remote sensing

Review

Land Use and Land Cover Products for Agricultural Mapping Applications in Brazil: Challenges and Limitations

Priscilla Azevedo dos Santos [1,*], Marcos Adami [1,2], Michelle Cristina Araujo Picoli [3], Victor Hugo Rohden Prudente [4], Júlio César Dalla Mora Esquerdo [5,6], Gilberto Ribeiro de Queiroz [2], Cleverton Tiago Carneiro de Santana [1,7] and Michel Eustáquio Dantas Chaves [8]

1 Postgraduation Program in Remote Sensing (PGSER), Coordination of Teaching, Research and Extension (COEPE), National Institute for Space Research (INPE), 1758 Astronautas Ave., São José dos Campos 12227-010, SP, Brazil; marcos.adami@inpe.br (M.A.); cleverton.santana@inpe.br (C.T.C.d.S.)
2 Earth Observation and Geoinformation Division (DIOTG), General Coordination of Earth Sciences (CG-CT), National Institute for Space Research (INPE), 1758 Astronautas Ave., São José dos Campos 12227-010, SP, Brazil; gilberto.queiroz@inpe.br
3 Statistics Division, Food and Agriculture Organization of the United Nations, 00153 Rome, Italy; michelle.picoli@weforest.org
4 School for Environment and Sustainability (SEAS), University of Michigan (UofM), 440 Church St., Ann Arbor, MI 48109, USA; victorrp@umich.edu
5 Embrapa Digital Agriculture, Brazilian Agricultural Research Corporation (Embrapa), 209 André Tosello St., Campinas 13083-886, SP, Brazil; julio.esquerdo@embrapa.br
6 School of Agricultural Engineering, University of Campinas, Campinas 13083-875, SP, Brazil
7 Management of Crop Monitoring (GEASA), Superintendence of Agricultural Information (SUINF), Directorate of Agricultural Policy and Information (DIPAI), National Food Supply Company (CONAB), SGAS I Setor de Grandes Áreas Sul 901 s/n, Asa Sul, Brasília 70390-010, DF, Brazil
8 School of Sciences and Engineering, São Paulo State University (UNESP), Tupã 17602-496, SP, Brazil; michel.dantas@unesp.br
* Correspondence: priscilla.agricart@hotmail.com or priscilla.santos@inpe.br

Abstract

Reliable remote sensing-based Land Use and Land Cover (LULC) information is crucial for assessing Earth's surface activities. Brazil's agricultural dynamics, including year-round cropping, multiple cropping, and regional climate variability, make LULC monitoring a highly challenging task. The country has thirteen remote sensing-based LULC products specifically tailored for this purpose. However, the differences and the results of these products have not yet been synthesized to provide coherent guidance in assessing their spatio-temporal agricultural dynamics and identifying promising approaches and issues that affect LULC analysis. This review represents the first comprehensive assessment of the advantages, challenges, and limitations, highlighting the main issues when dealing with contrasting LULC maps. These challenges include incompatibility, a lack of updates, non-systematic classification ontologies, and insufficient data to monitor Brazilian LULC information. The consequences include impacts on intercropping estimation, diminished representation or misrepresentation of croplands; temporal discontinuity; an insufficient number of classes for subannual cropping evaluation; and reduced compatibility, comparability, and spectral separability. The study provides insights into the use of these products as primary input data for remote sensing-based applications. Moreover, it provides prospects for enhancing existing mapping efforts or developing new national-level initiatives to represent the spatio-temporal variation of Brazilian agriculture.

Keywords: LULC change; cropland; thematic maps; mapping; remote sensing; Brazil

check for updates

Academic Editor: Lin Yan

Received: 20 May 2025
Revised: 30 June 2025
Accepted: 1 July 2025
Published: 7 July 2025

Citation: Santos, P.A.d.; Adami, M.; Picoli, M.C.A.; Prudente, V.H.R.; Esquerdo, J.C.D.M.; Queiroz, G.R.d.; Carneiro de Santana, C.T.; Chaves, M.E.D. Land Use and Land Cover Products for Agricultural Mapping Applications in Brazil: Challenges and Limitations. *Remote Sens.* **2025**, *17*, 2324. https://doi.org/10.3390/rs17132324

1. Introduction

Land Use and Land Cover (LULC) refers to the physical and biological characteristics of Earth's surface cover (Land Cover), including natural, semi-natural, and human-modified areas (Land Use), as well as their socioeconomic purpose, such as industrial, urban, commercial, agricultural, mining, forestry, livestock, and energy [1,2]. Given the relevance of this information, LULC mapping initiatives have increased since the 20th century, driven by technological developments, especially in the computing and remote sensing fields. The advances in sensor resolutions [3,4], data transmission, satellite capabilities, and satellite constellations have enabled more reliable target identification and cost-effective LULC products [5–7]. These advances have improved our understanding of the impact of natural and human-induced processes (e.g., disasters, climate change, deforestation, flood, and agriculture, among others) on Earth's systems [8–15].

The increased focus on global issues such as climate change and sustainability (as represented by the United Nations Sustainable Development Goals) has driven LULC mapping efforts with diverse characteristics and applications [13,16–21]. Open data policies in remote sensing, along with cloud computing platforms for big Earth observation data management and analysis—such as Google Earth Engine (GEE), Sentinel Hub, Open Data Cube (ODC), System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL), Open Source Earth Observation Data Interface (openEO), the Joint Research Centre Earth Observation Data and Processing Platform (JEODPP), and the Cloud-enabled High-performance Remote Sensing Data Processing System (pipsCloud)—have further facilitated access to these products for research, providing consistent, frequent, and extensive Earth system measurements to support the decision making [16,17,22–26]. However, the utility of maps derived from orbital remote sensing is limited by sensor characteristics, target variability, atmospheric effects, scale, and intended application [27,28].

In the context of agricultural remote sensing, several factors may influence the analysis, including crop type, complexity of existing cropping systems, field size, agricultural calendar, edaphoclimatic variability, regional management practices, land fragmentation (smallholder farms), and phenological dynamics [29,30]. These factors imply the use of images with increasingly refined spatial and temporal resolutions. Such images are crucial for capturing the spectral–temporal characteristics of these targets across both space and time [31–33]. In this sense, improvements in methods and techniques for classifying remote sensing images jointly with advances in sensor systems have revolutionized the way agricultural landscapes and their dynamics are monitored and analyzed, enhancing our ability to gather detailed data on crop characteristics, soil properties, and field conditions for precision and digital agriculture [33–38]. This wealth of information has paved the way for more sophisticated approaches to promote crop mapping and monitoring, allowing for more precise and timely assessments of crop health, yield estimation, sustainability, and land changes [36,39–43].

Building on these technological capabilities, accurate crop mapping estimates emerge as a crucial tool for gathering comprehensive information about croplands, supporting the supply chain that is fundamental to establishing public policies related to product prices, stocks, food security, and decision making [44,45]. Nevertheless, in applications such as yield estimation and productivity, cultivated area estimation, and rural development for small to large producers, the use of reliable and accurate information on the extent and location of crops allows decision makers to formulate profitable, sustainable, and transparent strategies to address internal and external markets [46–48].

The importance of accurate LULC data is particularly evident in countries with significant agricultural production and relevance in the international commodities market, such as Brazil, which ranks among the top 20 global commodities exporters, leading in soybean exports and holding the position of eighth-largest maize producer [49]. Moreover, Brazil continuously expands its agricultural frontier, demonstrating its territorial capacity for increasing production [50]. Brazilian croplands range from extensive large-scale farms to smallholder arable lands, creating a diverse agricultural landscape [51]. This heterogeneous context (Figure 1), characterized by edaphoclimatic variability, vast vegetation gradient, and diversity in cropping systems poses significant challenges for LULC mapping [52].

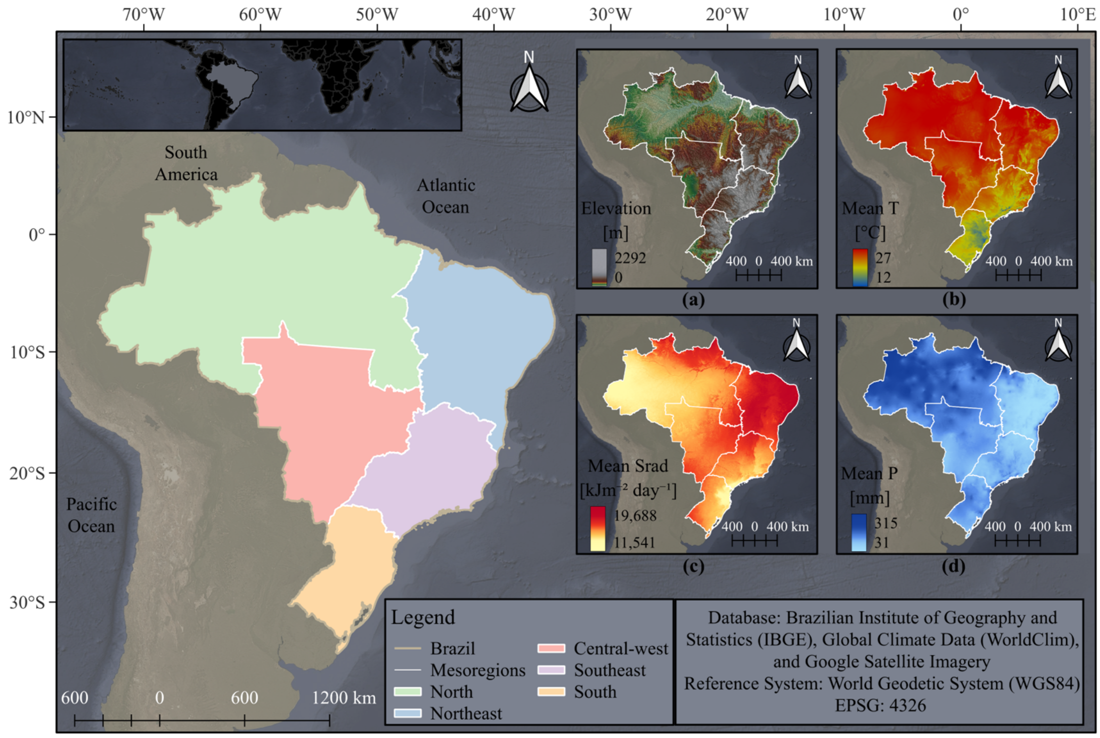


Figure 1. Brazilian mesoregions division and physiographic characteristics. Inset maps display variables associated with topography and climate: (**a**) elevation, (**b**) mean temperature (T), (**c**) mean solar radiation (Srad), and (**d**) mean precipitation (P). Elevation data were acquired from SRTM at 15-arcsecond resolution [53] and climate data from WorldClim at 30-arcsecond resolution [54].

Brazil's continental dimensions create significant solar energy balance, temperature, and precipitation gradients that directly influence agricultural zoning and crop selection [55]. The southeastern region experiences lower temperatures, while the semi-arid northeastern regions experience higher temperatures with distinct seasonal patterns, which led to the development of specialized agricultural zones in Brazil, with subtropical crops concentrated in the southern regions and tropical varieties dominating the central and northern areas [55]. The study by Silva et al. [56] indicates that soybean production increases when climate parameters (e.g., temperature) are above average, potentially raising soybean production by 44% in the municipalities in the Cerrado and Amazon biomes. Tropical regions benefit from exceptional soil (e.g., topographic patterns, soil potential, water retention, and humidity) and climate conditions (e.g., abundant summer solar radiation, rain regimes, and high temperatures) throughout the year, which favor specialized intensive cultivation systems, allowing multiple harvests annually, enabling the potential expansion of areas, increasing productivity, and mitigating impacts on land [57,58]. In Brazil, this regime allows the practice of agricultural calendars at different timelines along the crop year (Figure 2) with a wide diversity of grain, fiber, coffee, and sugarcane crops aimed at production, agricultural stock, domestic consumption and export [59]. The agricultural calendar can include many different types of crops spanning between one to three crop years (e.g., corn, soybeans, and beans).

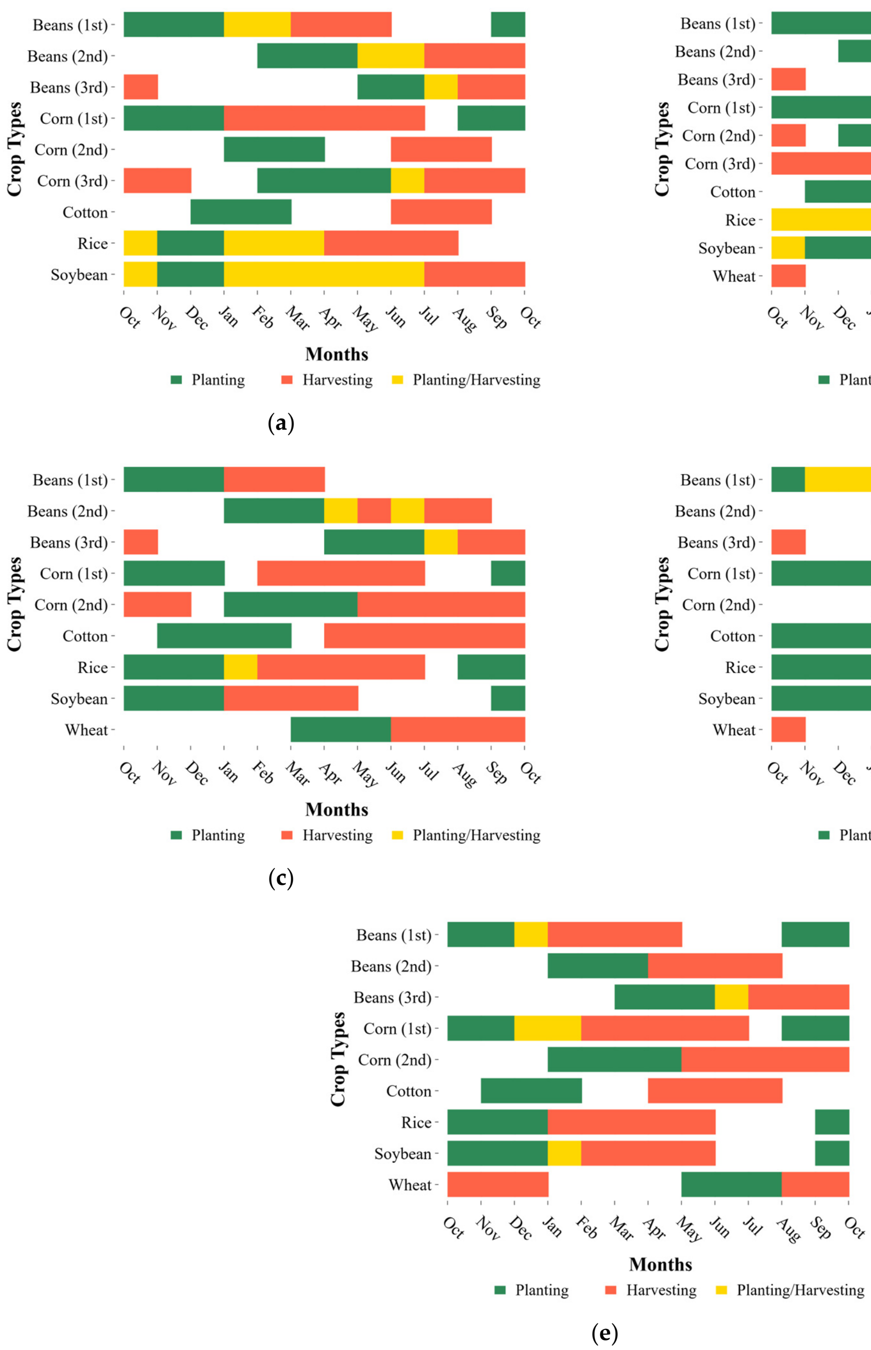


Figure 2. Agricultural calendars for the planting and harvesting of Brazil's main annual grain crops, aggregated by mesoregion, where (**a**) north; (**b**) northeast; (**c**) central-west; (**d**) southeast; and (**e**) south. The calendars begin in October of the beginning year and end in October of the next year. Brazil's seasonality regime occurs in the following periods: Spring (22 September–21 December), Summer (21 December–20 March), Autumn (20 March–21 June), and Winter (21 June–22 September). Crop planting (green) and harvesting (orange) calendars vary according to the mesoregion's agricultural management practices and may occur early or late (yellow) across seasons. Beans and corn can have up to three harvests per year. Adapted from Brazilian National Supply Company (CONAB) agricultural calendars [59].

Recent advances in the integration of remote sensing products and statistical methodologies have resulted in significant achievements for agricultural monitoring and crop estimation in Brazil. Adami et al. [60] presented a robust methodology for estimating soybean crop area across the states of Maranhão, Tocantins, Piauí, and Bahia, leveraging multi-source satellite imagery, including Terra MODIS, OLI Landsat series, and MSI Sentinel-2, processed through platforms such as GEE and R computing. The study successfully combined objective mapping with field-based validation, enabling the timely generation of crop area estimates with high accuracy (98.7%) and strong agreement with official statistics, as evidenced by a mere 1.1% difference from CONAB's estimates on the regional scale. The research underscores the effectiveness of integrating remote sensing products and statistical sampling in delivering reliable, transparent, and auditable agricultural statistics, thereby supporting informed decision making in both public and private sectors [60].

Furthermore, Campos et al. [61] expanded these advances by applying a comprehensive methodology that integrates remote sensing, machine learning, and geostatistics to map and estimate soybean cultivated areas across major producing Brazil's states, including Mato Grosso, Mato Grosso do Sul, Goiás, Rondônia, and the MATOPIBA region. Their approach, which combined multi-source satellite imagery, stratified random sampling, and in situ field data, enabled the production of high-accuracy soybean maps and robust area estimates with coefficients of variation generally below 10%. Overall accuracy exceeded 96% in all regions and reached 98.7% in MATOPIBA. These results further highlight the value of integrating advanced geotechnologies and statistical frameworks to support timely, reliable, and transparent crop monitoring, thereby reinforcing the foundation for effective agricultural policy and sustainable land management in Brazil [61].

Currently, we know that approximately 60% of the Brazilian territory remains as native vegetation [62,63]. However, there are uncertainties regarding the exact areas occupied by croplands. Nationwide initiatives still lack updated time series LULC information [64] to effectively answer the questions of "what", "where", "when", and "how" crop development occurs in the country. A deeper understanding of spatio-temporal cropland dynamics is essential for sustainable agricultural development, effective policymaking, and ensuring Brazil's continued position in global agriculture while preserving its unique ecosystems and natural resources [65]. This study represents the first comprehensive assessment of the suitability of LULC initiatives for Brazil, focusing on tropical agricultural dynamics.

Given this, the objective of this review article is to explore and assess recent freely available LULC global, national, and regional initiatives for mapping purposes, with a special focus on Brazilian agriculture. To the best of our knowledge, this is the first study to analyze the specific characteristics, methodologies, and approaches behind these maps, evaluating their suitability and potential applicability for mapping Brazil's tropical agricultural dynamics. Notably, this pioneering review includes national-level initiatives in Brazil, covering governmental products that have only been briefly addressed in previous studies and remain largely unknown to the global academic community. We highlight key challenges and limitations that arise when integrating, analyzing, and comparing data from multiple sources. This review provides a comprehensive synthesis of the state-of-the-art LULC mapping in Brazil across different temporal and spatial scales, emphasizing the datasets, data sources, methodologies, classification systems, temporal and spatial extents, and accessibility. Our goal is to identify reliable and suitable LULC products for agricultural mapping in Brazil, ensuring their accuracy and usability. Additionally, we share our practical experiences with these datasets, offering valuable insights into real-world challenges and limitations when using this information to produce maps that accurately represent agriculture in Brazil.

2. Satellite-Based Mapping Products for Land Use and Land Cover and Agriculture Purposes

2.1. Overview of Map Products Initiatives

For decades, researchers have been dedicating efforts to proposing new techniques and methods aimed at producing LULC maps and systematizing the production and availability of these data. This scenario marks an evolution in the quantity of datasets available at different levels of legend (global, continental, regional, and local) and scales [66]. In this way, various initiatives have emerged to promote LULC monitoring through the production of maps derived from single images as well as time series remote sensing data.

Global initiatives that produced maps on specific dates include several projects, such as the University of Maryland Land Cover Classification (UMD-LC) [67], Global Land Cover Characterization 2.0 (GLCC) [68], Global Land Cover 2000 (GLC2000) [69–71], Land Degradation Assessment in Drylands (LADA LUC) [72], and the Global Land Cover-SHARE (GLC-SHARE) [73], with 1 km spatial resolution. CROPGRIDS is another example of a single-date, global, georeferenced dataset, comprising the spatial distribution of 173 or 175 harvested and crop (physical) areas at 0.05° (approximately 5.6 km at the equator) and 10 km spatial resolutions for the years 2000 and 2020, respectively [74]. As an example of crowdsourcing mapping initiative with a specific date, we can cite the 300 m spatial resolution Geo-Wiki Hybrid maps [75].

Regarding global initiatives that produce time series maps, we can highlight Global Land Surface Satellite Global Land Cover (GLASS-GLC) [76], Land Cover Climate Change Initiative (LC-CCI) [77], Global Land Cover 30 (GLC30) and 250 (GLC250) [78–81], MODIS/Terra + Aqua Land Cover Type (MCD12Q1) [82–84], Global Land Cover by National Mapping Organization (GLCNMO) [85,86], ESA Global Land Cover (GlobCover) [87], Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) [88,89], and Copernicus Global Land Service Dynamic Land Cover 100 (CGLS-LC100) [21,90], with different spatial resolutions.

Currently, high spatial resolution (<30 m) global LULC products have become increasingly accessible, such as the 10 m Sentinel-2-based initiatives Google Dynamic World (GDW) [20], produced by Google; World Cover (WC), produced by the European Space Agency (ESA) [91,92]; and the 10 m Annual LULC (ESRI-10m LULC) [18], produced by Environmental Systems Research Institute (ESRI). The OpenStreetMap (OSM) LULC product is a single-date product that also has a finer spatial resolution of 10 m but particularly derives from collaboratively and voluntarily collected geodata or Volunteered Geographic Information (VGI) at the field level [93].

The University of Maryland (UMD) is one of the pioneering institutions in LULC mapping. Its first map was produced in 1994 using data from the Advanced Very High Resolution Radiometer (AVHRR) with a coarse spatial resolution of one degree [94] and, subsequently, two improved maps using 1 km resolution data from the same sensor [67]. Currently, UMD produces time series maps from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat imagery with a moderate spatial resolution of up to 30 m [5,31,95,96].

The accuracy of these products to monitor LULC changes at local or global levels has been discussed in the literature. Venter et al. [97] and Xu et al. [19] suggest a critical and careful evaluation by users regarding desired applications, considering the trade-offs (e.g., performance, class definition, ability to handle landscape elements, and level of detail in different morphologies) that a high-resolution thematic mapping may entail.

Concerning the characterization of agricultural cover, a variety of global thematic products have been produced, with a significant focus on providing information on the extent, percentage of cover, and expansion/retraction of agricultural areas, with some of these products also providing information on the management of irrigated areas. Some of these global products include the 1 km International Institute for Applied Systems Analysis–International Food Policy Research Institute (IIASA-IFPRI) Cropland Product [98,99]; the 250 m Global Cropland Extent (GCE) [100]; the 1 km Global Food Security-support Analysis Data Crop Mask (GFSAD1KCM) and Crop Dominance (GFSAD1KCD) [101,102]; the 1 km Anomaly hot Spots of Agricultural Production (ASAP) Land Cover Masks [103]; the 500 m Global Rainfed, Irrigated, and Paddy Croplands (GRIPC) [104]; the 500 m Self-adapting Statistics Allocation Model (SASAM) Global Synergy Cropland Map [105,106]; the 250 m Unified Cropland Layer (UCL) [107]; the 30 m GFSAD Cropland Extend [108,109]; and the 30 m Global Maps of Cropland Extent [13].

These datasets are quite limited due to their low to moderate spatial resolutions and insufficient mapping intervals (most of them are based on a single image), which hamper their potential application and thematic classification. Only the GCE had a longer mapping period of eight years, making it less susceptible to temporal variability when analyzing thematic classification for monitoring purposes. The GFSAD1KCM and GFSAD1KCD maps are the only ones comprising five or more classes focusing on cropland, even though they only refer to agricultural extension and dominance. All these products have no planned updates and potential for change detection analysis.

There are also many other initiatives for nationwide LULC mapping, such as the CORINE Land Cover in Europe [110,111], the AFRICOVER in Africa [112], and the United States Land Change Monitoring System Database [113]. Regionally, there exist the Land Cover Map [114] for North America and the Soybean Maps [95] for South America. In Brazil, TerraClass [115] and MapBiomas [116,117] can be cited as examples of LULC initiatives.

These products present issues linked to regular updates, especially on global and national scales. Concerning croplands, they focused on large-area representation instead of detailed-scale mappings due to the coarse spatial resolution of the sensors available at the time. This scenario reinforces the need to understand their usability and applications before using them for thematic purposes.

2.2. Map Products at Global and Continental Levels

2.2.1. Copernicus Global Land Cover Service (CGLS) Dynamic Land Cover

The Copernicus Global Land Cover Service (CGLS) Dynamic Land Cover is a 100 m spatial resolution map initiative derived from PROBA-V Analysis-Ready archives fusion using Random Forest and regression as classification methods for generating the Annual Consistent Land Cover Maps and Cover Fraction Layers (CGLS-LC100) products. CGLS maps were released annually from 2015 (base map) to 2019, with subsequent years processed using the 2015 base map. The five available maps provide 10 major thematic classes in which all crop types are assembled into a single class named “cropland” as a result of a generalization. CGLS classified “cropland” as lands covered with temporary crops followed by harvest and a bare soil period at single and multiple cropping systems. Perennial woody crops were appropriately classified as forest or shrubland cover types. The overall accuracy (OA) results for these maps reached 80.6% in 2015 and 80.3% in 2019 [21,118].

2.2.2. Google Dynamic World (GDW)

The Google Dynamic World (GDW) map produced by Google in partnership with the World Resources Institute [20] is generated using a near real-time automated classification approach on Sentinel-2 imagery, combining a cloud-based system and a deep learning fully convolutional network technique [20]. A key characteristic of the GDW map is the ability to generate near real-time predictions, which are continuously updated as new images are acquired. Since the methodology is based on a semi-supervised machine learning approach, the generation of diverse and balanced training dataset annotations requires a large volume of spatial data (over 20,000 image blocks) from the data augmentation process [20]. GDW annotations are considered to be taxonomic classes inspired by other widely used LULC classification systems [78,116,119–121]. Since 2017, the GDW has provided classified LULC images and estimated probability information for nine classes, with agriculture occupying the class "crops" (row and paddy crops). The map OA is greater than 73.8% [122].

2.2.3. ESRI Maps for Good Initiative 10 m Annual LULC (ESRI-10m LULC)

The ESRI-10m Annual LULC maps are part of the Maps for Good Initiative, developed by the ESRI and the Impact Observatory (IO) to generate annual maps from 10 m Sentinel-2 classified images using deep learning and cloud computing approaches from 2017 to 2024 [123]. The methodology is based on a U-Net convolutional neural network (CNN) architecture trained from scratch using 100 epochs parameters, 20,000 Sentinel-2 tiles, and a geographically balanced hand-labeled dataset including ten classes collected across fourteen major biomes. Annual products with nine LULC classes can be downloaded at no cost [124,125], whereas annual or subannual products with fifteen classes are available for purchase via an on-demand system through the IO store [123]. Agriculture is represented as a one-level class named "crops" for the nine-class product, while the fifteen-class maps also include "inactive cropland" and "active cropland" classes. The class includes human-planted and plotted cereals, grasses, and crops not at tree height (e.g., corn, wheat, soy, and fallow plots of structured land). The products achieved OAs of over 85% across ten classes [18].

2.2.4. The University of Maryland Global Land Cover (UMD-GLC)

UMD's Global Land Analysis and Discovery (GLAD) laboratory produced two-decade (2000–2020) bitemporal LULC change maps that characterize the distribution, properties, and change regarding dominant LULC types globally. Using a consistently processed Landsat ARD time series, a set of phenology metrics was derived to enable global model calibration and application. Different supervised classification models were implemented to map separated thematic classes: individual decision tree models for mapping croplands and perennial snow and ice, regression trees for detecting forest heights, and a deep learning U-Net CNN algorithm for identifying built-up lands. The four maps for the 2000, 2005, 2010, and 2015 periods are updated every four years, in which agriculture is mapped as "cropland" class. Cropland is defined as land used for annual and perennial herbaceous crops for human consumption, forage (including hay), and biofuel according to the FAO arable land class (temporary crops, meadows, and fallow). The definition excludes perennial woody crops, permanent pastures, and shifting cultivation. The product's OA is over 85.0% [5], which was accessed via an independently validated statistical sample analysis. The dataset is publicly available at 10×10 degree tiles archive in the GLAD's repository web portal and GEE platform [126,127].

2.2.5. Global Pasture Watch (GPW) Global Grassland Class and Extent Maps (GPW)

The Global Pasture Watch (GPW) Global Grassland Maps is a mapping initiative developed by the Land & Carbon Lab research consortium and by experts around the globe. The initiative meets the need for global-scale monitoring of grassland products, supporting researchers in creating monitoring solutions on topics like degraded landscape restoration, agriculture and food system improvement, natural ecosystem protection, and greenhouse gas emissions reduction [128,129]. GPW maps were produced using Earth Observation (EO) data combined with covariates obtained from climate, landform, and proximity data statistics for an annual time interval evaluation from 2000 to 2022. The EO data encompass GLAD Analysis-Ready Data (ARD-2) 30 m Landsat image archives and 1 m spatial resolution MODIS MOD11A2 and MCD19A2 products [128,129]. Independent machine learning algorithms (Random Forest, Gradient-boosted Tree, and Artificial Neural Network) were trained using visually interpreted Google and Bing Very High Resolution (VHR) images. Three major classes are represented: Grassland classes are classified as cultivated grassland (CG), natural/semi-natural grassland classes (NSG), and "other Land Cover" (OLC), where only the first two of them are agriculture-related (pasture). The accuracy results showed Random Forest as the best model, with an F1 score of 64% and 75% for the CG and NSG classes, respectively. In terms of prediction results, the achieved precision and recall were both approximately equal to 64% and 76% for CG and NSG classes, respectively [128].

2.2.6. The University of Maryland South America Soybean Maps (UMD-SASM)

The UMD's GLAD laboratory also produced the South America Soybean Maps, a result of the "Commodity Crop Mapping and Monitoring in South America" project focused on mapping annual soybean cover over the Southern Hemisphere of South America extent at 30 m spatial resolution and a temporal interval from 2000 to 2019 (the first map was created in 2001). This project mapped soybean, first-season corn, and second-season corn areas across South America, aiming to identify patterns of land intensification and expansion and to assess their role as drivers of natural vegetation loss, including deforestation, degradation, and land use conversion in the South America biomes (Amazonia, Atlantic Forest, Cerrado, Chaco, Chiquitania, Pampas, Pantanal, and Caatinga). Combined methods of regression, visual interpretation, and decision trees were applied to produce 30 m detailed maps of soybeans in a 2000–2023 time interval using Landsat, MODIS, and Sentinel-2 imagery datasets. The twenty-four maps have two main classes: 0—no data (other classes)—and 1—agriculture (first-season soybean crop and second-season corn crop) [96]. The OAs were determined using field data selected based on a stratified two-stage cluster sampling design over the images sampled pixels, achieving above 94% [31].

2.2.7. European Space Agency World Cover (ESA-WC)

The European Space Agency (ESA) World Cover provides global land cover maps for 2020 and 2021 at 10 m spatial resolution based on Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 (optical) satellite imagery. The methodology involved three main steps: data pre-processing, classification, and map generation. The pre-processing step involved Sentinel-1 and Sentinel-2 image correction from cloud cover and terrain, while the classification step was based on a gradient-boosted decision tree algorithm (CatBoost) for labels and class probabilities prediction under multiple scenarios. Finally, the different scenarios were combined into a final land cover map through the application of different expert rules from auxiliary datasets. There are inconsistencies between the 2020 and 2021 maps, which were due to changes in the algorithm used—versions v100 and v200, respectively. ESA-WC comprises eleven land cover classes, conceptualized based on the UN-FAO Land Cover Classification System (LCCS), where agriculture is classified as "cropland". Cropland was defined as land covered with annual crops harvestable at least once in a 12-month period after the sowing and planting date and can sometimes be combined with some tree or woody vegetation fractions due to the production of an herbaceous cover. The reported OAs for ESA-WC OA are 74.4% and 76.7% for the 2020 v100 and 2021 v200 products, respectively [91,92].

2.2.8. European Space Agency WorldCereal Crop and Irrigation Mapping (ESA-WorldCereal)

WorldCereal is a dynamic open-source system initiative founded by the ESA with the aim to generate reproducible information about crop and irrigation mapping at a global level, including temporary crop extent, seasonal maize, seasonal cereal maps, seasonal irrigation maps, seasonal active cropland maps, and model confidence layers for product quality insights [130,131]. The products were derived from EO optical (Sentinel-2), radar (Sentinel-1), and thermal (Landsat 8) satellite time series data, comprising mainly 2021. Image preprocessing was applied using cloud and shadow masks at regular intervals temporal compositions (10 days for optical, 12 days for radar, and 16 days for thermal). Spatial and temporal stratifications were performed, dividing the globe into 203 homogeneous Agro-Ecological Zones (AEZs) based on global crop calendars for maize and cereals and simulated in areas lacking existing data coverage. Spectral indices were calculated for temporary crop mapping, along with temporal statistics (percentiles, interquartile range, and temporal profile characteristics). Seasonal crop features (start, peak, and end dates of the crop cycle) and metrics related to evapotranspiration, precipitation deficit, and soil moisture were added to the analysis. The 2021 Annual and Seasonal maps were generated employing a binary classification modeling from the CatBoost algorithm (e.g., 1-temporary crop vs. 0-other land cover types). For crop types and irrigation, independent datasets and qualitative comparisons with existing maps and national statistics were used to ensure consistency. Agricultural features were represented as temporary (one-year cycle) crops, winter cereals, spring cereals, main-season maize, and second-season maize layers. The results showed global user and producer accuracies of 88.5% and 92.1%, respectively. The global OA for annual crops reached 97.8%, while for seasonal crops, the value was 82.5% [130].

A summary of the information of the abovementioned global and continental levels products from Sections 2.2.1–2.2.8 is presented in Table 1. These initiatives are particularly poor at detecting croplands, especially low agriculture intensification areas and small farms, due to spectral similarity with grassland patterns and the small number of agricultural classes. An exception is WorldCereal, which is devoted to pasture classification. Agriculture is often represented by the generalist classes, mixing perennial and temporary crops, fallow areas, and pasture. The number of classes is insufficient, not allowing for the spectral separation of agricultural targets, as well as their cycle, crop year, and even type of crop practiced.

Table 1. Summary specifications of available LULC and agriculture products at global and continental levels.

Product	Spatial Resolution [m]	Available Temporal Interval	Update Interval	Reference System (EPSG)	Methodology Approach	Total Number of Classes	Number of Agriculture Classes	Capability	Accuracy [%]	Reference
CGLS	100	2015–2019	Annual	4326	Hybrid	10	1	Mixed temporary crops	≥83.3	[21,90,118,132,133]
GDW	10	2017–present	Near-real-time [1]	Window-related	Deep Learning	9	1	Row crops and paddy crops	≥73.8	[20,122,134,135]
ESRI-10m LULC	10	2017–2024	Annual or Sub-annual [2]	32,600 North; 32,700 South	Deep Learning	9 or 15 [2]	1	Mixed human-planted cereals, grasses, and non-tree-height crops	≥85.0	[18,123,125,136,137]
UMD-GLC	30	2000, 2005, 2015, 2020	Quadrennial	4326	Machine Learning	7	1	Arable land (annual and perennial herbaceous crops, meadows, and fallow)	≥85.0	[5,126,127]
GPW	30	2000–2022	Biennial	4326	Machine Learning	3 [3]	2	Natural and semi-natural pasture	64.0 (CG) 76.0 (NSG) ≥91.0 (OLC)	[128,129]
UMD-SASM	30	2000–2023	Annual	4326	Hybrid	2	1	First season soybean and second season corn	≥94.0	[95,96]
ESA-WC	10	2020–2021	Annual	4326	Machine Learning	11	1	Annual cropland mixed with some tree or woody vegetation	2020: 74.4 2021: 76.7	[91,92,138]
WorldCereal	10	2021	Annual (A) and Seasonal (S)	4326	Machine Learning	5 [4]	5	Temporary crops, winter cereals, spring cereals, maize	(A) [5]: 97.8 (S) [6]: 82.5	[130,131]

Note: [1] Updated according to the temporal resolution/availability of new Sentinel-2 images. [2] Only products acquired by order can achieve a total of 15 mapped classes with both annual and subannual temporal monitoring in the time interval. [3] Cultivated grassland (CG), natural/semi-natural grassland (NSG), and "other Land Cover" (OLC) class. [4] Refers to the product layer name (one class per layer). All layers, except for the temporary crops map, have an associated active irrigation map. [5] Overall accuracy varies according to the mapped world region. Lower values were achieved for Africa (97.2%), while higher values were achieved for Australia and Oceania (99.0%). [6] Overall agreement in validation at the global level. Accuracy varies according to WorldCereal products datasets classes: other crops (75.5%), maize (85.8%), and cereals (93.6%).

2.3. Map Products at Brazilian National and Regional Levels

2.3.1. National Institute for Spatial Research Deforestation, Warnings, and Vegetation for Brazilian Biomes (PRODES, DETER)

The Brazilian Amazon Forest Satellite Monitoring Program (PRODES) and the Real-time Deforestation Detection System (DETER) are two of the three operational projects of the Amazon and Other Biomes Monitoring Program (PAMZ+) developed by the National Institute for Space Research (INPE) to monitor deforestation in the Brazilian Legal Amazon (BLA) using remote sensing images [139–142]. PRODES started in 1988 with the primary objective of estimating the annual deforestation rate of primary vegetation in the BLA, while DETER started in 2004 to serve as a warning system supporting inspection by mapping forest suppression and degradation in the BLA and areas with suppression of primary natural vegetation in the Cerrado biome. The current PRODES methodology identifies and quantifies annual deforestation rates based on satellite imagery from 30 m Landsat-8, 30 m Landsat-9, 10 m Sentinel-2, and/or 56 m CBERS-4/4A. The deforestation rates reflect the deforestation that happened between August 1st of the previous year (year T) and July 31st of the mapping year (year T + 1), known as the "PRODES year". These images undergo RGB compositing, enhancement, and expert visual interpretation to delineate deforestation polygons with an area over 1 hectare using specific criteria. To ensure data consistency across the entire historical series beginning in 1988, only polygons exceeding 6.25 hectares in the Amazon are published and included in the rate calculation. Deforestation features are subsequently classified.

The DETER system uses a methodology based on the interpretation of satellite imagery from 250 m MODIS (until 2015), 56 m CBERS-4/4A, and 64 m Amazônia-1 (since 2015). By employing RGB band compositions, the system identifies vegetation cover changes, specifically deforestation and degradation. Additionally, a Linear Spectral Mixture Model (LSMM) is applied to estimate the fractional portions of soil, shadow, and vegetation within the images, assisting photo interpreters in identifying features. In this way, DETER provides daily notifications about vegetation changes affecting areas of at least three hectares. Agriculture classes are mixed as "non-forest area", whereas PRODES and DETER use TerraClass agricultural masks to define deforestation (conversion by suppression of areas of primary vegetation by anthropogenic actions). The OAs of PRODES and DETER mapping are 93.0% [139].

2.3.2. Brazilian Agricultural Research Corporation (EMBRAPA) LULC in the Amazon and Cerrado Biomes (TerraClass)

The TerraClass project derives from a technical partnership between INPE and EMBRAPA to address the Brazilian Federal Government's demand to monitor LULC changes in the BLA and the Cerrado biome. It complements the PAMZ+ PRODES with systematic information about the spatial distribution and regional statistics of LULC in deforested areas, providing scientific information for studies on biological impacts, socioeconomic dynamics, land change implications, and drivers in deforestation/post-deforestation quantification processes [143]. The TerraClass methodology combines high spatial and temporal resolution products to increase LULC mapping in Amazon and Cerrado biomes. The first edition maps from 2008 to 2016 were based on 30 m Landsat series imagery supported by 250 m MODIS MOD13Q1 and MYD13Q1 time series products [143,144]. Currently, TerraClass maps from 2018 to present are based on MSI Sentinel-2 time series and OLI Landsat- and Landsat-9 imagery. Polygons defined as deforestation areas in PRODES [139] are used in the classification process to produce a mask using geoprocessing methods. Currently, the TerraClass methodology is based on a hybrid approach that uses visual interpretation processes for complex classes (e.g., mining and urban areas) and automated processes for broader and larger classes, such as pastures, agriculture, and secondary vegetation. These processes rely on time series classification employing robust machine learning algorithms, mainly deep learning and Random Forest, combined with the Satellite Image Time Series (SITS) package version 1.5.2 [145] and Brazil Data Cube (BDC) [146] project workflows and structure as a basis. Agriculture is represented by "temporary agriculture crops" in Amazon products, while the Cerrado map also includes "perennial agricultural crops", "semi-perennial agricultural crops", "temporary agricultural crops of 1 cycle", and "temporary agricultural crops of more than 1 cycle" classes. The class "pasture" is differentiated from agriculture features. The "pasture" class is distinct from agricultural features and is subdivided into "shrub/arboreal pasture" and "herbaceous pasture" only for the Amazon product. The OAs were 76.64% for maps produced up to 2008 [143]. New maps have reported better accuracy results: 90.9% $\pm$ 1.6% for 2022 Cerrado [147] and 93.9% $\pm$ 1.2% for 2022 Amazonia [148].

2.3.3. MapBiomas Project Initiative Collection

MapBiomas is a project of the Greenhouse Gas Emission Estimation and Removal System (SEEG) initiative from the Climate Observatory, co-created by a network of non-governmental organizations (NGOs), universities, and technology companies, to produce annual LULC maps for Brazil, offering significant improvements in terms of cost, speed, and timeliness while also capturing the historical land record of recent decades [116]. The project currently has nine map collections [117,149] through a methodology that consists of seven main steps, where the classification is performed for each resource space attribute based on the Random Forest algorithm and/or U-Net CNN (aquaculture, mining, irrigation, rice, citrus, and palm oil classes only) based on 30 m Landsat series imagery. The products were hierarchically integrated based on prevalence rules by analyzing LULC transitions and changes, and spatial–temporal filters were reapplied to the integrated maps. Final maps were then analyzed statistically, considering different spatial categories, and their accuracies were measured using the best practices principles [150–152]. For MapBiomas collections eight (c.8) and nine (c.9), the classification scheme encompassed up to four categorical levels, where level 1 of the hierarchical classification is composed of six classes (forest, non-forest natural formation, farming, non-vegetated area, water, and not observed), while level 2 has sixteen classes distributed among those mentioned in level 1. Agriculture is the only class that comprises up to level 4 in the classification, with nine subclasses. At level 3, the agriculture class includes the subclasses perennial, temporary, planted forest, and a mosaic of other uses. Collection nine has a time interval ranging from 1985 to 2023 at 30 m spatial resolution. In total, twenty-nine classes are described. The overall accuracy obtained for collection eight (c.8) was 90.0% for level 1 and 85.8% for levels 2 and 3 [153], while for collection nine (c.9), it was 93.0% for level 1 and 90.0% for levels 2 and 3 [149].

2.3.4. Brazilian Institute of Geography and Statistics (IBGE) Monitoring Land Coverage and Use in Brazil (IBGE-MLCU)

The IBGE-MLCU monitoring products were derived from visual interpretation of remote sensing imagery, using a 1 km^2 statistical mapping grid as a reference, auxiliary information produced by the Brazilian Institute of Geography and Statistics (IBGE), and datasets from other agencies, such as the crop maps produced by CONAB. The methodology involved the acquisition and preparation of inputs for mapping—including data from Embrapa's SATVeg [154] and Landsat App [155] web platforms and Brazil's division into 450 $\times$ 450 km grid blocks—to perform a visual interpretation of OLI Landsat-8 images for maps integration and compatibility. Seeking to reduce regional uncertainties, IBGE conducted field campaigns in different Brazilian biomes, determining LULC changes for approximately 8.7 million 1 km^2 cells of the statistical grid [156]. Since the project's conceptualization in 2015, the products have undergone conceptual and methodological improvements [156,157].The older products involved annual mapping intervals (2000–2010) and biennial intervals (2010–2012, 2012–2014, 2014–2016, and 2016–2018), with the current series covering from 2018 to 2020 [158]. Fourteen classes are mapped, considering the vegetation structure and phytophysiognomies that compose the Brazilian biomes. Agriculture is represented as a "cropland" class, being separated from the "pasture" class. IBGE-MLCU also has the class "Mosaic of uses in forest area" and "Mosaic of uses in grassland", which can also relate to agriculture occurrence by mixing (generalization). The accuracy assessment of the mapping is not reported.

2.3.5. CONAB Agricultural Mapping (CONAB-AM)

The CONAB agricultural mapping based on remote sensing currently contributes to estimating the area and productivity of the main seasonal grains produced in Brazil, which are cotton, irrigated rice, coffee, sugarcane, corn, soybean, other summer and winter crops (peanut, oat, canola, rye, barley, beans, sesame, sunflower, castor bean, sorghum, wheat, and triticale), and sugarcane mill. The results obtained from these mappings assist in the analysis of declared information against verification data measured in the field—estimation of agricultural areas—and facilitate crop monitoring for yield prediction due to knowledge about the location of arable lands, agrometeorological information (precipitation, temperature, and water storage), and spectral analysis [159]. Given the vast territorial extent of Brazil, the mapping considers the geographical (regional) and climatic distribution of each state, the crop type, and the crop year to which it refers. Summer and winter grains, coffee, and sugarcane are the main Brazilian agricultural products evaluated in surveys and monitoring processes [160]. Each crop has a distinct methodology developed for the estimation of its area and productivity, commonly involving the recognition of crop types through image visual interpretation, machine learning, principal component analysis, and regression. The methodology involves spectral indices time series analysis, mainly using MOD13Q1 MODIS, MSI Sentinel-2, and Landsat series (TM/Landsat-5, OLI/Landsat-8, and OLI/Landsat-9) data [160]. The available time interval for each crop varies according to the mesoregion and state of Brazil and does not constitute a continuous time series. The mapping data are in vector format. Only coffee and soybean crops have reported overall mapping accuracy information, with values of 97.0% (Random Forest) and 95.0% (regression), respectively [61,160].

The abovementioned national and regional levels products from Sections 2.3.1–2.3.5 are summarized in Table 2. Unlike global and continental initiatives, the products presented in Section 2.3 better delineate the variability and characteristics of agriculture. However, most products are still unable to represent fallow and pasture areas. A very common practice in these cases is the use of a "Mosaic" class to represent everything that the model or analyst was unable to spectrally distinguish. The IBGE-MLCU and CONAB-AM mappings are available in vector format, which is a concern when dealing with comparative and quantitative analyses with raster format mappings information.

Table 2. Summary specifications of available LULC and agriculture products at national and regional levels.

Product	Spatial Resolution [m]	Available Temporal Interval	Update Interval	Reference System (EPSG)	Methodology Approach	Total Number of Classes	Number of Agriculture Classes	Capability	Accuracy [%]	Reference
PRODES, DETER	20, 30 (P) 56, 64 (D)	2000–2023	Annual	4674	Visual Interpretation (P), Hybrid (D)	5 (P), 3 (D)	1	Non-forest area	93.0	[139,142,161–163] [140,141,162,164]
TerraClass Amazon (A) and Cerrado (C)	10	2008 (A), 2010 (A), 2012 (A), 2014 (A), 2016 (A), 2018 (A, C), 2020 (A, C), 2022 (A, C)	Biennial	4674	Hybrid	18 (A), 15(C)	7	Pasture (shrub/arboreal pasture and herbaceous); perennial, semi-perennial, and temporary crops (1 cycle, more than 1 cycle)	93.9, 90.9	[115,143,165]
MapBiomas	30	1985–2023	Annual	4326	Hybrid	29	13	Pasture, temporary crops, soybean, sugar cane, rice, cotton, other temporary crops, coffee, citrus, oil palm, other perennial crops, forestry plantation, mosaic of uses	93.0	[116,117,149,153]
IBGE-MLCU	30	2000–2020	Biennial	4674	Visual Interpretation	12	3	Croplands, mosaic of uses in forest area, mosaic of uses in grassland	Not reported	[156,157,166,167]
CONAB-AM	20, 30	Variable [1]	Annual [2]	4674	Hybrid	8	1 [2]	Cotton, irrigated rice, coffee, sugarcane, corn, soybean, and other summer/winter crops	Incomplete [3]	[61,159,160,168]

Note: INPE's product information can also be visualized and downloaded from the Georeferenced Information Base (BIG) Program Platform at https://data.inpe.br/ [169,170]. [1] The mapping intervals available for the National Supply Company (CONAB) data vary according to the agricultural target (crop type), location (state and mesoregion), and mapped crop year. For additional information, consult the references provided. [2] By crop year and mapping. [3] Information available in the mapping metadata is only for soybean (97.0% $\pm$ 1.05) and coffee (95.0%) crops.

3. Discussion

Despite numerous initiatives to produce LULC maps, the literature reveals significant disparities among them. These disparities often arise from issues in the representation of phenomena due to differences in their legends (e.g., agriculture) [171], the number of thematic classes and their spatial categorization [172], the geolocation of pixels [173], the scale and spatial resolution [19], and other factors. All these discrepancies affect aspects such as the quality and uncertainty of the information produced [6]. Therefore, the following sections highlight the challenges and limitations of LULC products in characterizing agricultural use, with a particular emphasis on Brazil.

3.1. Data Standardization and Harmonization

Regarding spatial reference, most of the initiatives listed adopt the World Geodetic System 1984 (EPSG:4326) and the Geocentric Reference System for the Americas (SIRGAS-2000) (EPSG:4674) as standards (Tables 1 and 2). However, since GDW involves near-real-time analysis closely linked to the Sentinel-2 tile system, its reference system will depend on the study area defined by the user (i.e., geographical location and the number of tiles) at the time of classification and the subsequent download of products after classification. ESRI-10m LULC adopted the World Geodetic System 1984 Universal Transverse Mercator (UTM) as the reference system for grid-based data downloading [124]. This system was designed for the entire global level, varying from 32,600 for the northern hemisphere to 32,700 for the southern hemisphere of the globe. The impact of using different reference systems on maps during analysis leads to the need for procedures such as reprojection and merging of adjacent tiles, which can be computationally expensive. Maps that are projected, like the ESRI-10m LULC map, may require a reprojection process to a non-projected system before performing any other analysis operations (crop, stack, overlay, etc.). For example, in a country like Brazil, which has a continental territorial extent, basic geoprocessing operations in programming environments or geographic information systems (GIS), such as a clipping data to the country's geopolitical boundary, require that the reference system be geographic and non-projected.

Therefore, a significant portion of mapping initiatives at the national and regional levels prefer geographic systems over projected systems (Table 2). Reprojection is just one of the limitations of these products; there is also a need to perform data merging and cropping. Merging tiles is unavoidable for Brazil when mapping products are provided individually in projected degree granules, as is the case with ESRI-10m LULC products, or non-projected, as in the case of UMD-GLC, UMD-SASM, CGLS, and ESA Word Cover products, at global and continental levels. In contrast, national and regional products are available for the entire extent of Brazil, without the need to perform merging. A clear example of this practice is MapBiomas, which primarily provides maps within the extent of the Brazilian political–territorial boundary. Additionally, these maps can be custom filtered into smaller units, such as biomes, states, and municipalities. The computational and time costs for pre-processing maps are high, as reprojecting and merging individual tiles to cover the entire extent of Brazil demands significant processing power. Even robust processing packages and libraries designed for handling large volumes of data, such as GDAL, often encounter memory allocation issues when assembling the final mosaic. Progressively, this mosaic reaches a maximum threshold that the computer can process, even using all processor cores and parallelism strategies in languages like R version 4.3.1 and Python version 3.12.2, thus requiring the user to acquire more powerful computers. Cloud computing can be an alternative for these operations, even though it has limitations in aspects of how a computation workflow is managed, such as resource allocation, parallelism, data distribution, and retries, leaving the decision of how to design and use the processing environment strictly to the system [174]. The GEE system can manage extremely large computations, but scaling challenges such as the option of configuring arbitrarily large machines not being available, the limit on the amount of data that can be brought into a server being hard, individual objects to be cached not being able to exceed 100 MB in size, and machine accommodation capacity at requests involving tile-based computations being limited to avoid system users monopolization, which can limit their application [174].

Regarding spatial resolution (SR), the initiatives differ significantly based on the choice of sensor systems used for image acquisition and subsequent map production. The preference for using moderate (SR ≥ 30 m) to fine (SR < 30 m) spatial resolution images is easily identified when observing the characteristics of the initiatives (Figure 3).

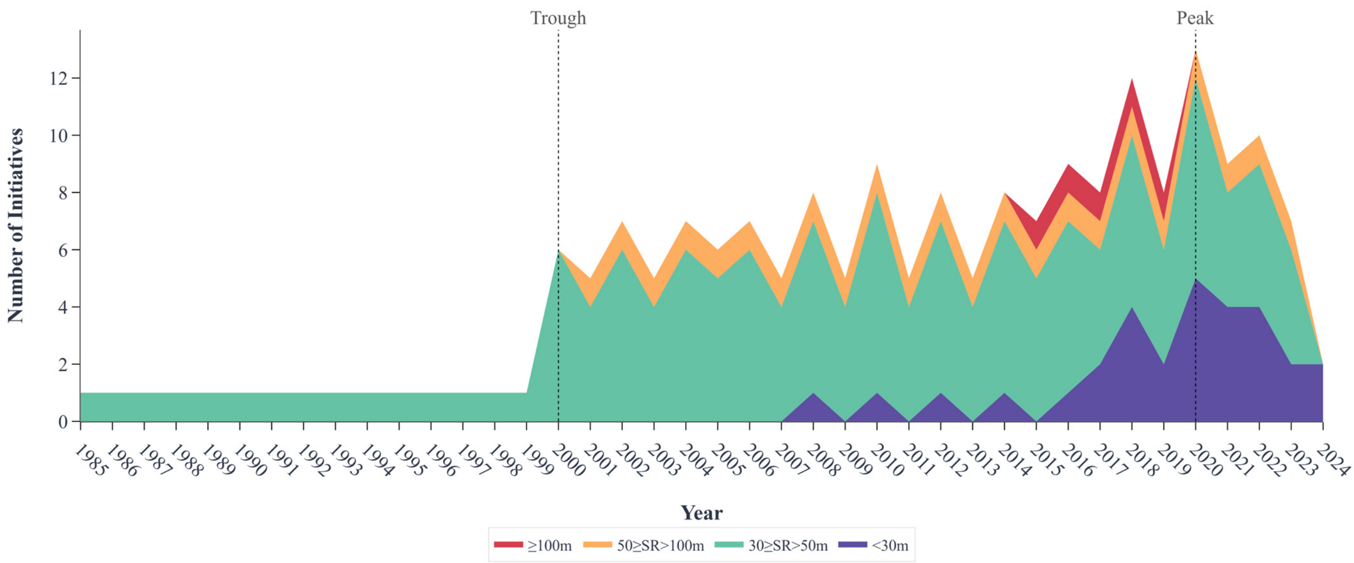


Figure 3. Evolution of spatial resolution (SR) in initiatives' available time interval.

The stability observed before 2000 in Figure 3 indicates the exclusive presence of MapBiomas data, which cover the period from 1985 to 2023, although the project itself was only launched in 2015. After 2000, there was a marked increase and diversification in the number of initiatives and spatial resolutions, culminating in a peak around 2020, which underscores the expansion and technological evolution of LULC mapping efforts in recent years. Most initiatives fall within the 30 ≥ SR > 50 m spatial resolution class at both global (UMD-GLC, GPW, and UMD-SASM) and national levels (MapBiomas, IBGE-MLCU, and CONAB-AM), with emerging contributions from finer resolutions (SR < 30 m) in the last five years. The temporal dynamics reflect broader trends in remote sensing, including the proliferation of open-access satellite data (e.g., Landsat and Sentinel), advances in computational capacity, and the adoption of novel classification methodologies such as machine learning, driven increasingly by artificial intelligence models (e.g., machine learning and deep learning), robust statistical assessments methods, and even hybrid approaches (Tables 1 and 2).

3.2. Standardization and Harmonization of Classes and Legends

When discussing the integration and comparison of LULC maps, harmonization is a fundamental pre-processing step described in various studies [6,175,176]. As LULC products originate from initiatives designed for specific purposes or scales to represent phenomena for defined applications, the generated maps often become unsuitable for other initiatives or purposes [2], which directly impacts the process of mapping correspondence. Although some initiatives are inspired by pre-consolidated classification systems, the lack of general standardization is a critical issue. This lack of standardization is related to classification purposes, systematic consistency in representing phenomena, alignment with a common objective, and the classification approach (whether a priori or a posteriori) [2]. Ideally, these initiatives would present a single, comprehensive classification system, involving the largest possible number of levels and sublevels for describing not only the cover but also the uses, such as the UN-FAO LCCS [2]. However, many LULC mapping initiatives highlight differences in the formulation of their classification systems for the representation of their LULC classes. These distinctions directly impact the number of classes, the levels of representation of the phenomena, the correct delimitation of the manifested phenomenon, and even the composition of the legend (definition of the class names and a color palette).

The global and continental products listed in this review feature broad legends for the phenomena they aim to represent, often underestimating the number of classes needed to capture highly radiometrically variable phenomena (e.g., agriculture) [177]. In most cases, they focus on representing these phenomena at the coverage level rather than the use level. This is because the images acquired from remote sensors can highlight the surface phenomena associated with land cover, while the task of inferring land use is left to the analyst or specialist. This process relies on their experience in visual interpretation, which is heavily dependent on prior field knowledge. As a result, this leads to the generalization of a given phenomenon, implying smaller quantities of classes and greater possibilities of discrepancies occurring when comparing LULC products with each other (Figure 4).

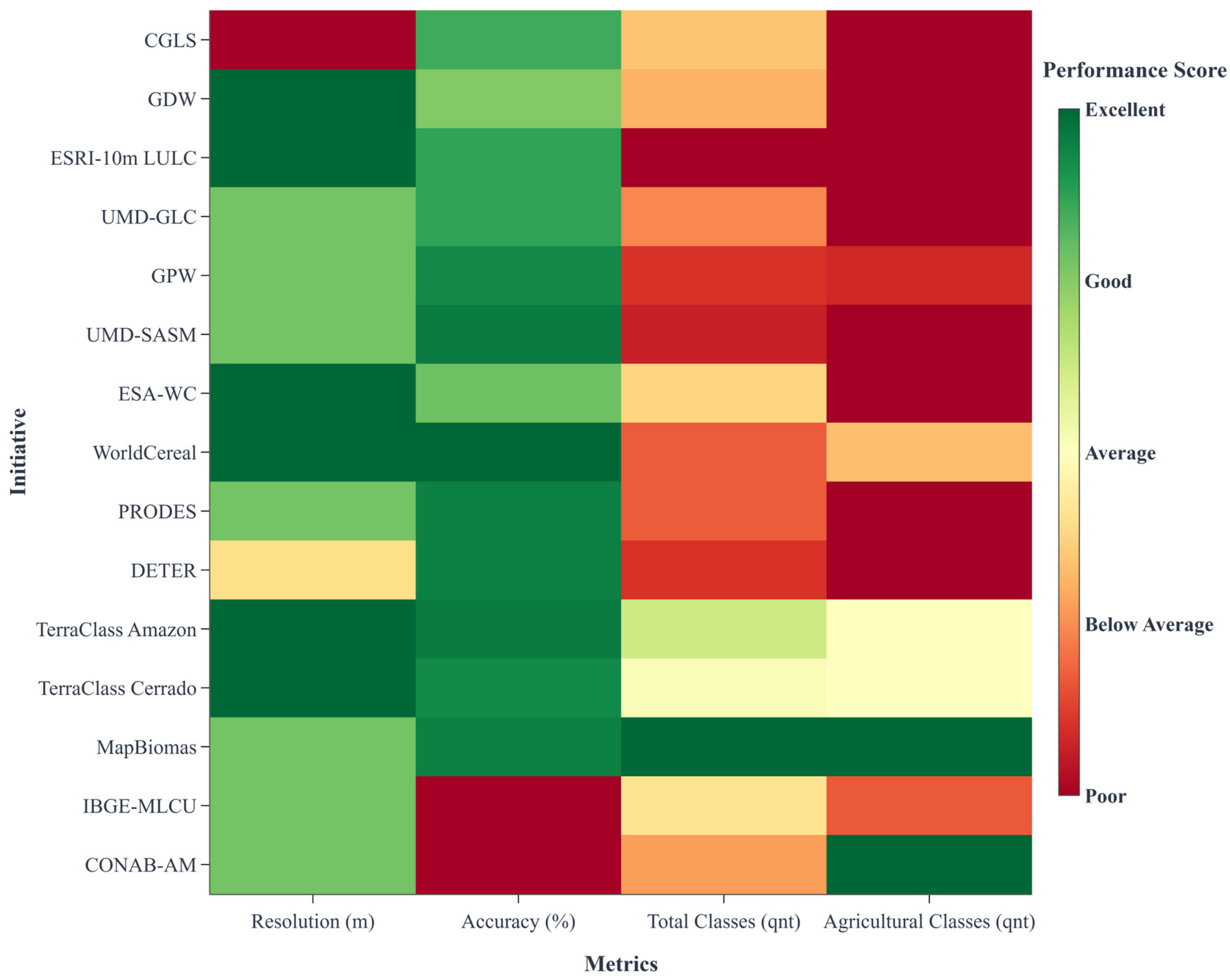


Figure 4. Performance scores of mapping initiatives according to resolution, accuracy, total classes, and agricultural classes. Initiatives ranked from global to regional levels (from top to bottom). qnt = quantity.

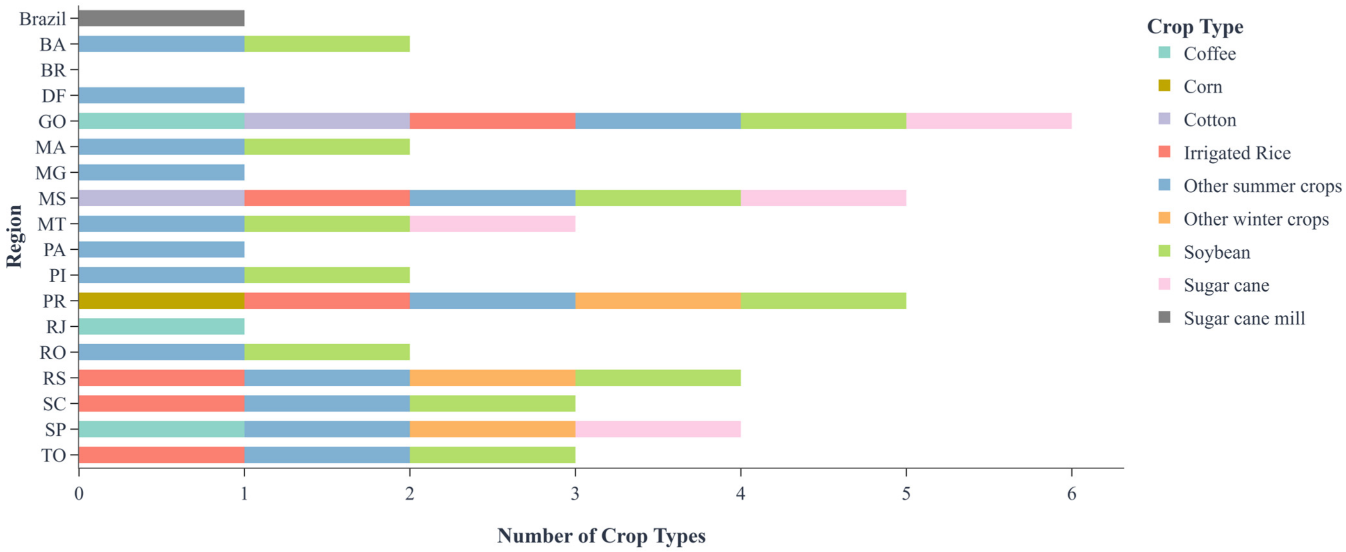
This generalization is a limitation when LULC maps are used for studies of phenomena at the regional or even local level, such as small-scale agriculture, whose occurrence is mapped poorly, or not at all, by these initiatives. CGLS maps face these limitations in identifying both highly and minimally fragmented landscapes, particularly mixed areas with very small cropland fields (<0.5 ha) and vastly sparse cropland fields, due to PROBA-V 100 m spatial resolution, which can lead to croplands overestimation or underestimation, respectively [21]. Therefore, when evaluating products at the national and regional levels, especially the initiatives carried out in Brazil, there is an improvement in the classification hierarchy and, consequently, the composition of the legend. This involves subdividing the coverage classes into one or more sublevels, as evidenced to a lesser extent by the IBGE maps and primarily by the TerraClass and MapBiomas maps (Table 2).

Local initiatives such as MapBiomas and TerraClass (Amazon/Cerrado) offer a better trade-off spatial resolution, high classification accuracy, and detailed agricultural classes, making them ideal for fine-scale monitoring in Brazil's diverse landscapes (Figure 4). In contrast, global products like CGLS, GDW, UMD-GLC, and ESA-WorldCover typically feature coarser resolution and fewer agricultural classes, though some maintain good overall accuracy, reflecting their broader, less granular focus (Figure 4). MapBiomas uniquely combines thematic richness with agricultural detail, directly supporting advanced crop monitoring, whereas IBGE-MLCU and CONAB-AM often exhibit lower accuracy and detail due to reliance on costly census and field campaigns in a continental-scale context. Update cycles for different local products generally follow annual or multi-year schedules for temporal consistency, while global datasets leverage modern platforms for more frequent updates at the expense of spatial and thematic precision (Figure 4). Ultimately, selecting an LULC product requires balancing resolution, thematic detail, temporal frequency, and operational feasibility relative to Brazil's scale and resource constraints.

The CONAB initiative, aimed at mapping crops, focuses specifically on describing agricultural use classes for this purpose (Figure 5). No differentiation or characterization is applied between annual crops and intercrop types present in each crop field mapped feature (vectorial data), working more like an agricultural mapping mask rather than a product representing LULC in Brazil. The presence of intraseasonal crops cultivated throughout the year (e.g., oats, sorghum, peanuts), as well as their spatial and temporal occurrence, is neither reported nor characterized in the mappings, making it impossible to assign features to these elements. However, when integrated with other mapping datasets, these data can contribute to the refinement of the mappings, improving the identification of agricultural targets in Brazil. CONAB-AM agricultural mapping data (Figure 5) are available for the following Brazilian states: Bahia (BA), Distrito Federal (DF), Goiás (GO), Maranhão (MA), Minas Gerais (MG), Mato Grosso do Sul (MS), Mato Grosso (MT), Pará (PA), Piauí (PI), Paraná (PR), Rio de Janeiro (RJ), Rondônia (RO), Rio Grande do Sul (RS), Santa Catarina (SC), São Paulo (SP), and Tocantins (TO).

While the importance of continuous time series analysis for land use and land cover (LULC) monitoring is well recognized, the feasibility of implementing regular updates in resource-constrained environments remains a significant challenge. In the specific case of CONAB-AM (Figure 5), which relies on estimates based on census data and field campaigns to achieve up-to-date temporal interval mapping for all crop types distributed along Brazil's vast territory during multiple crop years, a high financial cost would be required, which often becomes unfeasible. The effort to produce regular sampling and updates, combined with the limitations of the environment (e.g., relief, climate, etc.), logistical delineation (e.g., cooperation with farmers), sociocultural barriers, and the intrinsic dynamics of Brazilian agriculture, is a major limitation for continuous time series analysis in a continental countries like Brazil, especially for institutions with limited governmental resources and limited access to advanced technological infrastructure. Also, it impacts the collection of robust ground truth data to use as validation points, becoming a critical topic for agriculture. As a result, the production of continuous, high-quality time series LULC data remains a major challenge in continental-scale countries like Brazil, underscoring the need for innovative, cost-effective approaches to support regular updates in such contexts like yield and area estimation using remote sensing data and employing statistical and machine learning approaches to predict the cropland variability, distribution, and/or without the need for a great amount of ground truth data. The consequences for agricultural mappings are critical: spatial fragmentation of the data, discontinuity in updating mappings, a lack of data to cover a time series analysis interval, and a low representation of agriculture across agricultural classes.

(**a**)



(**b**)

Figure 5. Available information for CONAB-AM initiative according to crop types practiced in Brazil and region (states): (**a**) Spatio-temporal distribution. (**b**) Crop diversity. Agricultural mapping data correspond to the compilation of vectorial information organized by mesoregion, state, and crop year for main Brazilian crops: coffee, corn, cotton, irrigated rice, other winter and summer crops, soybean, sugar cane, and sugarcane mill (Table 2). Data on winter and summer crops cover the first and second cropping seasons.

The spatial resolution (Figure 3) of the images used for map generation is not the sole decisive factor in defining the classes and the classification legend, although its refinement contributes to improved target discrimination. What stands out in this regard is the methodology of map generation and its applicability. An example of this is the UMD-GLC initiative, which, compared to other initiatives using medium to high spatial resolution, defines seven classes. The classes are derived from the discretization of continuous intervals of 255 subclasses, described in the mapping to evidence the loss and gain of classes, as well as the percentage of vegetation cover and tree height. Therefore, the applicability of UMD-GLC maps goes beyond LULC analysis, enabling studies focused on, for example, forest disturbances, carbon emissions, and others. However, in the ESRI-10m LULC, GDW, and ESA WorldCover initiatives, the use of 10 m resolution images does not impact the generation of a significantly larger number of LULC classes (Table 1), even though the potential existed to describe the phenomena with more detailed hierarchical levels.

Furthermore, the representation capacity of maps produced by high-resolution LULC images should be improved to correspond to their respective spatial resolution, which does not occur, for example, in heterogeneous areas when compared to homogeneous areas. Xu et al. [19] point out that the existing inconsistencies in the definition of legends, particularly classes that are notoriously difficult to separate are grouped through remote sensing (e.g., shrubs, herbaceous and flooded vegetation, urban, and "built-up" areas). This issue, evident in high-resolution products such as GDW and ESRI-10m LULC, leads to low user accuracy and requires a focused look at standardizing the classes defined by these mappings, aiming to improve the consistency and comparability of these products with LULC maps at larger scales. Nevertheless, the need for physical and spectral differentiation of these particularly difficult to represent classes in heterogeneous areas is highlighted, suggesting the use of time series for dynamic analysis in their models [19]. Tubiello et al. [178] discuss the applicability of global products in measuring cropland area. The authors state that differences across maps to international standards limit effectiveness in describing important trends and reduce the relevance of the monitoring process in agriculture's productivity and sustainability goals [178]. One of the impacts mentioned is the ineffectiveness of using global cropland area estimation measures in analyses of agricultural dynamics, which are reduced to mere trend analyses in arable land, since classes such as woody permanent crops are excluded [178]. Also, heterogeneity in LULC definitions leads to distinct trend estimates, generating mapping products with specific cropland subcomponents like arable land and temporary crops, which is contrary to what is reported in statistical censuses (e.g., FAOSTAT) [178].

3.3. Methodology and Product Quality Information

Reliability is one of the most important pillars in the production of maps monitoring LULC changes, as it ensures accuracy in the representation of the information provided for more assertive decision making by specialists, managers, and researchers. In this context, the use of satellite images as input in map production has contributed significantly to the faithful representation and spatial and temporal monitoring of LULC phenomena, one of which is agriculture. However, in LULC products derived from optical remote sensing images, areas with dense cloud cover can lead to low classification accuracy values [28,179,180]. Moreover, the lack of filtering of shadowed pixels during the pre-processing process can generate incorrect classification problems. The CGLS product presents some of these problems, particularly in dealing with temporarily dry and flooded areas and extremes, due to the inability to capture meteorological patterns such as La Niña and El Niño events [21].

In the process of LULC maps validation, it is crucial to quantify and account for reference data errors, selecting validation methods that consider spatial context and dealing with reference data uncertainty, like the ESA "Land Use and Coverage Area frame Survey" (LUCAS) dataset [181]. Also, agricultural sampling data present a challenge in Brazil because they encounter barriers due to territorial extent and topography, as well as financial support to execute large field campaigns, which make such data scarce. Even with global initiatives that use collaborative information uniting efforts from campaigns all over the world, the quantity of available agricultural samplings for Brazil is scarce. Xu et al. [19] suggest for products originating from high spatial resolution a shift from single-pixel reference data to neighborhood-based approaches, especially in heterogeneous regions to deal with mismatches. Kerner et al. [182] found disparities between eleven cropland prediction maps from eight analyzed countries in Sub-Saharan Africa, pointing out a low consensus in mappings. All maps mutually agreed with less than 0.5% of pixels, a smaller estimated percentage of land that is used for agricultural purposes, with F1 scores ranging from 0.21 ± 0.22 (Mali) to 0.71 ± 0.16 (Rwanda) and average below 0.70 [182].

Additionally, incorporating land dynamics, particularly for targets that have a high variability through time and are spectrally and physically alike, like cropland/fallow crops, time series analysis can improve validation reliability, capture intra- and interannual variations and lead to fewer misclassifications. Another way to reduce data uncertainty is to ensure the accuracy and applicability of the results by producing transparent reporting of validation methods, showing not only the global accuracy but also the individual class accuracy performance and the classification probability associated with each pixel of the map.

Many of the cited products in this paper, even though they have reported a good performance in mapping LULC classes, are made for a unique research purpose only, not delving deeper into other mapped classes. This purpose is established at the beginning by the researchers, guided by the question they wish to answer, defining the purpose that mapping will achieve. Consequently, LULC products meet desirable quality metrics but often prioritize the accuracy of certain classes over others, being high at a global level to the detriment of local levels and limiting the applicability of the mapping to meet other research demands. Considering that the mappings are generally available and researchers commonly suggest that users use their products to solve LULC problems, this goal is ultimately not achieved owing to the lower level of detail and representativeness of the other classes relative to the primary class of interest.

3.4. Other Challenges and Limitations

To be representative of a given phenomenon, a map must be generated at the frequency of the phenomenon's occurrence in time and space. Thus, maps should be generated for agricultural applications at subannual or annual time intervals, considering interannual crop management [19]. Therefore, another limitation is the inconsistent temporal coverage among LULC products, which hinders direct map comparison (Figures 5 and 6). Products obtained from high-resolution sensors, such as the ESRI-10m LULC, GDW, and ESA WorldCover initiatives, began their mappings in 2017—the year that the Sentinel-2B satellite was launched and two years after the launch of the Sentinel-2A satellite. In other words, the initiation of these mappings is directly linked to the availability of Sentinel-2 images, which shortens the period available for analysis (Table 1). For the WorldCeral initiative, this becomes critical, because the mapping began in 2021 and remains single-date outdated mapping (Table 1, Figure 6). On the other hand, initiatives with moderate spatial resolutions, based on the Landsat satellite series, such as UMD-GLC, UMD-SASM, PRODES, DETER, TerraClass (until 2018), MapBiomas, IBGE-MLCU, and CONAB-AM, have a longer time interval, allowing for the composition of a historical time series for applications in studies involving the continuous monitoring of the Earth's surface (Table 2). With the increasing quality of spatial resolution of sensors, initiatives that used moderate to coarse spatial resolution satellites, such as CGLS, have fallen into disuse in LULC initiatives (Table 1). As a result, these products have distinct time intervals, meaning comparisons between maps are only possible when they align temporally (Figures 5 and 6). Therefore, considering the continental and global level products presented, only 2017, 2018, and 2019 mappings have temporal overlap with each other, except for the UMD-GLC product.

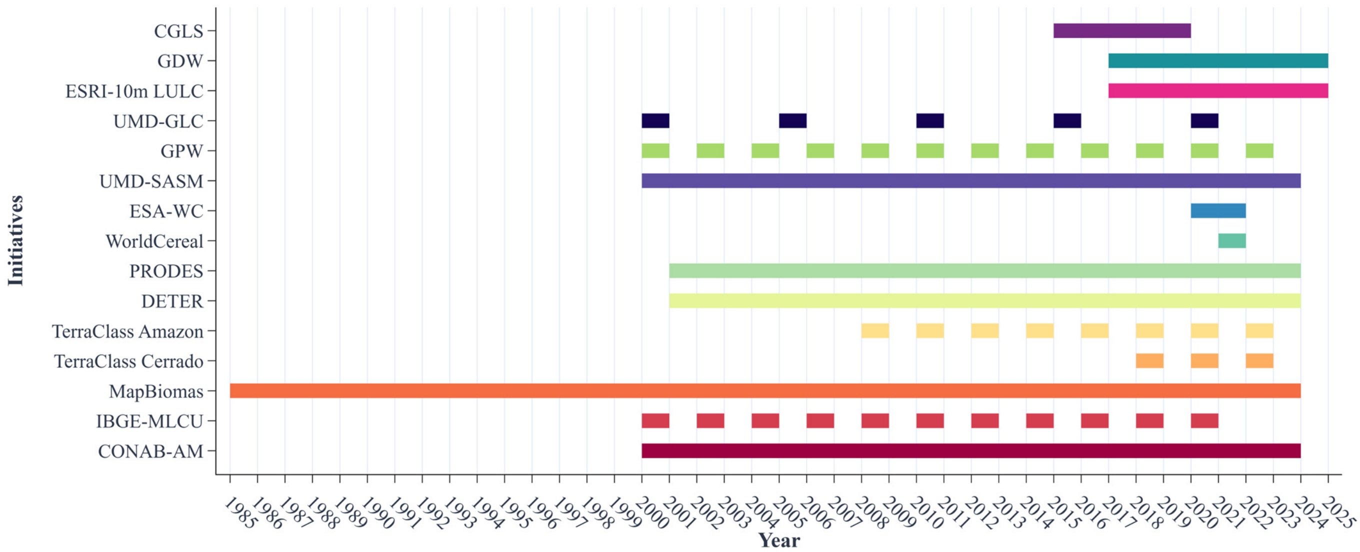


Figure 6. Initiatives timeline based on temporal interval availability. Gaps associated with unavailability of data in the temporal interval. The analysis does not consider the CONAB-AM initiative due to its highly variable time frame. CONAB-AM details are shown in Figure 5.

The absence of a continuous time series is one of the major challenges faced by users of LULC products, as most of the mappings cited in this paper have a sequence of maps at discontinuous intervals in time. This discontinuity appears both at the boundary limits of the time interval (beginning and end) and in the temporal sequence (annual, biennial) of the available maps (Figure 6). It affects the comparability and integration of the produced information, preventing users from making assertive decisions when selecting a product or initiative for their specific analytical purpose. Global and national mapping initiatives exhibit temporal and update frequency discontinuities in their coverage intervals, failing to provide a common reference year that would enable proper comparative analysis following remote sensing best practices and statistical analyses that would typically benchmark accuracy, applicability, confusion matrix assessment, and thematic granularity. Figure 6 reveals the extent of this temporal fragmentation, illustrating that there is no single year covered by all initiatives across global, national, and regional scales. Even when grouping the initiatives by levels, i.e., global and continental in group 1, and national and regional in group 2, no common year covers all initiatives. The nature of the data, coverage scale, temporal discontinuity, spatial fragmentation, and the frequency of map updates are key findings to understand the complexity in dealing with LULC mapping for agriculture purposes. These findings reinforce methodological constraints and demonstrate that comparative analysis is only feasible at specific scales and limited temporal windows.

The fragmentation of intervals (Figure 6), as observed, for example, in the UMD-GLC maps (2000, 2005, 2015, and 2020 reference years), limits comparability with the data provided by the global initiatives CGLS, GPW, GDW, ESRI-10m LULC, UMD-SASM, ESA-WC, and ESA-WorldCereal (Table 1), as well as national initiatives (Table 2), as the existence of a product intersecting the same year in the evaluated interval is absent or minimal/reduced, restricting the time series analysis to a point-in-time analysis (Figure 6). When we think about agriculture, this limitation becomes more pronounced because the nature of crops implies the use of at least two images at different times to evaluate a large part of the phenomena arising from their spatial and temporal dynamics, such as the estimation of planting and harvesting dates, quantification of the expansion or retraction of agricultural areas, and estimation of the productivity of a given crop. Added to this, the great variety of crop types in Brazil (Table 2, Figure 2), the particularities of the tropical climate (Figure 1), and the agricultural calendar practiced in different regions of the country (Figure 2) make the use of time series data almost an imposition in the analysis of agricultural dynamics. In single-crop practice, the number of cloud-free images required for agricultural interpretation is at least two images for the same period (along one year) considering the crop calendar [46]. In intensive farming systems with multiple crops (e.g., double or triple cropping), three or more cloud-free images are required for intercropping pattern recognition considering the distinct vegetative stages of crop growth [46]. Further, complex land features, particularly woody permanent crops and fallow, have limited attention devoted to distinguishing within agricultural lands and, in most cases, do not have a specifically delimitated class in the mapping, which leads to omission and mismatches in classification contrasting to other LULC classes [178,183].

Another important point that corroborates the discontinuity of these series is the lack of updated LULC products. This can occur due to several factors such as the discontinuation of the mapping initiative due to the technological advancement of sensor systems (e.g., PROBA-V CGLS), the lack of interest or financial resources on the part of the provider to maintain an initiative, the migration in the use of one satellite mission versus another due to the greater availability and better characteristics of the data (e.g., Landsat to Sentinel-2—PRODES and DETER), the achievement or not of the purpose of the initiative and/or of its associated project, the end of a monitoring mission, trade-offs in spatial resolution (Figure 3), and other adverse situations. An example that we cite is the CGLS initiative, which was discontinued due to the end of the life of the PROBA-V mission in October 2021. The fact is that all mapping initiatives are subject to these possibilities of updating issues and discontinuity, which can negatively affect research that uses these data, leading to critical decision-making situations for the user.

3.5. Recommendations and Future Directions

Based on our findings and the current literature, we recommend that LULC users carefully evaluate datasets not only for accuracy but also for spatial resolution, thematic detail, class definitions, and uncertainty information, considering the specific area of interest and its regional variations. This is particularly crucial for agricultural applications, where understanding the specific crop types within the "cropland" class is essential for analyses such as yield estimation, phenology, and management practices. Users should prioritize datasets that provide clear, precise definitions for agricultural classes, ensuring that all relevant land cover and use types are represented to avoid information gaps that could compromise study outcomes.

For producers, we emphasize the importance of adopting standardized coverage and use classes to promote consistency, comparability, and integration across different LULC products and initiatives [184,185]. Validation should be conducted at multiple scales, ensuring that maps are reliable not only in broad extents but also in smaller, heterogeneous regions. Enhancing thematic detail and class representation, especially in products with coarser spatial resolution, is vital for accurately capturing the diversity of agricultural systems. Methodological improvements, such as the integration of machine learning and deep learning techniques, should be pursued to address these challenges, alongside systematic reporting of uncertainty and quality metrics to strengthen the robustness of both training and validation processes, enhance the discrimination of spectrally similar classes, and improve the mapping of complex canopy structures [184,186–188]. In the same way, we recognizing the value of local knowledge and the need for fine-scale data, especially in heterogeneous regions such as the Amazon and Cerrado biomes, where we advocate for the integration of participatory mapping approaches [189,190].

To address persistent semantic discrepancies among Brazilian LULC products, we advocate for the implementation of automated harmonization pipelines based on machine learning, leveraging transformer-based language models to encode class definitions and metadata, and using graph-based algorithms to ensure semantic and structural consistency [191,192]. Participatory mapping approaches, including mobile applications for community-contributed geotagged observations, should be integrated to enhance the validation and representation of local land use practices, particularly in heterogeneous regions like the Amazon and Cerrado biomes.

In terms of promoting product updates, establishing regular, transparent update cycles ideally annually or biannually is essential to allow users to follow data releases. This strategy should be complemented by robust user feedback mechanisms, such as online platforms or structured forms, enabling analysts to report errors, suggest new classes, or request region-specific improvements, thereby directly informing future product versions and fostering a collaborative environment. Additionally, integrating automated change detection pipelines based on machine learning can systematically identify regions of significant land cover change, prioritizing these areas for manual review, remove bias in change detection, and allow for targeted updates in subsequent releases [193]. The development of frameworks based on the Open Data Cube (ODC) is an alternative to provide resources for accessing and analyzing large volumes of free, frequently updated remote sensing data collections, allowing the integration of information from different sensors to meet the available space–time, cloud-free image demand [146,194]. An example of usage is the Brazil Data Cube (BDC) initiative in Brazil [146]. Also, software tools like the Web Land Trajectory Service (WLTS) should provide LULC trajectories integration, harmonization, and metrics extraction from classified maps [195]. To further enhance methodological robustness, we advocate for multi-level validation protocols and context-metrics that assess LULC products at both global and subregional scales, ensuring their applicability and reliability for local contexts, especially in heterogeneous landscapes [150,172,196,197]. Uncertainty quantification, including comprehensive metrics, such as confidence intervals, confusion matrices, and disagreement components, should be embedded within product metadata to support robust training, validation, and decision-making workflows [150,197,198].

Finally, access to publicly accessible benchmark datasets, as well as transparent reporting of detailed documentation on class definitions, mapping methodologies, ontology frameworks, and quality assessment procedures aligned with FAIR data and Open Science principles, is crucial for reproducibility and informed use, facilitating collaboration and integration across different remote sensing initiatives. These concrete measures should provide clear guidance for producers and users to enhance the actionability and practicability of LULC mapping efforts.

4. Conclusions

This paper presents a review of the available LULC products, exploring the current challenges and limitations of using pre-existing maps for land representation and monitoring. An emphasis is placed mainly on agricultural classes, seeking to understand the applicability of these LULC products to issues related to crop mapping in Brazil. We discuss LULC map products from available sources at global, national, and regional levels, showing their potential and the challenges faced in representing agricultural dynamics, including the Brazilian context. Eight LULC mapping initiatives at the global/continental level (CGLS, GDW, ESRI-10m LULC, UMD-GLC, GPW, UMD-SASM, ESA-WC, and ESA-WorldCereal) and five initiatives at the national/regional level (PRODES, DETER, MapBiomas, IBGE-MLCU, and CONAB-AM) have been discussed, featuring distinct conceptualization approaches, nature of data, satellites and sensors employed, classification methodologies, legends, class representations, and reported quality.

Our discussion reveals differences in the approaches considered by the initiatives, highlighting gaps in the mapping of agricultural classes, such as the need for standardization in legends, missing or insufficient information about crop types mapped, scarcity of reference field samples, discontinuities in map updates to analyze changes and trajectories, and gaps in temporal intervals.

With advances in remote sensing, computer science, and improved classification methods, it is crucial that the production of LULC maps follows standardization to ensure the credibility, reliability, and applicability of these map initiatives for diverse research themes, assisting researchers in solving problems at different levels and scales in their areas of interest. By operationalizing the recommendations evidenced in Section 3.5 through regular product updates, harmonized classification systems, collaborative validation campaigns, and open data sharing;both users and producers can significantly enhance the consistency, comparability, and practical utility of LULC products for diverse applications.

Author Contributions: Conceptualization, P.A.d.S., M.A., M.C.A.P., V.H.R.P., J.C.D.M.E., G.R.d.Q., and C.T.C.d.S.; Methodology, P.A.d.S. and M.A.; Formal Analysis, P.A.d.S., M.A., M.C.A.P., V.H.R.P., J.C.D.M.E., G.R.d.Q., and C.T.C.d.S.; Investigation, P.A.d.S. and M.A.; Resources, P.A.d.S. and M.A.; Data Curation, P.A.d.S., M.A., M.C.A.P., V.H.R.P., J.C.D.M.E., G.R.d.Q., and C.T.C.d.S.; Writing—Original Draft Preparation, P.A.d.S.; Writing—Review and Editing, P.A.d.S., M.A., M.C.A.P., V.H.R.P., J.C.D.M.E., G.R.d.Q., C.T.C.d.S., and M.E.D.C.; Visualization, P.A.d.S.; Supervision, M.A., M.C.A.P., V.H.R.P., J.C.D.M.E., G.R.d.Q., and C.T.C.d.S.; Project Administration, P.A.d.S. and M.A.; Funding Acquisition, P.A.d.S. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brazil (CAPES)—Finance Code 001.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this document are included in the article. Further inquiries can be directed at the corresponding author.

Acknowledgments: The authors acknowledge the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), the National Institute for Space Research (INPE) Post-Graduation Program in Remote Sensing (PGSER), and the Brazilian Space Agency (AEB) for the support that contributed to the conception of this article. The authors are grateful to the Brazilian National Council for Scientific and Technological Development (CNPq) for the Research productivity Fellowship of Adami, M. [grant number PQ 309045/2023-1]; and the São Paulo Research Foundation (FAPESP) for the financial support of Chaves, M.E.D. [grant number 2021/07382-2].

Conflicts of Interest: The authors Júlio César Dalla Mora Esquerdo and Cleverton Tiago Carneiro de Santana are employed by the Brazilian Agricultural Research Corporation (EMBRAPA) and National Food Supply Company (CONAB), respectively. All authors declare that the research was conducted in the absence of any personal, commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. European Commission. *Directive 2007/2/EC of the European Parliament and of the Council of 14 March 2007 Establishing an Infrastructure for Spatial Information in the European Community (INSPIRE) 2007*; European Commission: Brussels, Belgium, 2007.
2. Di Gregorio, A.; Jansen, L.J.M. *Land Cover Classification System: Classification Concepts and User Manual*; Software Version 2; Food and Agriculture Organization of the United Nations (FAO), Ed.; Environment and natural resources service series GEO-spatial data and information; Food and Agriculture Organization of the United Nations: Rome, Italy, 2005; ISBN 978-92-5-105327-0.
3. García-Álvarez, D.; Nanu, S.F. Land Use Cover Datasets: A Review. In *Land Use Cover Datasets and Validation Tools*; García-Álvarez, D., Camacho Olmedo, M.T., Paegelow, M., Mas, J.F., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 47–66, ISBN 978-3-030-90997-0.
4. Loveland, T.R.; Dwyer, J.L. Landsat: Building a Strong Future. *Remote Sens. Environ.* **2012**, *122*, 22–29. [CrossRef]
5. Potapov, P.; Hansen, M.C.; Pickens, A.; Hernandez-Serna, A.; Tyukavina, A.; Turubanova, S.; Zalles, V.; Li, X.; Khan, A.; Stolle, F.; et al. The Global 2000–2020 Land Cover and Land Use Change Dataset Derived from the Landsat Archive: First Results. *Front. Remote Sens.* **2022**, *3*, 856903. [CrossRef]
6. Verburg, P.H.; Neumann, K.; Nol, L. Challenges in Using Land Use and Land Cover Data for Global Change Studies. *Glob. Change Biol.* **2011**, *17*, 974–989. [CrossRef]
7. Macarringue, L.S.; Bolfe, É.L.; Pereira, P.R.M. Developments in Land Use and Land Cover Classification Techniques in Remote Sensing: A Review. *JGIS J. Geogr. Inf. Syst.* **2022**, *14*, 1–28. [CrossRef]
8. Don, A.; Schumacher, J.; Freibauer, A. Impact of Tropical Land-Use Change on Soil Organic Carbon Stocks—A Meta-Analysis: Soil Organic Carbon and Land-Use Change. *Glob. Change Biol.* **2011**, *17*, 1658–1670. [CrossRef]
9. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global Consequences of Land Use. *Science* **2005**, *309*, 570–574. [CrossRef]
10. Grimm, N.B.; Faeth, S.H.; Golubiewski, N.E.; Redman, C.L.; Wu, J.; Bai, X.; Briggs, J.M. Global Change and the Ecology of Cities. *Science* **2008**, *319*, 756–760. [CrossRef]
11. Pan, Y.; Birdsey, R.A.; Fang, J.; Houghton, R.; Kauppi, P.E.; Kurz, W.A.; Phillips, O.L.; Shvidenko, A.; Lewis, S.L.; Canadell, J.G.; et al. A Large and Persistent Carbon Sink in the World's Forests. *Science* **2011**, *333*, 988–993. [CrossRef]
12. Song, X.-P.; Huang, C.; Saatchi, S.S.; Hansen, M.C.; Townshend, J.R. Annual Carbon Emissions from Deforestation in the Amazon Basin between 2000 and 2010. *PLoS ONE* **2015**, *10*, e0126754. [CrossRef]
13. Potapov, P.; Turubanova, S.; Hansen, M.C.; Tyukavina, A.; Zalles, V.; Khan, A.; Song, X.-P.; Pickens, A.; Shen, Q.; Cortez, J. Global Maps of Cropland Extent and Change Show Accelerated Cropland Expansion in the Twenty-First Century. *Nat. Food* **2021**, *3*, 19–28. [CrossRef]
14. Vancutsem, C.; Achard, F.; Pekel, J.-F.; Vieilledent, G.; Carboni, S.; Simonetti, D.; Gallego, J.; Aragão, L.E.O.C.; Nasi, R. Long-Term (1990–2019) Monitoring of Forest Cover Changes in the Humid Tropics. *Sci. Adv.* **2021**, *7*, eabe1603. [CrossRef]
15. Curtis, P.G.; Slay, C.M.; Harris, N.L.; Tyukavina, A.; Hansen, M.C. Classifying Drivers of Global Forest Loss. *Science* **2018**, *361*, 1108–1111. [CrossRef] [PubMed]
16. Estoque, R. A Review of the Sustainability Concept and the State of SDG Monitoring Using Remote Sensing. *Remote Sens.* **2020**, *12*, 1770. [CrossRef]
17. Burke, M.; Driscoll, A.; Lobell, D.B.; Ermon, S. Using Satellite Imagery to Understand and Promote Sustainable Development. *Science* **2021**, *371*, eabe8628. [CrossRef]
18. Karra, K.; Kontgis, C.; Statman-Weil, Z.; Mazzariello, J.C.; Mathis, M.; Brumby, S.P. Global Land Use/Land Cover with Sentinel 2 and Deep Learning. In Proceedings of the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 11 July 2021; pp. 4704–4707.
19. Xu, P.; Tsendbazar, N.-E.; Herold, M.; De Bruin, S.; Koopmans, M.; Birch, T.; Carter, S.; Fritz, S.; Lesiv, M.; Mazur, E.; et al. Comparative Validation of Recent 10 M-Resolution Global Land Cover Maps. *Remote Sens. Environ.* **2024**, *311*, 114316. [CrossRef]
20. Brown, C.F.; Brumby, S.P.; Guzder-Williams, B.; Birch, T.; Hyde, S.B.; Mazzariello, J.; Czerwinski, W.; Pasquarella, V.J.; Haertel, R.; Ilyushchenko, S.; et al. Dynamic World, Near Real-Time Global 10 m Land Use Land Cover Mapping. *Sci. Data* **2022**, *9*, 251. [CrossRef]
21. Buchhorn, M.; Bertels, L.; Smets, B.; De Roo, B.; Lesiv, M.; Tsendbazar, N.-E.; Masiliunas, D.; Li, L. *Copernicus Global Land Service: Land Cover 100 m: Version 3 Globe 2015–2019: Algorithm Theoretical Basis Document*; Zenodo: Geneva, Switzerland, 2020.
22. Gomes, V.; Queiroz, G.; Ferreira, K. An Overview of Platforms for Big Earth Observation Data Management and Analysis. *Remote Sens.* **2020**, *12*, 1253. [CrossRef]
23. Velastegui-Montoya, A.; Montalván-Burbano, N.; Carrión-Mero, P.; Rivera-Torres, H.; Sadeck, L.; Adami, M. Google Earth Engine: A Global Analysis and Future Trends. *Remote Sens.* **2023**, *15*, 3675. [CrossRef]
24. Wang, L.; Ma, Y.; Yan, J.; Chang, V.; Zomaya, A.Y. pipsCloud: High Performance Cloud Computing for Remote Sensing Big Data Management and Processing. *Future Gener. Comput. Syst.* **2018**, *78*, 353–368. [CrossRef]

25. Soille, P.; Burger, A.; De Marchi, D.; Kempeneers, P.; Rodriguez, D.; Syrris, V.; Vasilev, V. A Versatile Data-Intensive Computing Platform for Information Retrieval from Big Geospatial Data. *Future Gener. Comput. Syst.* **2018**, *81*, 30–40. [CrossRef]
26. Pebesma, E.; Wagner, W.; Schramm, M.; Von Beringe, A.; Paulik, C.; Neteler, M.; Reiche, J.; Verbesselt, J.; Dries, J.; Goor, E.; et al. *OpenEO—A Common, Open Source Interface Between Earth Observation Data Infrastructures and Front-End Applications*; Zenodo: Geneva, Switzerland, 2017. [CrossRef]
27. Atzberger, C. Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. *Remote Sens.* **2013**, *5*, 949–981. [CrossRef]
28. Whitcraft, A.K.; Vermote, E.F.; Becker-Reshef, I.; Justice, C.O. Cloud Cover throughout the Agricultural Growing Season: Impacts on Passive Optical Earth Observations. *Remote Sens. Environ.* **2015**, *156*, 438–447. [CrossRef]
29. Whitcraft, A.K.; Becker-Reshef, I.; Justice, C.O. Agricultural Growing Season Calendars Derived from MODIS Surface Reflectance. *Int. J. Digit. Earth* **2015**, *8*, 173–197. [CrossRef]
30. Whitcraft, A.; Becker-Reshef, I.; Justice, C. A Framework for Defining Spatially Explicit Earth Observation Requirements for a Global Agricultural Monitoring Initiative (GEOGLAM). *Remote Sens.* **2015**, *7*, 1461–1481. [CrossRef]
31. Song, X.-P.; Potapov, P.V.; Krylov, A.; King, L.; Di Bella, C.M.; Hudson, A.; Khan, A.; Adusei, B.; Stehman, S.V.; Hansen, M.C. National-Scale Soybean Mapping and Area Estimation in the United States Using Medium Resolution Satellite Imagery and Field Survey. *Remote Sens. Environ.* **2017**, *190*, 383–395. [CrossRef]
32. Wulder, M.A.; Masek, J.G.; Cohen, W.B.; Loveland, T.R.; Woodcock, C.E. Opening the Archive: How Free Data Has Enabled the Science and Monitoring Promise of Landsat. *Remote Sens. Environ.* **2012**, *122*, 2–10. [CrossRef]
33. Whitcraft, A.; Becker-Reshef, I.; Killough, B.; Justice, C. Meeting Earth Observation Requirements for Global Agricultural Monitoring: An Evaluation of the Revisit Capabilities of Current and Planned Moderate Resolution Optical Earth Observing Missions. *Remote Sens.* **2015**, *7*, 1482–1503. [CrossRef]
34. You, L.; Sun, Z. Mapping Global Cropping System: Challenges, Opportunities, and Future Perspectives. *Crop Environ.* **2022**, *1*, 68–73. [CrossRef]
35. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of Remote Sensing in Precision Agriculture: A Review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
36. Khanal, S.; Kc, K.; Fulton, J.P.; Shearer, S.; Ozkan, E. Remote Sensing in Agriculture—Accomplishments, Limitations, and Opportunities. *Remote Sens.* **2020**, *12*, 3783. [CrossRef]
37. Fuentes-Peñailillo, F.; Gutter, K.; Vega, R.; Silva, G.C. Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management. *JSAN J. Sens. Actuator Netw.* **2024**, *13*, 39. [CrossRef]
38. Whitcraft, A.K.; McNairn, H.; Lemoine, G.; LeToan, T.; Sobue, S.-I. The Power of Synthetic Aperture Radar for Global Agricultural Monitoring. In *Proceedings of the Global Agricultural Monitoring (GEOGLAM)*; CEOS: Geneva, Switzerland, 2016; pp. 1–4.
39. Muruganantham, P.; Wibowo, S.; Grandhi, S.; Samrat, N.H.; Islam, N. A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing. *Remote Sens.* **2022**, *14*, 1990. [CrossRef]
40. Ji, Z.; Pan, Y.; Zhu, X.; Wang, J.; Li, Q. Prediction of Crop Yield Using Phenological Information Extracted from Remote Sensing Vegetation Index. *Sensors* **2021**, *21*, 1406. [CrossRef] [PubMed]
41. Getahun, S.; Kefale, H.; Gelaye, Y. Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review. *Sci. World J.* **2024**, *2024*, 2126734. [CrossRef] [PubMed]
42. Aznar-Sánchez, J.A.; Piquer-Rodríguez, M.; Velasco-Muñoz, J.F.; Manzano-Agugliaro, F. Worldwide Research Trends on Sustainable Land Use in Agriculture. *Land Use Policy* **2019**, *87*, 104069. [CrossRef]
43. Prudente, V.H.R.; Skakun, S.; Oldoni, L.V.; Xaud, H.A.M.; Xaud, M.R.; Adami, M.; Sanches, I.D. Multisensor Approach to Land Use and Land Cover Mapping in Brazilian Amazon. *ISPRS J. Photogramm. Remote Sens.* **2022**, *189*, 95–109. [CrossRef]
44. Adami, M.; Moreira, M.A.; Rudorff, B.F.T.; Freitas, C.D.C.; Faria, R.T.D. Expansão Direta Na Estimativa de Culturas Agrícolas Por Meio de Segmentos Regulares. *Rev. Bras. Cartogr.* **2009**, *57*, 22–27. [CrossRef]
45. Benami, E.; Jin, Z.; Carter, M.R.; Ghosh, A.; Hijmans, R.J.; Hobbs, A.; Kenduiywo, B.; Lobell, D.B. Uniting Remote Sensing, Crop Modelling and Economics for Agricultural Risk Management. *Nat. Rev. Earth Environ.* **2021**, *2*, 140–159. [CrossRef]
46. Mahlayeye, M.; Darvishzadeh, R.; Nelson, A. Cropping Patterns of Annual Crops: A Remote Sensing Review. *Remote Sens.* **2022**, *14*, 2404. [CrossRef]
47. Jain, M.; Mondal, P.; DeFries, R.S.; Small, C.; Galford, G.L. Mapping Cropping Intensity of Smallholder Farms: A Comparison of Methods Using Multiple Sensors. *Remote Sens. Environ.* **2013**, *134*, 210–223. [CrossRef]
48. Vishnoi, S.; Goel, R.K. Climate Smart Agriculture for Sustainable Productivity and Healthy Landscapes. *Environ. Sci. Policy* **2024**, *151*, 103600. [CrossRef]
49. FAO—Food and Agriculture Organization of the United Nations. FAOSTAT: Top 20 Commodities, Export Value by Country 2022. Available online: https://www.fao.org/faostat/en/#rankings/major_commodities_exports (accessed on 11 November 2024).
50. IBGE—Brazilian Institute of Geography and Statistics. *Produção Agrícola Municipal 2023*; IBGE: Rio de Janeiro, Brazil, 2024.

51. Cherubin, M.R.; Damian, J.M.; Tavares, T.R.; Trevisan, R.G.; Colaço, A.F.; Eitelwein, M.T.; Martello, M.; Inamasu, R.Y.; Pias, O.H.D.C.; Molin, J.P. Precision Agriculture in Brazil: The Trajectory of 25 Years of Scientific Research. *Agriculture* **2022**, *12*, 1882. [CrossRef]
52. IBGE—Brazilian Institute of Geography and Statistics. IBGE Cidades: Panorama Brasil. Available online: https://cidades.ibge.gov.br/brasil/panorama (accessed on 19 September 2024).
53. Tozer, B.; Sandwell, D.T.; Smith, W.H.F.; Olson, C.; Beale, J.R.; Wessel, P. Global Bathymetry and Topography at 15 Arc Sec: SRTM15+. *Earth Space Sci.* **2019**, *6*, 1847–1864. [CrossRef]
54. Fick, S.E.; Hijmans, R.J. WorldClim 2: New 1-km Spatial Resolution Climate Surfaces for Global Land Areas. *Int. J. Climatol.* **2017**, *37*, 4302–4315. [CrossRef]
55. Aparecido, L.E.D.O.; Batista, R.M.; Moraes, J.R.D.S.C.D.; Costa, C.T.S.; Moraes-Oliveira, A.F.D. Agricultural Zoning of Climate Risk for Physalis Peruviana Cultivation in Southeastern Brazil. *Pesqui. Agropecuária Bras.* **2019**, *54*, e00057. [CrossRef]
56. Silva, M.A.S.D.; Matos, L.N.; Santos, F.E.D.O.; Dompieri, M.H.G.; Moura, F.R.D. Tracking the Connection Between Brazilian Agricultural Diversity and Native Vegetation Change by a Machine Learning Approach. *IEEE Lat. Am. Trans.* **2022**, *20*, 2371–2380. [CrossRef]
57. Cerri, C.E.P.; Sparovek, G.; Bernoux, M.; Easterling, W.E.; Melillo, J.M.; Cerri, C.C. Tropical Agriculture and Global Warming: Impacts and Mitigation Options. *Sci. Agric.* **2007**, *64*, 83–99. [CrossRef]
58. Harvey, C.A.; Chacón, M.; Donatti, C.I.; Garen, E.; Hannah, L.; Andrade, A.; Bede, L.; Brown, D.; Calle, A.; Chará, J.; et al. Climate-Smart Landscapes: Opportunities and Challenges for Integrating Adaptation and Mitigation in Tropical Agriculture. *Conserv. Lett.* **2014**, *7*, 77–90. [CrossRef]
59. CONAB—Brazilian National Supply Company. *Calendário de Plantio e Colheita de grãos no Brasil 2022*; CONAB: Brasília, Brazil, 2022.
60. Adami, M.; Campos, P.M.; Fernandes, L.B.; Souza, R.d.S.; Lima, F.A.S.; dos Santos, P.A.; de Santana, C.T.C.; Santos, C.M.R.; Sanches, I.D. *Rumo a Estimativa Objetivas de Safras Agrícolas*; Instituto Nacional de Pesquisas Espaciais (INPE): São Paulo, Brazil, 2023; p. e156102.
61. Campos, P.M.; Souza, R.; Lima, F.A.; Fernandes, L.B.; Adami, M.; Gotijo, E.; Piffer, T.; de Santana, C.T.C.; Santos, C.; Sanches, I.D. Estimativa E Mapeamento de áReas Cultivadas Com Soja. In *Proceedings of the Anais do XX Simpósio Brasileiro de Sensoriamento Remoto*; Gherardi, D.F.M., Sanches, I.D.A., de Aragão, L.E.O.e.C., Eds.; INPF: Florianópolis, Brasil, 2023; Volume 20, pp. 709–711.
62. INPE—National Institute for Space Research. *INPE Apresenta Dados Inéditos de Desmatamento para Todo Brasil*; INPE: São Paulo, Brazil, 2022.
63. FAO—Food and Agriculture Organization of the United Nations. FAOSTAT Land Use Statistics. Available online: https://www.fao.org/faostat/en/#data/RL (accessed on 20 March 2025).
64. Alencar, A.; Shimbo, J.Z.; Lenti, F.; Balzani Marques, C.; Zimbres, B.; Rosa, M.; Arruda, V.; Castro, I.; Fernandes Márcico Ribeiro, J.; Varela, V.; et al. Mapping Three Decades of Changes in the Brazilian Savanna Native Vegetation Using Landsat Data Processed in the Google Earth Engine Platform. *Remote Sens.* **2020**, *12*, 924. [CrossRef]
65. Meyfroidt, P.; Roy Chowdhury, R.; De Bremond, A.; Ellis, E.C.; Erb, K.-H.; Filatova, T.; Garrett, R.D.; Grove, J.M.; Heinimann, A.; Kuemmerle, T.; et al. Middle-Range Theories of Land System Change. *Glob. Environ. Change* **2018**, *53*, 52–67. [CrossRef]
66. García-Álvarez, D.; Camacho Olmedo, M.T.; Mas, J.-F.; Paegelow, M. Land Use Cover Mapping, Modelling and Validation. A Background. In *Land Use Cover Datasets and Validation Tools*; García-Álvarez, D., Camacho Olmedo, M.T., Paegelow, M., Mas, J.F., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 21–33, ISBN 978-3-030-90997-0.
67. Hansen, M.C.; Defries, R.S.; Townshend, J.R.G.; Sohlberg, R. Global Land Cover Classification at 1 Km Spatial Resolution Using a Classification Tree Approach. *Int. J. Remote Sens.* **2000**, *21*, 1331–1364. [CrossRef]
68. Loveland, T.R.; Reed, B.C.; Brown, J.F.; Ohlen, D.O.; Zhu, Z.; Yang, L.; Merchant, J.W. Development of a Global Land Cover Characteristics Database and IGBP DISCover from 1 Km AVHRR Data. *Int. J. Remote Sens.* **2000**, *21*, 1303–1330. [CrossRef]
69. Bartholomé, E.; Belward, A.S. GLC2000: A New Approach to Global Land Cover Mapping from Earth Observation Data. *Int. J. Remote Sens.* **2005**, *26*, 1959–1977. [CrossRef]
70. Fritz, S.; Bartholomé, E.; Belward, A.; Hartley, A.; Hans-Jurgen, S.; Eva, H.; Mayaux, P.; Bartalev, S.; Latifovic, R.; Kolmert, S.; et al. *Harmonisation, Mosaicing and Production of the Global Land Cover 2000 Database (Beta Version)*; Commission, E., Centre, J.R., Eds.; European Union Publications Office: Brussels, Belgium, 2003; ISBN 92-894-6332-5.
71. Hua, T.; Zhao, W.; Liu, Y.; Wang, S.; Yang, S. Spatial Consistency Assessments for Global Land-Cover Datasets: A Comparison among GLC2000, CCI LC, MCD12, GLOBCOVER and GLCNMO. *Remote Sens.* **2018**, *10*, 1846. [CrossRef]
72. Biancalani, R.; Nachtergaele, F.; Petri, M.; Bunning, S. *Land Degradation Assessment in Drylands. LADA Project Methodology and Results*; LADA Project; FAO: Rome, Italy, 2013; pp. 1–63.
73. Latham, J.; Cumani, R.; Rosati, I.; Bloise, M. *Global Land Cover SHARE (GLC-SHARE) Database Beta-Realease Version 1.0—2014*; GLC-SHARE; FAO: Rome, Italy, 2014; pp. 1–40.
74. Tang, F.H.M.; Nguyen, T.H.; Conchedda, G.; Casse, L.; Tubiello, F.N.; Maggi, F. CROPGRIDS: A Global Geo-Referenced Dataset of 173 Crops. *Sci. Data* **2024**, *11*, 413. [CrossRef] [PubMed]

75. See, L.; Schepaschenko, D.; Lesiv, M.; McCallum, I.; Fritz, S.; Comber, A.; Perger, C.; Schill, C.; Zhao, Y.; Maus, V.; et al. Building a Hybrid Land Cover Map with Crowdsourcing and Geographically Weighted Regression. *ISPRS J. Photogramm. Remote Sens.* **2015**, *103*, 48–56. [CrossRef]
76. Liu, H.; Gong, P.; Wang, J.; Clinton, N.; Bai, Y.; Liang, S. Annual Dynamics of Global Land Cover and Its Long-Term Changes from 1982 to 2015. *Earth Syst. Sci. Data* **2020**, *12*, 1217–1243. [CrossRef]
77. ESA—European Space Agency. *Land Cover CCI Product User Guide Version 2*; ESA CCI Land Cover time-series v2.0.7 (1992–2015); European Space Agency, European Union: Brussels, Belgium, 2017; pp. 1–105.
78. Chen, J.; Chen, J.; Liao, A.; Cao, X.; Chen, L.; Chen, X.; He, C.; Han, G.; Peng, S.; Lu, M.; et al. Global Land Cover Mapping at 30m Resolution: A POK-Based Operational Approach. *ISPRS J. Photogramm. Remote Sens.* **2015**, *103*, 7–27. [CrossRef]
79. Ping, T.; Hongwei, Z.; Yongchao, Z.; Zhenguo, N.; Bo, Z.; Changmiao, H.; Xiaojun, S.; Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences; National Geomatics Center of China; Institute of Electronics, Chinese Academy of Sciences. Practice and Thoughts of the Automatic Processing of Multispectral Images with 30 m Spatial Resolution on the Global Scale. *Natl. Remote Sens. Bull.* **2014**, *18*, 231–253. [CrossRef]
80. Wang, J.; Zhao, Y.; Li, C.; Yu, L.; Liu, D.; Gong, P. Mapping Global Land Cover in 2001 and 2010 with Spatial-Temporal Consistency at 250m Resolution. *ISPRS J. Photogramm. Remote Sens.* **2015**, *103*, 38–47. [CrossRef]
81. Xie, H.; Tong, X.; Meng, W.; Liang, D.; Wang, Z.; Shi, W. A Multilevel Stratified Spatial Sampling Approach for the Quality Assessment of Remote-Sensing-Derived Products. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 4699–4713. [CrossRef]
82. Friedl, M.A.; Sulla-Menashe, D.; Tan, B.; Schneider, A.; Ramankutty, N.; Sibley, A.; Huang, X. MODIS Collection 5 Global Land Cover: Algorithm Refinements and Characterization of New Datasets. *Remote Sens. Environ.* **2010**, *114*, 168–182. [CrossRef]
83. Friedl, M.A.; McIver, D.K.; Hodges, J.C.F.; Zhang, X.Y.; Muchoney, D.; Strahler, A.H.; Woodcock, C.E.; Gopal, S.; Schneider, A.; Cooper, A.; et al. Global Land Cover Mapping from MODIS: Algorithms and Early Results. *Remote Sens. Environ.* **2002**, *83*, 287–302. [CrossRef]
84. Sulla-Menashe, D.; Gray, J.M.; Abercrombie, S.P.; Friedl, M.A. Hierarchical Mapping of Annual Global Land Cover 2001 to Present: The MODIS Collection 6 Land Cover Product. *Remote Sens. Environ.* **2019**, *222*, 183–194. [CrossRef]
85. Kobayashi, T.; Tateishi, R.; Alsaaideh, B.; Sharma, R.C.; Wakaizumi, T.; Miyamoto, D.; Bai, X.; Long, B.D.; Gegentana, G.; Maitiniyazi, A.; et al. Production of Global Land Cover Data—GLCNMO2013. *JGG J. Geogr. Geol.* **2017**, *9*, 1. [CrossRef]
86. Tateishi, R.; Uriyangqai, B.; Al-Bilbisi, H.; Ghar, M.A.; Tsend-Ayush, J.; Kobayashi, T.; Kasimu, A.; Hoan, N.T.; Shalaby, A.; Alsaaideh, B.; et al. Production of Global Land Cover Data—GLCNMO. *Int. J. Digit. Earth* **2011**, *4*, 22–49. [CrossRef]
87. Bicheron, P.; Defourny, P.; Brockmann, C.; Schouten, L.; Vancutsem, C.; Huc, M.; Bontemps, S.; Leroy, M.; Achard, F.; Herold, M.; et al. *GLOBCOVER Products Description and Validation Report*; European Space Agency, UCLouvain: Louvain-la-Neuve, Belgium, 2008; pp. 1–47.
88. Gong, P.; Wang, J.; Yu, L.; Zhao, Y.; Zhao, Y.; Liang, L.; Niu, Z.; Huang, X.; Fu, H.; Liu, S.; et al. Finer Resolution Observation and Monitoring of Global Land Cover: First Mapping Results with Landsat TM and ETM+ Data. *Int. J. Remote Sens.* **2013**, *34*, 2607–2654. [CrossRef]
89. Yu, L.; Wang, J.; Gong, P. Improving 30 m Global Land-Cover Map FROM-GLC with Time Series MODIS and Auxiliary Data Sets: A Segmentation-Based Approach. *Int. J. Remote Sens.* **2013**, *34*, 5851–5867. [CrossRef]
90. Tsendbazar, N.-E.; Tarko, A.; Li, L.; Herold, M.; Lesiv, M.; Fritz, S.; Maus, V. *Copernicus Global Land Service: Land Cover 100 m: Version 3 Globe 2015–2019: Validation Report*; Zenodo: Geneva, Switzerland, 2021.
91. Zanaga, D.; Van De Kerchove, R.; Daems, D.; De Keersmaecker, W.; Brockmann, C.; Kirches, G.; Wevers, J.; Cartus, O.; Santoro, M.; Fritz, S.; et al. *ESA WorldCover 10 m 2021 V200*; Zenodo: Geneva, Switzerland, 2022.
92. Zanaga, D.; Van De Kerchove, R.; De Keersmaecker, W.; Souverijns, N.; Brockmann, C.; Quast, R.; Wevers, J.; Grosu, A.; Paccini, A.; Vergnaud, S.; et al. *ESA WorldCover 10 m 2020 V100*; Zenodo: Geneva, Switzerland, 2021.
93. Schultz, M.; Voss, J.; Auer, M.; Carter, S.; Zipf, A. Open Land Cover from OpenStreetMap and Remote Sensing. *Int. J. Appl. Earth Obs. Geoinf.* **2017**, *63*, 206–213. [CrossRef]
94. Defries, R.S.; Townshend, J.R.G. NDVI-Derived Land Cover Classifications at a Global Scale. *Int. J. Remote Sens.* **1994**, *15*, 3567–3586. [CrossRef]
95. Song, X.-P.; Hansen, M.C.; Potapov, P.; Adusei, B.; Pickering, J.; Adami, M.; Lima, A.; Zalles, V.; Stehman, S.V.; Di Bella, C.M.; et al. Massive Soybean Expansion in South America since 2000 and Implications for Conservation. *Nat. Sustain.* **2021**, *4*, 784–792. [CrossRef]
96. UMD—University of Maryland; GLAD—Global Land Analysis and Discovery Laboratory; Hansen, M.C.; Potapov, P. Global Land Analysis & Discovery (GLAD): Commodity Crop Mapping and Monitoring in South America. Available online: https://glad.umd.edu/projects/commodity-crop-mapping-and-monitoring-south-america (accessed on 11 September 2024).
97. Venter, Z.S.; Barton, D.N.; Chakraborty, T.; Simensen, T.; Singh, G. Global 10 m Land Use Land Cover Datasets: A Comparison of Dynamic World, World Cover and Esri Land Cover. *Remote Sens.* **2022**, *14*, 4101. [CrossRef]

98. Fritz, S.; See, L.; McCallum, I.; You, L.; Bun, A.; Moltchanova, E.; Duerauer, M.; Albrecht, F.; Schill, C.; Perger, C.; et al. Mapping Global Cropland and Field Size. *Glob. Change Biol.* **2015**, *21*, 1980–1992. [CrossRef]
99. Fritz, S.; You, L.; Bun, A.; See, L.; McCallum, I.; Schill, C.; Perger, C.; Liu, J.; Hansen, M.; Obersteiner, M. Cropland for Sub-Saharan Africa: A Synergistic Approach Using Five Land Cover Data Sets: A New Calibrated Cropland Data Set. *Geophys. Res. Lett.* **2011**, *38*, L04404. [CrossRef]
100. Pittman, K.; Hansen, M.C.; Becker-Reshef, I.; Potapov, P.V.; Justice, C.O. Estimating Global Cropland Extent with Multi-Year MODIS Data. *Remote Sens.* **2010**, *2*, 1844–1863. [CrossRef]
101. Teluguntla, P.; Thenkabail, P.S.; Xiong, J.; Gumma, K.M.; Giri, C.; Milesi, C.; Mutlu, O.; Congalton, R.G.; Tilton, J.; Sankey, T.T.; et al. Global Food Security Support Analysis Data at Nominal 1 km (GFSAD1km) Derived from Remote Sensing in Support of Food Security in the Twenty-First Century: Current Achievements and Future Possibilities. In *Land Resources Monitoring, Modeling, and Mapping with remote Sensing*; Remote Sensing Handbook; CRC Press, Taylor and francis Group: Boca Raton, FL, USA, 2015; Volume 2, p. 30, ISBN 978-0-429-08944-2.
102. USGS—United States Geological Survey; Earth Resources Observation and Science (EROS) Center. *NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-Support Analysis Data (GFSAD) 1 km Datasets: User Guide*; National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS): Sioux Falls, SD, USA, 2017; pp. 1–15.
103. Rembold, F.; Meroni, M.; Urbano, F.; Csak, G.; Kerdiles, H.; Perez-Hoyos, A.; Lemoine, G.; Leo, O.; Negre, T. ASAP: A New Global Early Warning System to Detect Anomaly Hot Spots of Agricultural Production for Food Security Analysis. *Agric. Syst.* **2019**, *168*, 247–257. [CrossRef]
104. Salmon, J.M.; Friedl, M.A.; Frolking, S.; Wisser, D.; Douglas, E.M. Global Rain-Fed, Irrigated, and Paddy Croplands: A New High Resolution Map Derived from Remote Sensing, Crop Inventories and Climate Data. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *38*, 321–334. [CrossRef]
105. Lu, M.; Wu, W.; You, L.; See, L.; Fritz, S.; Yu, Q.; Wei, Y.; Chen, D.; Yang, P.; Xue, B. A Cultivated Planet in 2010—Part 1: The Global Synergy Cropland Map. *Earth Syst. Sci. Data* **2020**, *12*, 1913–1928. [CrossRef]
106. Yu, Q.; You, L.; Wood-Sichra, U.; Ru, Y.; Joglekar, A.K.B.; Fritz, S.; Xiong, W.; Lu, M.; Wu, W.; Yang, P. A Cultivated Planet in 2010—Part 2: The Global Gridded Agricultural-Production Maps. *Earth Syst. Sci. Data* **2020**, *12*, 3545–3572. [CrossRef]
107. Waldner, F.; Fritz, S.; Di Gregorio, A.; Plotnikov, D.; Bartalev, S.; Kussul, N.; Gong, P.; Thenkabail, P.; Hazeu, G.; Klein, I.; et al. A Unified Cropland Layer at 250 m for Global Agriculture Monitoring. *Data* **2016**, *1*, 3. [CrossRef]
108. Gumma, M.K.; Thenkabail, P.S.; Teluguntla, P.G.; Oliphant, A.; Xiong, J.; Giri, C.; Pyla, V.; Dixit, S.; Whitbread, A.M. Agricultural Cropland Extent and Areas of South Asia Derived Using Landsat Satellite 30-m Time-Series Big-Data Using Random Forest Machine Learning Algorithms on the Google Earth Engine Cloud. *GISci. Remote Sens.* **2020**, *57*, 302–322. [CrossRef]
109. Phalke, A.R.; Özdoğan, M.; Thenkabail, P.S.; Erickson, T.; Gorelick, N.; Yadav, K.; Congalton, R.G. Mapping Croplands of Europe, Middle East, Russia, and Central Asia Using Landsat, Random Forest, and Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* **2020**, *167*, 104–122. [CrossRef]
110. Büttner, G. CORINE Land Cover and Land Cover Change Products. In *Land Use and Land Cover Mapping in Europe: Practices & Trends*; Manakos, I., Braun, M., Eds.; Remote Sensing and Digital Image Processing; Springer: Dordrecht, The Netherlands, 2014; Volume 18, pp. 55–74, ISBN 978-94-007-7969-3.
111. Buttner, G.; Kosztra, B.; Kleeschulte, S.; Hazeu, G.; Vittek, M.; Schroder, C.; Littkopf, A. *Copernicus Land Monitoring Service: Corine Land Cover (from 1990 to 2018) and Corine Land Cover Changes User Manual*; Copernicus Land Monitoring Service (CLMS), European Space Agency: Copenhagem, Denmark, 2021; p. 129.
112. FAO—Food and Agriculture Organization of the United Nations. *AFRICOVER: Land Cover Classification.*; Food and Agriculture Organization of The United Nations (FAO): Rome, Italy, 1997; p. 84.
113. Jin, S.; Homer, C.; Yang, L.; Danielson, P.; Dewitz, J.; Li, C.; Zhu, Z.; Xian, G.; Howard, D. Overall Methodology Design for the United States National Land Cover Database 2016 Products. *Remote Sens.* **2019**, *11*, 2971. [CrossRef]
114. Stone, T.A.; Schlesinger, P.; Houghton, R.A.; Woodwell, G.M. A Map of the Vegetation of South America Based on Satellite Imagery. *ASPRS Am. Soc. Photogramm. Remote Sens.* **1994**, *60*, 541–551.
115. EMBRAPA—Brazilian Agricultural Research Corporation; INPE—National Institute for Space Research. TerraClass: Download de Dados. Available online: https://www.terraclass.gov.br/download-de-dados (accessed on 11 September 2024).
116. Souza, C.M.; Shimbo, J.Z.; Rosa, M.R.; Parente, L.L.; Alencar, A.A.; Rudorff, B.F.T.; Hasenack, H.; Matsumoto, M.; Ferreira, L.G.; Souza-Filho, P.W.M.; et al. Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. *Remote Sens.* **2020**, *12*, 2735. [CrossRef]
117. MapBiomas.parent Plataforma MapBiomas Brasil. Available online: https://plataforma.brasil.mapbiomas.org/ (accessed on 11 September 2024).
118. Buchhorn, M.; Smets, B.; Bertels, L.; De Roo, B.; Lesiv, M.; Tsendbazar, N.-E.; Li, L.; Tarko, A. *Copernicus Global Land Service: Land Cover 100 m: Version 3 Globe 2015–2019: Product User Manual*; Zenodo: Geneva, Switzerland, 2021.

119. Jones, A.; Fernandez-Ugalde, O.; Scarpa, S. *LUCAS 2015 Topsoil Survey. Presentation of Dataset and Results.*; Joint Research Center (JCR) Technical Reports; Publications Office of the European Union: Luxemburg, 2020; p. 83.
120. Penman, J.; Gytarsky, M.; Hiraishi, T.; Krug, T.; Kruger, D.; Pipatti, R.; Buendia, L.; Miwa, K.; Ngara, T.; Tanabe, K.; et al. *Good Practice Guidance for Land Use, Land-Use Change and Forestry. The Intergovernmental Panel on Climate Change*; Institute for Global Environmental Strategies (IGES) for the IPCC: Hayama, Japan, 2003; ISBN 978-4-88788-003-0.
121. Anderson, J.R.; Hardy, E.E.; Roach, J.T.; Witmer, R.E. *A Land Use and Land Cover Classification System for Use with Remote Sensor Data*; USGS Numbered Series; United States Geological Survey, USGS: Washington, DC, USA, 1976; p. 28.
122. Brown, C.F.; Brumby, S.P.; Guzder-Williams, B.; Birch, T.; Hyde, S.B.; Mazzariello, J.; Czerwinski, W.; Pasquarella, V.J.; Haertel, R.; Ilyushchenko, S.; et al. *Dynamic World Test Tiles*; Zenodo: Geneva, Switzerland, 2021.
123. Impact Observatory [IO] Impact Observatory Maps for Good: Open Acess Global Land Cover Maps. Available online: https://www.impactobservatory.com/maps-for-good/ (accessed on 27 September 2024).
124. ESRI—Environmental Systems Research Institute; IO—Impact Observatory. ESRI Sentinel-2 Land Cover Explorer. Available online: https://livingatlas.arcgis.com/landcoverexplorer/ (accessed on 25 September 2024).
125. IO—Impact Observatory. Sentinel-Hub EO Browser: IO Land Use Land Cover Map (9-Class). Available online: https://apps.sentinel-hub.com/eo-browser/?zoom=10&lat=41.9&lng=12.5&themeId=DEFAULT-THEME&visualizationUrl=U2FsdGVkX1932REiIrm8sGm/+nudLl/H89TjvzZuhIuxaPKX1fKxVblLDFyYFDYyIPeqHkmoKGeRx5+wMHTFmat+Bt5P1wLW/nz5To3Db8CnIcQKMv/hcI2O3j92c75G&datasetId=IO_LULC_10M_ANNUAL&fromTime=2022-01-01T00:00:00.000Z&toTime=2022-01-01T23:59:59.999Z&layerId=IO-LAND-USE-LAND-COVER-MAP&demSource3D=%22MAPZEN%22 (accessed on 27 September 2024).
126. UMD—University of Maryland; GLAD—Global Land Analysis and Discovery Laboratory. Global Land Cover and Land Use 2000 and 2020. Available online: https://storage.googleapis.com/earthenginepartners-hansen/GLCLU2000-2020/v2/download.html (accessed on 11 September 2024).
127. UMD—University of Maryland; GLAD—Global Land Analysis and Discovery Laboratory. Global Land Cover and Land Use Change, 2000–2020. Available online: https://glad.umd.edu/dataset/GLCLUC2020 (accessed on 11 September 2024).
128. Parente, L.; Sloat, L.; Mesquita, V.; Consoli, D.; Stanimirova, R.; Hengl, T.; Bonannella, C.; Teles, N.; Wheeler, I.; Hunter, M.; et al. Annual 30-m Maps of Global Grassland Class and Extent (2000–2022) Based on Spatiotemporal Machine Learning. *Sci. Data* **2024**, *11*, 1303. [CrossRef] [PubMed]
129. Parente, L.; Sloat, L.; Mesquita, V.; Consoli, D.; Stanimirova, R.; Hengl, T.; Carmelo, B.; Teles, N.; Wheeler, I.; Hunter, M.; et al. Global Pasture Watch—Global Machine Learning Model for Prediction of Cultivated and Natural/Semi-Natural Grassland. *Int. Inst. Appl. Syst. Anal.* **2024**. [CrossRef]
130. Van Tricht, K.; Degerickx, J.; Gilliams, S.; Zanaga, D.; Battude, M.; Grosu, A.; Brombacher, J.; Lesiv, M.; Bayas, J.C.L.; Karanam, S.; et al. WorldCereal: A Dynamic Open-Source System for Global-Scale, Seasonal, and Reproducible Crop and Irrigation Mapping. *Earth Syst. Sci. Data* **2023**, *15*, 5491–5515. [CrossRef]
131. Van Tricht, K.; Degerickx, J.; Gilliams, S.; Zanaga, D.; Savinaud, M.; Battude, M.; Buguet de Chargère, R.; Dubreule, G.; Grosu, A.; Brombacher, J.; et al. *ESA WorldCereal 10 m 2021 V100*; Zenodo: Geneva, Switzerland, 2023.
132. Buchhorn, M. *Copernicus Global Land Service: Global Biome Cluster Layer for the 100 m Global Land Cover Processing Line*; Zenodo: Geneva, Switzerland, 2022.
133. Copernicus European Union's Space Programme. Land Monitoring Service: Dynamic Land Cover. Available online: https://land.copernicus.eu/en/products/global-dynamic-land-cover (accessed on 11 September 2024).
134. Google; WRI—World Resources Institute. Dynamic World V1 | Earth Engine Data Catalog. Available online: https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_DYNAMICWORLD_V1 (accessed on 11 September 2024).
135. Google; WRI—World Resources Institute. Dynamic World—10m Global Land Cover Dataset in Google Earth Engine. Available online: https://dynamicworld.app/ (accessed on 11 September 2024).
136. ESRI—Environmental Systems Research Institute; IO—Impact Observatory; Microsoft 10 m Annual Land Use Land Cover (9-Class)—Sentinel Hub Collections. Available online: https://collections.sentinel-hub.com/impact-observatory-lulc-map/ (accessed on 11 September 2024).
137. ESRI—Environmental Systems Research Institute; IO—Impact Observatory. Esri Land Cover. Available online: https://livingatlas.arcgis.com/ (accessed on 11 September 2024).
138. ESA—European Space Agency. WorldCover Products. Available online: https://esa-worldcover.org/en/data-access (accessed on 11 September 2024).
139. de Almeida, C.A.; Maurano, L.E.P.; Valeriano, D.d.M.; Câmara, G.; Vinhas, L.; da Motta, M.; Gomes, A.R.; Monteiro, A.M.V.; Souza, A.A.d.A.; Messias, C.G.; et al. *Metodologia UtiIizada nos Sistemas PRODES e DETER (2ª Edição Atualizada)*; INPE: São Paulo, Brazil, 2022.

140. Diniz, C.G.; Souza, A.A.D.A.; Santos, D.C.; Dias, M.C.; Luz, N.C.D.; Moraes, D.R.V.D.; Maia, J.S.A.; Gomes, A.R.; Narvaes, I.D.S.; Valeriano, D.M.; et al. DETER-B: The New Amazon Near Real-Time Deforestation Detection System. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 3619–3628. [CrossRef]
141. Pinheiro, T.P.; Almeida, C.A.; Pinheiro, L.M.; Valeriano, D.M.; Gomes, A.R.; Adami, M.; Scheide, A.; Nogueira, S.H. The near Real-Time Deforestation Detection System: Case Study of the DETER System for the Cerrado Biome. *Appl. Earth Sci. Trans. Inst. Min. Metall.* **2023**, *132*, 271–280. [CrossRef]
142. Messias, C.G.; De Almeida, C.A.; Silva, D.E.; Soler, L.S.; Maurano, L.E.; Camilotti, V.L.; Alves, F.C.; Da Silva, L.J.; Reis, M.S.; De Lima, T.C.; et al. Unaccounted for Nonforest Vegetation Loss in the Brazilian Amazon. *Commun Earth Environ.* **2024**, *5*, 451. [CrossRef]
143. Almeida, C.A.D.; Coutinho, A.C.; Esquerdo, J.C.D.M.; Adami, M.; Venturieri, A.; Diniz, C.G.; Dessay, N.; Durieux, L.; Gomes, A.R. High Spatial Resolution Land Use and Land Cover Mapping of the Brazilian Legal Amazon in 2008 Using Landsat-5/TM and MODIS Data. *Acta Amaz.* **2016**, *46*, 291–302. [CrossRef]
144. Mello, E.M.K.; Moreira, J.C.; Santos, J.R.D.; Shimabukuro, E.; Duarte, V.; Souza, I.D.M.; Clemente, C. Técnicas de Modelo de Mistura Espectral, Segmentação E Classificação de Imagens TM—Landsat Para O Mapeamento Do Desflorestamento Da Amazônia. In Proceedings of the Anais do XI Simpósio Brasileiro de Sensoriamento Remoto—SBSR; SBSR: Belo Horizonte, Brasil, 2003; Volume 1, pp. 2807–2814.
145. Simoes, R.; Camara, G.; Queiroz, G.; Souza, F.; Andrade, P.R.; Santos, L.; Carvalho, A.; Ferreira, K. Satellite Image Time Series Analysis for Big Earth Observation Data. *Remote Sens.* **2021**, *13*, 2428. [CrossRef]
146. Ferreira, K.R.; Queiroz, G.R.; Vinhas, L.; Marujo, R.F.B.; Simoes, R.E.O.; Picoli, M.C.A.; Camara, G.; Cartaxo, R.; Gomes, V.C.F.; Santos, L.A.; et al. Earth Observation Data Cubes for Brazil: Requirements, Methodology and Products. *Remote Sens.* **2020**, *12*, 4033. [CrossRef]
147. EMBRAPA—Brazilian Agricultural Research Corporation; INPE—National Institute for Space Research. TerraClass: Acurácia Cerrado. Available online: https://www.terraclass.gov.br/acuracia-cer (accessed on 20 September 2024).
148. EMBRAPA—Brazilian Agricultural Research Corporation; INPE—National Institute for Space Research. TerraClass: Acurácia Amazônia. Available online: https://www.terraclass.gov.br/acuracia-amz (accessed on 20 September 2024).
149. MapBiomas Project. MapBiomas General "Handbook"—Algorithm Theoretical Basis Document (ATBD)—Collection 9, MapBiomas Data, V2, 2024. Available online: https://data.mapbiomas.org/dataset.xhtml?persistentId=doi:10.58053/MapBiomas/ICCL5B (accessed on 24 March 2025). [CrossRef]
150. Olofsson, P.; Foody, G.M.; Herold, M.; Stehman, S.V.; Woodcock, C.E.; Wulder, M.A. Good Practices for Estimating Area and Assessing Accuracy of Land Change. *Remote Sens. Environ.* **2014**, *148*, 42–57. [CrossRef]
151. Stehman, S.V. Sampling Designs for Accuracy Assessment of Land Cover. *Int. J. Remote Sens.* **2009**, *30*, 5243–5272. [CrossRef]
152. Stehman, S.V. Estimating Area and Map Accuracy for Stratified Random Sampling When the Strata Are Different from the Map Classes. *Int. J. Remote Sens.* **2014**, *35*, 4923–4939. [CrossRef]
153. MapBiomas Project. MapBiomas General "Handbook"—Algorithm Theoretical Basis Document (ATBD)—Collection 8, MapBiomas Data, V2, 2023. Available online: https://data.mapbiomas.org/dataset.xhtml?persistentId=doi:10.58053/MapBiomas/OJ0EDK (accessed on 27 August 2024). [CrossRef]
154. EMBRAPA—Brazilian Agricultural Research Corporation. SATVeg: Sistema de Análise Temporal da Vegetação. Available online: https://www.satveg.cnptia.embrapa.br/satveg/login.html (accessed on 11 September 2024).
155. ESRI—Environmental Systems Research Institute. Landsat Explorer Classic. Available online: https://livingatlas2.arcgis.com/landsatexplorer/ (accessed on 11 September 2024).
156. IBGE—Brazilian Institute of Geography and Statistics, Ed. *Monitoramento da Cobertura e Uso da Terra do Brasil: 2018/2020*; Coleção Ibgeana; IBGE: Rio de Janeiro, Brasil, 2022; ISBN 978-85-240-4544-8.
157. IBGE—Brazilian Institute of Geography and Statistics. *Monitoramento da Cobertura e Uso da Terra do Brasil: 2016–2018*; Coleção Ibgeana; IBGE: Rio de Janeiro, Brasil, 2020.
158. IBGE—Brazilian Institute of Geography and Statistics. Banco de Dados e Informações Ambientais (BDiA): Consulta em Grade. Cobertura e Uso da Terra. Available online: https://bdiaweb.ibge.gov.br/#/consulta/pesquisa (accessed on 27 January 2025).
159. CONAB—Brazilian National Supply Company. Mapeamentos Agrícolas. Available online: http://www.conab.gov.br/info-agro/safras/mapeamentos-agricolas (accessed on 11 September 2024).
160. CONAB—Brazilian National Supply Company. Portal de Informações Agropecuárias: Downloads Mapeamentos. Available online: https://portaldeinformacoes.conab.gov.br/mapeamentos-agricolas-downloads.html (accessed on 11 September 2024).
161. Maurano, L.E.P.; Escada, M.I.S.; Renno, C.D. Padrões Espaciais de Desmatamento e a Estimativa Da Exatidão Dos Mapas Do PRODES Para Amazônia Legal Brasileira. *Ciênc. Florest.* **2019**, *29*, 1763–1775. [CrossRef]
162. Assis, L.F.F.G.; Ferreira, K.R.; Vinhas, L.; Maurano, L.; Almeida, C.; Carvalho, A.; Rodrigues, J.; Maciel, A.; Camargo, C. TerraBrasilis: A Spatial Data Analytics Infrastructure for Large-Scale Thematic Mapping. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 513. [CrossRef]

163. INPE—National Institute for Space Research. PRODES. Available online: http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes (accessed on 11 September 2024).
164. INPE—National Institute for Space Research. DETER. Available online: http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/deter/deter (accessed on 11 September 2024).
165. EMBRAPA—Brazilian Agricultural Research Corporation.Nota Técnica TerraClass 2024. Available online: https://drive.google.com/file/d/15LDuOJFUTaSp4iD4X6XRjUEawo9kTZzn/view?usp=embed_facebook (accessed on 16 June 2025).
166. IBGE—Brazilian Institute of Geography and Statistics. Monitoramento da Cobertura e Uso da Terra do Brasil (MCUT). Available online: https://www.ibge.gov.br/apps/monitoramento_cobertura_uso_terra/v1/#/home/ (accessed on 11 September 2024).
167. IBGE—Brazilian Institute of Geography and Statistics. Monitoramento da Cobertura e Uso da Terra: Downloads. Available online: https://www.ibge.gov.br/geociencias/informacoes-ambientais/cobertura-e-uso-da-terra/15831-cobertura-e-uso-da-terra-do-brasil.html?=&t=downloads (accessed on 11 September 2024).
168. CONAB—Brazilian National Supply Company. Portal de Informações Agropecuárias: Produção Agrícola. Available online: https://portaldeinformacoes.conab.gov.br (accessed on 27 January 2025).
169. INPE—National Institute for Space Research. Portal de Dados Geoespaciais: Programa Base de Informações Georreferenciadas (BIG) do INPE. Available online: https://data.inpe.br/big/web/ (accessed on 11 September 2024).
170. INPE—National Institute for Space Research. Terrabrasilis: Plataforma Web para Acesso, Consulta, Análise e Disseminação de Dados Geográficos dos Programas PRODES e DETER. Available online: https://terrabrasilis.dpi.inpe.br/ (accessed on 29 September 2024).
171. Fritz, S.; See, L. Identifying and Quantifying Uncertainty and Spatial Disagreement in the Comparison of Global Land Cover for Different Applications. *Glob. Change Biol.* **2008**, *14*, 1057–1075. [CrossRef]
172. Pontius, R.G. Statistical Methods to Partition Effects of Quantity and Location during Comparison of Categorical Maps at Multiple Resolutions. *Photogramm. Eng. Remote Sens.* **2002**, *68*, 1041–1049.
173. Gu, J.; Congalton, R.G. Analysis of the Impact of Positional Accuracy When Using a Single Pixel for Thematic Accuracy Assessment. *Remote Sens.* **2020**, *12*, 4093. [CrossRef]
174. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [CrossRef]
175. Fritz, S.; See, L.; McCallum, I.; Schill, C.; Obersteiner, M.; Van Der Velde, M.; Boettcher, H.; Havlík, P.; Achard, F. Highlighting Continued Uncertainty in Global Land Cover Maps for the User Community. *Environ. Res. Lett.* **2011**, *6*, 044005. [CrossRef]
176. See, L.; Fritz, S.; You, L.; Ramankutty, N.; Herrero, M.; Justice, C.; Becker-Reshef, I.; Thornton, P.; Erb, K.; Gong, P.; et al. Improved Global Cropland Data as an Essential Ingredient for Food Security. *Glob. Food Secur.* **2015**, *4*, 37–45. [CrossRef]
177. Volke, M.; Pedreros-Guarda, M.; Escalona, K.; Acuña, E.; Orrego, R. Assessment of Semi-Automated Techniques for Crop Mapping in Chile Based on Global Land Cover Satellite Data. *Remote Sens.* **2024**, *16*, 2964. [CrossRef]
178. Tubiello, F.N.; Conchedda, G.; Casse, L.; Pengyu, H.; Zhongxin, C.; De Santis, G.; Fritz, S.; Muchoney, D. Measuring the World's Cropland Area. *Nat. Food* **2023**, *4*, 30–32. [CrossRef]
179. Eberhardt, I.; Schultz, B.; Rizzi, R.; Sanches, I.; Formaggio, A.; Atzberger, C.; Mello, M.; Immitzer, M.; Trabaquini, K.; Foschiera, W.; et al. Cloud Cover Assessment for Operational Crop Monitoring Systems in Tropical Areas. *Remote Sens.* **2016**, *8*, 219. [CrossRef]
180. Prudente, V.H.R.; Martins, V.S.; Vieira, D.C.; Silva, N.R.D.F.E.; Adami, M.; Sanches, I.D. Limitations of Cloud Cover for Optical Remote Sensing of Agricultural Areas across South America. *Remote Sens. Appl. Soc. Environ.* **2020**, *20*, 100414. [CrossRef]
181. d'Andrimont, R.; Verhegghen, A.; Meroni, M.; Lemoine, G.; Strobl, P.; Eiselt, B.; Yordanov, M.; Martinez-Sanchez, L.; Van Der Velde, M. LUCAS Copernicus 2018: Earth-Observation-Relevant in Situ Data on Land Cover and Use throughout the European Union. *Earth Syst. Sci. Data* **2021**, *13*, 1119–1133. [CrossRef]
182. Kerner, H.; Nakalembe, C.; Yang, A.; Zvonkov, I.; McWeeny, R.; Tseng, G.; Becker-Reshef, I. How Accurate Are Existing Land Cover Maps for Agriculture in Sub-Saharan Africa? *Sci. Data* **2024**, *11*, 486. [CrossRef]
183. Rufin, P.; Bey, A.; Picoli, M.; Meyfroidt, P. Large-Area Mapping of Active Cropland and Short-Term Fallows in Smallholder Landscapes Using PlanetScope Data. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *112*, 102937. [CrossRef] [PubMed]
184. Naidu, D.S. Soft Artificial Computing in GIS And Remote Sensing. *IJAMSR Int. J. Adv. Multidiscip. Sci. Res.* **2018**, *1*, 122–127. [CrossRef]
185. Ghanbarzadeh, A.; Soleimani, H. Self-Supervised in-Domain Representation Learning for Remote Sensing Image Scene Classification. *Heliyon* **2024**, *10*, e37962. [CrossRef]
186. Khan, M.N.; Tan, Y.; Gul, A.A.; Abbas, S.; Wang, J. Forest Aboveground Biomass Estimation and Inventory: Evaluating Remote Sensing-Based Approaches. *Forests* **2024**, *15*, 1055. [CrossRef]
187. Min, J.; Lee, Y.; Kim, D.; Yoo, J. Bridging the Domain Gap: A Simple Domain Matching Method for Reference-Based Image Super-Resolution in Remote Sensing. *IEEE Geosci. Remote Sens. Lett.* **2024**, *21*, 8000105. [CrossRef]
188. Maffei Valero, M.A.; Araújo, W.F.; Melo, V.F.; Augusti, M.L.; Fernandes Filho, E.I. Land-Use and Land-Cover Mapping Using a Combination of Radar and Optical Sensors in Roraima—Brazil. *Eng. Agríc.* **2022**, *42*, e20210142. [CrossRef]

189. Woodward, K.D.; Pricope, N.G.; Stevens, F.R.; Gaughan, A.E.; Kolarik, N.E.; Drake, M.D.; Salerno, J.; Cassidy, L.; Hartter, J.; Bailey, K.M.; et al. Modeling Community-Scale Natural Resource Use in a Transboundary Southern African Landscape: Integrating Remote Sensing and Participatory Mapping. *Remote Sens.* **2021**, *13*, 631. [CrossRef]
190. Da Silva, C.N.; Dos Santos, Y.A.; Marinho, V.D.N.M.; Ferreira, G.D.C.; Reis Netto, R.M.; Araújo, A.R.D.O.; Dias, R.D.; Soares, D.A.S. The Way of Life in Amazonian Communities: An Example of the Application of Participatory Mapping in São Caetano de Odivelas (Pará, Amazônia, Brazil). *OLEL Obs. Econ. Latinoam.* **2023**, *21*, 3808–3832. [CrossRef]
191. Neumann, M.; Pinto, A.S.; Zhai, X.; Houlsby, N. In-Domain Representation Learning for Remote Sensing. *arXiv* **2019**, arXiv:1911.06721.
192. Tu, Z.; Yang, X.; He, X.; Yan, J.; Xu, T. RGTGAN: Reference-Based Gradient-Assisted Texture-Enhancement GAN for Remote Sensing Super-Resolution. *IEEE Trans. Geosci. Remote Sens.* **2024**, *62*, 5607221. [CrossRef]
193. Arévalo, P.; Olofsson, P.; Woodcock, C.E. Continuous Monitoring of Land Change Activities and Post-Disturbance Dynamics from Landsat Time Series: A Test Methodology for REDD+ Reporting. *Remote Sens. Environ.* **2020**, *238*, 111051. [CrossRef]
194. Carlos, F.M.; Gomes, V.C.F.; Queiroz, G.R.D.; Souza, F.C.D.; Ferreira, K.R.; Santos, R. Integrating Open Data Cube and Brazil Data Cube Platforms for Land Use and Cover Classifications. *Rev. Bras. Cartogr.* **2021**, *73*, 1036–1047. [CrossRef]
195. Zioti, F.; Ferreira, K.R.; Queiroz, G.R.; Neves, A.K.; Carlos, F.M.; Souza, F.C.; Santos, L.A.; Simoes, R.E.O. A Platform for Land Use and Land Cover Data Integration and Trajectory Analysis. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *106*, 102655. [CrossRef]
196. Pontius, R.G., Jr. *Metrics That Make a Difference: How to Analyze Change and Error*; Advances in Geographic Information Science; Springer International Publishing: Cham, Switzerland, 2022; ISBN 978-3-030-70764-4.
197. Pontius, R.G.; Francis, T.; Millones, M. A Call to Interpret Disagreement Components during Classification Assessment. *Int. J. Geogr. Inf. Sci.* **2025**, *39*, 1373–1390. [CrossRef]
198. Skakun, S. The Impact of Map Accuracy on Area Estimation with Remotely Sensed Data within the Stratified Random Sampling Design. *Remote Sens. Environ.* **2025**, *326*, 114805. [CrossRef]