as it is central to most large-scale studies, this definition may only be applicable in some cases. Furthermore, the methodology is adjustable case by case, making it difficult to generalize (Crowford et al., 2022; Yin et al., 2020; Estel et al., 2015). Overall, active agriculture leaves periodic disturbances noticeable in the land surface phenology (Fig. 7). Such signals are related to planting, fertilization, harvesting, and plowing in the case of crops, as well as mowing or grazing in the case of pastures, all of which can be detected with phenometrics derived from dense time series of vegetation indices.

Change detection and classification using annual agricultural maps generated with ML algorithms fed with these indices are used to verify land use trajectories and identify fallow over long periods (Wuyun et al., 2024; Yin et al., 2020; Castro et al., 2022; Estel et al., 2015). However, the same difficulties in mapping agricultural areas impact the ability to identify farmland abandonment. Time series must be dense enough to image management practices in time and capture irregularities left in phenological signatures. In tropical areas, temporal resolution needs to be high to increase the chances of imaging in clear-sky conditions (Wuyun et al., 2024; Yin et al., 2020; Castro et al., 2022; Estel et al., 2015). While high accuracies have been obtained in detecting farmland abandonment in modern, mechanized, and large-scale agriculture in Brazil and other countries, the same results cannot be achieved in fragmented areas with predominance of family farming (Wuyun et al., 2024; Yin et al., 2020). In these cases, there is a need for sensors with medium or high spatial resolution, such as Landsat and Sentinel-2 (Castro et al., 2022) or Planet Scope (Rufin et al., 2022). Additionally, prior knowledge of the studied regions is essential, as there are various factors influencing abandonment, and occurrences tend to be sparse (Yin et al., 2020). The scarcity of in situ samples can also impair mapping efforts because the spectral response of abandoned farmlands can be closely similar to grasslands and drylands, so efficient training and calibration is crucial to ensure class separability and produce models scalable both in time and space (Wuyun et al., 2024; Castro et al., 2022; Yin et al., 2020; Estel et al., 2015).

3.5.2. Cropland reduction

In Brazil, particularly within the Cerrado Biome, efforts to map farmland abandonment and cropland reduction remain limited, leaving our understanding of the drivers behind these processes, as well as the methodological constraints, still in an early stage. Spera et al. (2014) conducted a significant study on abandoned fields in Mato Grosso between 2002 and 2010, linking abandonment to environmental and logistical factors. By employing transition rules based on specific time periods (two, five, or nine years without agricultural activity), the author characterized agricultural decline, considering the transition from double-cropping (DC) to a single-crop system as a reduction. The study revealed an increasing trend in abandonment after 2005, showing that by 2010–2011, around 1 million hectares had been either fully abandoned or converted from DC to monoculture. These areas generally had higher temperatures, lower precipitation, steeper slopes, and were farther from logistical infrastructure than lands where agricultural activities expanded or persisted.

An analysis of annual maps generated with a time series of vegetation indices and a Random Forest classifier has shown promise in mapping farmland abandonment in Mato Grosso, identifying conservation policies as a key driver of abandonment. However, the structure of the landscape has led to critical variations in model performance in Goiás, where factors such as farm consolidation and commodity prices played a more significant role (Yin et al., 2020). Annual maps from 2022 to 2011 were used by Vieira et al. (2022) to map agriculture dynamics in Mato Grosso, considering the shift from DC to single-cropping as part of a reduction process. The authors identified a reduction of approximately 44,000 km^2 in cropland; however, it remains unclear how much of this represents actual abandonment. The mapping and monitoring approaches discussed offer valuable insights for identifying and characterizing agricultural reduction in the Cerrado. Nonetheless, it is essential to establish clear definitions for abandonment and reduction processes to enable methodological adjustments, accurately assess their impacts, and deepen the understanding of their underlying drivers.

4. Challenges and perspectives

Although several advances in sensor systems, processing platforms, and classification algorithms have made the mapping of agricultural dynamics faster, more frequent, more accurate, and more reproducible, some challenges still need to be overcome. One of the main obstacles to monitoring LULC dynamics has been the scarcity of spectral data balancing high or medium spatial resolution with sufficient revisit frequency and adequate spectral resolution (Weiss et al., 2020). The high temporal resolution makes MODIS the most used sensor in mapping studies of intensification processes in the Brazilian Savanna. However, the coarse spatial resolution (250–1000 m) imposes limitations and questions about reliability in more fragmented landscapes, such as family farming (Chen et al., 2018; Spera et al., 2014). Therefore, there is a need for more studies with medium-resolution data (Picoli et al., 2018; Bendini et al., 2019; Parreiras et al., 2022). As discussed, Bendini et al. (2019) revealed that OLI data can be used to map complex cropping systems. However, only Landsat 8 was available, and the authors used temporal interpolation and smoothing algorithms to fill gaps caused by cloud cover, making the time series more synthetic, which creates uncertainty about the data (Chen et al., 2018). In 2021, the launching of Landsat 9 improved the potential temporal resolution of Landsat OLI data to 8 days and up to 4 days in overlapping sites. In this context, new studies with Landsat can contribute to assessing the impact of this improvement on mapping intensive cropping.

The Cerrado is a tropical biome with a high occurrence of clouds during most of the year, especially during the rainy season, between September and February, when the frequency of cloud cover reaches 70%–80% in a large part of its territory (Prudente et al., 2020). Therefore, orbital RS is severely affected, especially during the growing season of summer crops. Thus, sensor systems with improved temporal resolution, such as Sentinel-2, are crucial for monitoring agriculture. The Sentinel-2 MSI dataset is an underused resource for monitoring the agricultural dynamics in the Brazilian Savanna, although it has shown high accuracy in detecting crops in western Bahia (Chaves and Sanches, 2023). MSI data have a 5-day temporal resolution, bands with pixels of 10 and 20 m, and a multispectral set of bands that includes Red-Edge wavelengths, which have stood out in remote sensing of vegetation (Chaves et al., 2020; Misra et al., 2020). Harmonization approaches, such as Harmonized Landsat Sentinel-2 (HLS), are the most promising alternatives for obtaining time series with balanced spatial and temporal resolution (Claverie et al., 2018; Parreiras et al., 2022; Bolfe et al., 2023a,b). These data are suitable for incorporating phenological parameters and trends into classification algorithms (Wulder et al., 2021). Since 2021, NASA has made the Sentinel-2 MSI and Landsat 8/9 OLI time series available as a single, harmonized, surface reflectance and atmospherically corrected dataset of 30 m and up to 2-day resolution for almost the entire globe (Claverie et al., 2018). However, despite the high potential for monitoring tropical agriculture, they remain underused, especially in Brazil (Parreiras et al., 2022; Bolfe et al., 2023a,b; Throughout 2023, the HLS historical multispectral dataset will also become available on GEE.

Furthermore, the Brazil Data Cube (BDC), an initiative by INPE. Instituto Brasileiro de Pesquisas Espaciais (2024), provides ready-to-use multispectral, multitemporal imagery from Landsat, Sentinel-2, and CBERS platforms, with temporal resolutions of up to 5 days and spatial resolutions of 2.5 m. Despite its potential, this resource remains underutilized, even though it underpins the TerraClass Project (INPE. Instituto Brasileiro de Pesquisas Espaciais, 2024) and could significantly enhance agricultural mapping and monitoring in the Cerrado (Chaves and Sanches, 2023; Chaves et al., 2023). To support the analysis of dense satellite image time series like those in BDC, INPE also offers the SITS tool for the R language (Simoes et al., 2021; Chaves et al., 2023).

An essential step in monitoring intensification and diversification has been the creation of a crop mask before the classification of crop types and cropping patterns. Most authors choose this strategy to isolate crop pixels, minimizing confusion with other spectral similarity classes (Arvor et al., 2012; Chen et al., 2018; Picoli et al., 2018; Bendini et al., 2019; Bolfe et al., 2023a,b; Chaves et al., 2023). However, confusion between crops and other targets, especially pastures, has been widely reported. This error harms the crop mask precision and significantly affects crop and intensification estimates. Müller et al. (2015) used spectro-temporal variability metrics (mean, median, standard deviation, and others) of Landsat multispectral time series as covariates in an RF model to map LULC in the Rio das Mortes watershed, MT State. The authors achieved a global accuracy of 93% when separating forests, savannas, pastures, and crops. However, pastures were still the class with the lowest accuracy, confused with crops in almost 30% of cases. The number of cloud-free observations impacted the results, and the authors stated that integration of Landsat and Sentinel-2 data could be pivotal for improving the results. More recently, the Image Processing and GIS Lab at the Federal University of Goiás (LAPIG/UFG) added Land Surface Temperature (LST) and Roads Proximity (RP) aiming to improve the MapBiomas pasture mapping methodology, which uses time series of Landsat 8 data and Random Forest algorithm, testing in the state of Mato Grosso. However, overall accuracy was maintained around 88%. As flooded pasture areas, LST sometimes decreased the models' performance (Mesquita et al., 2023).

The combination of Sentinel-2 and Landsat data is currently possible due to the HLS initiative from NASA (Claverie et al., 2018) and harmonization proposals developed by independent authors (Nguyen et al., 2020). Parreiras et al. (2022a) reached excellent results by separating pastures, annual crops, and sugar cane in a sub-basin in southern Goiás using the HLS time series and RF algorithm. Bolfe et al. (2023a,b) also managed to separate pastures from natural vegetation and crops, with less than 5% errors for the pasture class, based on spectral indices extracted from time series of HLS images and RF algorithm, mainly combining indices of different purposes. In 2030, NASA's highly anticipated Landsat Next will launch, boasting 26 spectral bands, a 6-day temporal resolution, and a spatial resolution of 10–20 m. Its radiometric calibration will seamlessly align with Landsat 8 and 9 missions, ensuring a smooth continuation of the program. This groundbreaking mission can potentially revolutionize the monitoring of tropical agriculture, especially in the Cerrado region. With its advanced resolutions, Landsat Next will facilitate a more precise reconstruction of crop phenological signatures, minimizing spectral mixing compared to HLS. This capability will enable near-real-time monitoring of harvests, early detection of pest and disease threats, and enhanced water efficiency by tracking evapotranspiration, opening up a world of possibilities for sustainable agriculture (NASA, 2024).

Currently, the primary challenge for RS in agriculture is acquiring sufficient ground-level data in adequate quantity and distribution. Ground samples are essential for constructing representative datasets to train and validate ML and DL algorithms (Lin et al., 2022; Maxwell et al., 2018). In ML, consensus suggests an optimal training subset size of 10 times the number of input variables (Maxwell et al., 2018). Congalton and Green (2009) argue for a general guideline of 50 samples per class for validating land use and cover classifications. YHowever, gathering in situ data involves intricate logistical planning, substantial financial costs, reliance on human resources, and access to farmlands, posing a considerable challenge in vast countries like Brazil. It is not always possible to determine, for example, the occurrence of integrated systems or successional cropping with just one fieldwork. Therefore, either more than one visit needs to be done, or it is necessary to conduct interviews with farmers (Manabe et al., 2018; Kuchler et al., 2022). In many studies, photointerpretation of high spatial resolution images represents a strategy to collect samples remotely (Cunha et al., 2020; Parreiras et al., 2022) and, in some cases, even temporal signatures of VI (Bolfe et al., 2023a,b; Vieira et al., 2022). Lopes et al.

(2020) present a tool for a systematic sample collection combining photointerpretation of Landsat images and analysis of temporal NDVI profiles from MODIS, called Temporal Visual Inspection (TVI). However, this process is not suitable for identifying crop types.

The lack of training and validation samples makes DL modeling unfeasible and harms the performance of ML models due to the problem of unbalanced learning (Douzas and Bacao, 2019; Maxwell et al., 2018). This issue compromises the quality of mappings, mainly affecting minority classes (Chaves et al., 2021) or those outside the sampling concentration areas (Kuchler et al., 2022; Chen et al., 2018). The imbalanced learning is associated with the uneven sample data distribution between classes in classification problems. Minority classes contribute less to maximizing accuracy in algorithms such as RF and SVM, designed to learn from reasonably balanced data sets. Consequently, models are biased toward majority classes, and overall accuracies are inflated (Douzas and Bacao, 2019). One effect of this problem could have been, for example, the low accuracies observed for minority classes, such as non-commercial crops (sorghum and millet), grown in the second harvest in smaller volumes (Arvor et al., 2011; Bendini et al., 2019; Bolfe et al., 2023a,b), as well as cotton, in the case of Kastens et al. (2017), and coffee, in the case of Chaves and Sanches (2023). Different crops share similarities in spectral signature and agricultural calendar, imposing challenges that require sufficient field information for further analyses of covariates and temporal, spectral, and spatial resolution best suited to improve the results.

When the imbalance is representative of the actual occurrence of classes in space, it may not be as harmful to classification models of complex systems, as was the case with Kuchler et al. (2022). However, some strategies can help overcome these challenges. Some algorithms to resize the sampling dataset generate synthetic samples of minority classes from the training dataset, such as the Synthetic Minority Oversampling Technique or SMOTE (Chawla et al., 2002), the most used algorithm in the case of LULC classifications (Cenggoro et al., 2017), used by Bolfe et al. (2023a,b). Lin et al. (2022) introduced a method known as the Historical Knowledge Transfer method based on decision boundaries, designed for multi-year mapping. This technique generates synthetic samples using historical data and topological relationships. It assumes the stability and consistency of decision boundaries sought by machine learning (ML) algorithms over time, implying that interannual variations in spectral response due to climate and management conditions can be evaluated to identify optimal transfer periods. However, this methodology has not yet been tested in Brazil.

In this context, the creation of a collaborative network for sharing data and geolocated information, aligned with the so-called FAIR principles (Findable, Accessible, Interoperable, Reusable), becomes crucial for expanding and improving studies and methodologies related to the agricultural dynamics of the Brazilian Savanna. Several researchers have played a significant role in making their field data available. Authors such as Câmara et al. (2017), Kastens et al. (2017), Sanches et al. (2018), Maus et al. (2016), and Oldoni et al. (2020) shared data reused in subsequent studies, such as those carried out by Chaves et al. (2021), Bendini et al. (2019) and Bolfe et al. (2023a,b).

The literature exhibits a relative concentration of studies carried out in the MT State. Although the state is the largest national agricultural producer, more studies carried out in other states and regions are crucial so that it is possible to understand the suitability of sensor systems, spectral covariates, and algorithms in more fragmented and complex landscapes with smaller agricultural properties, mainly those focused on family farming. Finally, regarding diversification with intercropping, most studies focus on detecting iCLs. Considering the economic, environmental, and animal welfare benefits of intercropping forest species with crops and pastures, it will be necessary to develop methodologies capable of identifying iCPFs and other AFS with orbital RS. If iCLs can be detected with pixel-by-pixel classification of dense VIs time-series, when crops or pasturelands are cultivated with forest species, pixel size becomes crucial. The spectral mixing in AFS presents a challenge for orbital RS that is more likely to be solved with high-resolution images, object-based classification, texture features (Bégué et al., 2018), and we hypothesize, DL algorithms.

5. Final considerations

This study analyzed some of the main points relating to the scientific trajectory of orbital optical remote sensing, identifying challenges and perspectives in mapping and monitoring the processes of expansion, conversion, diversification, intensification, and agricultural reduction of the Brazilian Savanna. Among the perspectives, we highlight:

- Mapping and monitoring of expansion, conversion, and intensification processes have become more frequent, faster, and more precise in the Brazilian Savanna with advances in orbital SR.
- The balance between temporal frequency and pixel size proves to be more decisive than the choice of classifier for monitoring agricultural dynamics. Nevertheless, non-parametric classification algorithms are the primary tools, particularly the Random Forest, fed with dense time series of vegetation indices.
- Multisensor strategies are at the forefront. Data integration improves temporal and spatial resolutions, favors the combination of resources, and improves results in different tasks. Although demanding statistical care and computational resources, these strategies are facilitated by robust algorithms and cloud computing.
- There is a high potential for the HLS and Landsat Next datasets to overcome cloud cover issues in mapping crop types and patterns in the Brazilian Savanna, contributing to monitoring intensification and diversification.
- High-resolution images coupled with deep learning algorithms present high potential for detecting and mapping intercropping, especially iCFL and AFS, as well as center pivots, strategies for intensification and diversification still challenging for orbital RS.
- Shared ground data and knowledge have been fundamental for developing methodologies to monitor agricultural dynamics in the Brazilian Savanna.
- Despite the undeniable advances, applications of orbital RS in monitoring agricultural dynamics in more complex and fragmented environments, especially in family farming, still need to advance.

CRediT authorship contribution statement

Taya Cristo Parreiras: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Édson Luis Bolfe:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Paulo Roberto Mendes Pereira:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Abner Matheus de Souza:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Vinícius Fernandes Alves:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly and Chat GPT to improve readability and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2025.101448.

Data availability

No data was used for the research described in the article.

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