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Land Cover and Land Use in Uruguay Using Land Cover Classification System Methodology

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Abstract: Mapping land cover in Uruguay is essential to meet the growing demand for accurate data to support sustainable development policies and manage natural resources, while also addressing the United Nations Sustainable Development Goals (SDGs) and other international conventions. In recent decades, collaboration between the FAO and the Government of Uruguay has led to the development of key products that strengthen the country's planning processes, including a detailed, standardized national land cover database. By using the FAO's Land Cover Classification System (LCCS), Uruguay has achieved a multitemporal national land cover database, through a legend specifically adapted to its national context and with classification accuracy improving from 85% in earlier products to 95% in the most recent ones. The use of LCCS has ensured semantic interoperability and provided reliable, up-to-date information on land cover distribution and change analysis. This progress has been supported by the enhancement of national capacities for change analysis, using international standards, remote sensing, and GIS technologies, integrated with national data. This article reviews the historical evolution and methodological advancements in the implementation of the LCCS in Uruguay, emphasizing the improvements in methodology and technology, and their impact on the sustainable management of the country's territory.

Keywords: land cover classification system; Uruguay land cover; National Directorate of Territorial Planning of Uruguay; Sustainable Development Goals

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1. Introduction

In Uruguay, land cover data, alongside the assessment and monitoring of its changes, have become vital tools for understanding and analyzing both natural and human-induced processes such as climate change and biodiversity loss. These data are crucial for supporting land use planning, disaster management, sustainable agriculture, and carbon stock accounting [1–3].

The country faces increasing pressures from various land uses, especially due to the expansion and intensification of agricultural and livestock production, as well as urban sprawl [4]. Additional conflicts arise from activities such as mining, energy generation, tourism, and industrial development, which compete with efforts to preserve landscapes and biodiversity [5,6].

The coexistence of diverse land uses requires careful planning and conflict resolution at multiple scales. To preserve natural resources and combat land degradation Uruguay implements policies promoting sustainable land management. Crop rotation, conservation tillage, and promoting forested areas near rivers are some of the key strategies to reduce erosion and restore soil health. There are now stricter regulations on agricultural practices, including incentives for sustainable practices that preserve soil quality. These regulations also promote reforestation and conservation of native species in key areas to improve biodiversity and reduce erosion. Additionally, to manage urban sprawl, Uruguay is pushing for compact city planning with mixed-use developments, improved transportation, and green corridors, so as to reduce the need to extend infrastructure, improve environmental impact, and minimize socio-economic disparities. These dual strategies help mitigate the impact of land degradation and urban sprawl, promoting a more sustainable and resilient Uruguay. Effective land use planning is therefore essential for enhancing decision-making processes. Uruguay's national land cover database has become an important tool in Integrated Land Use Planning (ILUP), providing the critical information needed to balance competing land use interests.

Moreover, the LCCS database plays a key role in reporting on several international frameworks and policies that aim to protect ecosystems, enhance biodiversity, and promote sustainable land use like Sustainable Development Goal (SDG) indicators and the United Nations Convention to Combat Desertification (UNCCD). SDG 15 focuses on the sustainable management of terrestrial ecosystems and emphasizes the need for sustainable management of forests, combatting desertification, and halting biodiversity loss, and SDG 11 (11.3.1 and 11.7.1) addresses sustainable cities and communities [7–9]. Uruguay's LCCS directly supports these goals by providing data to monitor and manage land use sustainably, especially in agriculture and forestry sectors and urban sprawl, to combat desertification and mitigate climate change impacts.

In 2005, Uruguay embarked on an initiative, supported by the FAO, to assess the country's land cover comprehensively. This initiative led to the development of a preliminary version of the land cover legend for Uruguay based on the FAO's Land Cover Classification System (LCCS) [10]. The first national land cover database was developed in 2008, driven by various state organizations, including the Ministry of Housing, Territorial Planning, and Environment (MVOTMA), and the Ministry of Livestock, Agriculture, and Fisheries (MGAP), under the United Nations pilot initiative 'United in Action' [11]. Supported by the National Directorate of Territorial Planning (DINOT), it was updated in subsequent years, culminating in a multitemporal database that reflects the evolution of land cover in Uruguay from 2000 onward [11,12].

This paper explores the application of the Land Cover Classification System (LCCS) in Uruguay, emphasizing its impact on enhancing the quality and accuracy of land cover data. It also examines how these improved data support more sustainable land use planning and informed decision-making.

2. Materials and Methods

2.1. FAO Standardized Classification System: LCCS

The creation of Uruguay's national land cover database followed the methodology developed by the Food and Agriculture Organization (FAO), specifically the Land Cover Classification System (LCCS), which was designed by the Global Land Cover Network (GLCN) of the FAO in collaboration with the United Nations Environment Programme (UNEP). The LCCS was specifically designed to provide a flexible, hierarchical structure that can adapt to varying geographic and ecological contexts, facilitating consistent land cover assessments across regions and scales [1,13].

The LCCS is a comprehensive and standardized classification system designed to meet the specific requirements of any user and created to map land cover, regardless of the scale or data sources used for mapping [10]. In this system, land cover is represented by basic objects rather than categories, called 'classifiers', which represent simple physiognomic features (e.g., trees, shrubs, buildings). Its parametric nature requires each class to be defined with clear and quantifiable parameters, making the classification process explicit and objective.

This methodology offers significant advantages over existing methods by providing well-defined landscape elements based on explicit and quantifiable classification criteria that minimize ambiguities and prevent overlaps between categories. Studies have demonstrated the flexibility and consistency of the LCCS in diverse geographic and ecological contexts, as well as its ability to harmonize land cover data from multiple sources [13,14]. Moreover, the adaptability of the LCCS allows it to be tailored to the specific conditions of our country while maintaining applicability to global land cover classification initiatives.

In Uruguay, the application of the LCCS has been instrumental in creating a reliable and accurate national land cover database. This database supports sustainable land use planning by providing critical insights into land cover changes, such as shifts in agricultural land use and forest cover, which are essential for assessing ecosystem health and informing decision-makers.

2.2. Methodological Stages

The national application of the LCCS methodology in Uruguay can be divided into two stages based on the processes, analyses, and materials used for classification (Figure 1).

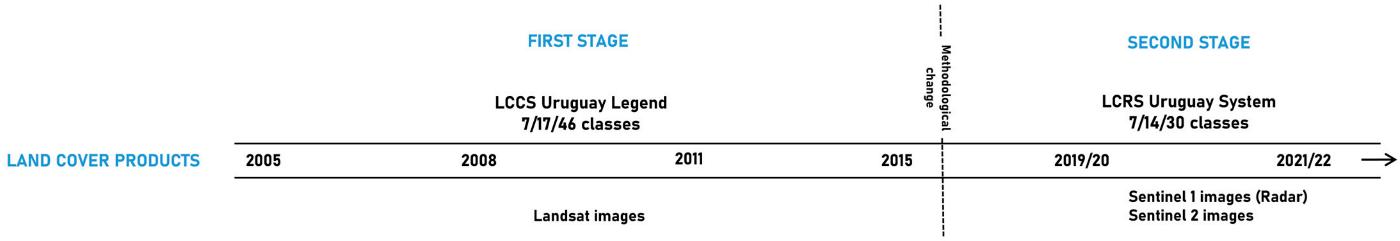


Figure 1. Timeline for LCCS application in Uruguay and its derived products.

First Stage (2000–2015): During this phase, land cover products were generated for the years 2000, 2008, 2011, and 2015. This was achieved through a combination of automatic and semi-automatic classification techniques along with visual interpretation using Landsat imagery [6,11,12,15].

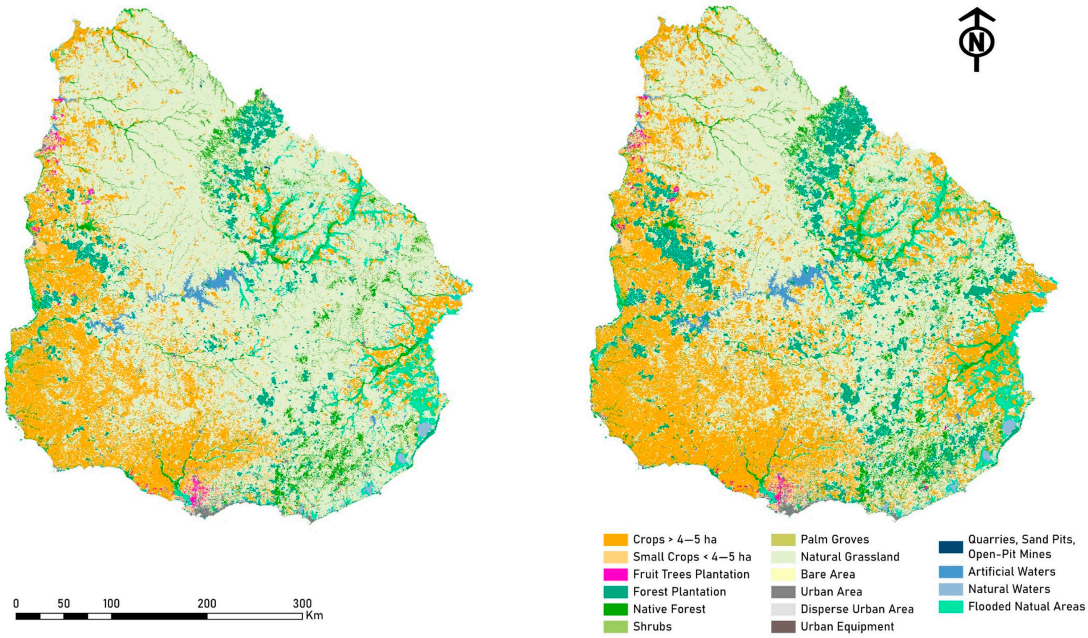
Second Stage (2019–2022): In the second phase, updated land cover products were created for 2019/2020 and 2021/2022, using more advanced methodologies. This included the use of Sentinel 1 and Sentinel 2 satellite data, as well as cloud computing platforms like Google Earth Engine (GEE) and FAO's SEPAL [14–19]. Machine learning techniques were also incorporated to improve the accuracy and speed of the classification process [20].

In both phases, Object-Based Image Analysis (OBIA) was used to classify high-resolution satellite imagery. OBIA is particularly effective in enhancing classification accuracy for high-resolution satellite images by grouping pixels into 'objects' based on their spectral, textural, and spatial properties [21]. These objects, which represent contextually meaningful units, were classified using either visual interpretation or machine learning algorithms, such as Random Forest [22,23]. This approach leverages spatial context to reduce the 'salt-and-pepper' noise typical in pixel-based classifications, thereby improving accuracy and providing a more coherent interpretation of satellite imagery [20–23].

Additionally, a range of software tools—including ArcGIS (versions 10.x and Pro), QGIS (versions 3.x), eCognition (versions 7.x, 8.7, and 10.1), and RStudio (version 1.3.1093 and a subsequent versions)—were used to support the analysis and classification processes. The integration of these advanced tools and methodologies has enabled Uruguay to develop a detailed, harmonized national land cover database using the LCCS framework.

2.2.1. First Stage (2000–2015)

The first stage, spanning from 2000 to 2015, focuses on the development of initial LCCS legends and the creation of land cover maps for 2000, 2008, 2011, and 2015 (Figures 1 and 2). The primary input for classification during this period was Landsat satellite imagery [11,15].



(**a**) (**b**)

Figure 2. Land cover maps of Uruguay using LCCS of years 2000 and 2015: (**a**) LCCS land cover map of 2000; (**b**) LCCS land cover map of 2015.

LCCS Uruguay 2008

The 2008 land cover map was the first product of the LCCS in Uruguay [6]. This map was developed through a multi-phase image interpretation approach, using the FAO's MAD-CAT (Mapping Device–Change Analysis Tool) software (version 3.0.10). The software facilitated classification using a variety of techniques (visual, semi-automatic, and automatic), along with change detection and validation through land cover change statistics [24].

To generate the map, 14 Landsat 5 TM images from 2007 and 2008 were used, covering Uruguay's entire territory. The images were provided by Brazil's National Institute for Space Research (INPE) and were selected based on seasonality and cloud cover (less than 20%). The images were segmented using eCognition 7 software, resulting in a shapefile vector layer consisting of 637,000 polygons nationwide, with each image scene containing around 60,000 polygons [11].

These polygons were classified according to the first LCCS legend, producing the first land cover vector layer. This classification was achieved through a combination of automatic, semi-automatic, and visual interpretation, supported by high-resolution Google Earth images and input from relevant institutions. Preliminary interpretations were field-verified, and the classification's accuracy was assessed.

LCCS Uruguay 2011

For the 2011 land cover map, the 2008 LCCS layer was used as a base, but the images from 2011 were newly interpreted [11]. The original legend was adapted, reducing the number of classes from 48 to 17, following FAO's hierarchical modular dichotomous approach [1].

A mosaic of 14 Landsat TM images from 2011, downloaded from the United States Geological Survey (USGS) EarthExplorer portal, was used, with each image selected based on cloud cover (less than 20%) [25]. The classification was based on the 2008 segmentation, with the polygons being reclassified and showing changes by using a combination of visual interpretation and supervised classification of the 2011 images.

LCCS Uruguay 2000

The 2000 land cover layer was generated retrospectively to analyze land cover changes over the decade, a period of significant economic and policy-driven transformations (Figure 2a). Landsat TM images from 2000 were used alongside the 2011 segmentation as a base. Special attention was given to six dynamic land cover classes: large rainfed crops, large irrigated crops, forest plantations, artificial water, consolidated urban areas, and dispersed urban areas [12].

Polygons in these categories showing changes were reclassified, while those without changes were incorporated from the 2011 layer. Change detection was conducted using MAD-CAT software (version 3.3.32), along with other GIS tools.

LCCS Uruguay 2015

The 2015 land cover layer was developed using the same methodology as previous iterations but benefited from advances in satellite imagery and classification tools (Figure 2b). Landsat images from 2015 were used to generate new segmentation by re-segmenting the 2000/2008/2011 layers, using Landsat images from 2015, incorporating three images per scene from Landsat 5, 7, and 8 sensors, ensuring minimal cloud cover and improved accuracy [15].

Automatic and semi-automatic classification methods were combined with visual interpretation to refine the land cover map (Figure 2). The greater availability of satellite imagery in 2015 allowed for more precise classification, helping to correct errors in earlier versions [12].

Change Assessment 2000–2011–2015

The LCCS, with its parametric classification approach, facilitated a systematic and quantifiable assessment of land cover changes (Figures 2 and 3). Change detection involved a multitemporal analysis of data from 2000, 2011, and 2015, supported by MAD-CAT tools and GIS processes. The combination of automatic segmentation and change labeling ensured a fast, objective analysis. The results revealed significant dynamism in forested areas and rainfed crops, with natural herbaceous areas experiencing the greatest change as they were replaced by agricultural and forestry expansion.

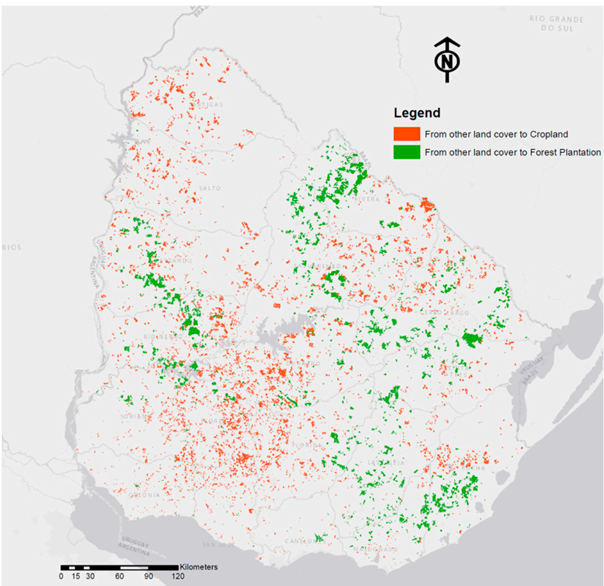


Figure 3. Land cover change map of Uruguay (2000–2011) using LCCS methodology. The map highlights the two main land cover transitions observed in recent decades: (1) the conversion of other land types to cropland (orange) and (2) the expansion of forest plantations (green). These changes reflect the significant agricultural and forestry developments in Uruguay during this period.

2.2.2. Second Stage (2019–2022)

A second stage in the national application of the LCCS methodology commenced with the mapping of land cover for the 2019/2020 period and has since continued, extending to the 2021/2022 period [11]. This stage marks a significant shift in both methods and materials compared to the initial stage (2000–2015).

Description of the New Classification Process

A new mapping procedure was introduced, enhancing the precision and detail of maps produced for the 2019/2020 and 2021/2022 periods (Figure 4). While the LCCS remains central, advancements in remote sensing technologies, combined with the integration of new classification techniques, have enabled greater precision and detail in the maps generated for the 2019/2020 and 2021/2022 periods (Figure 5).

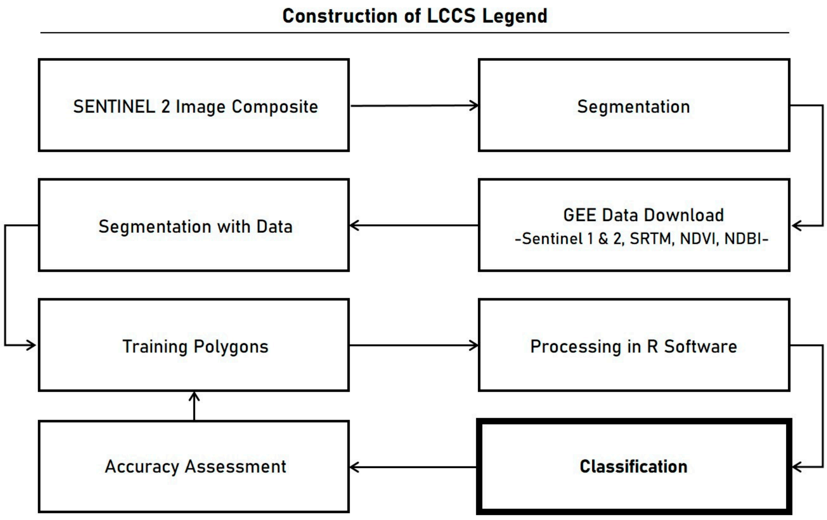
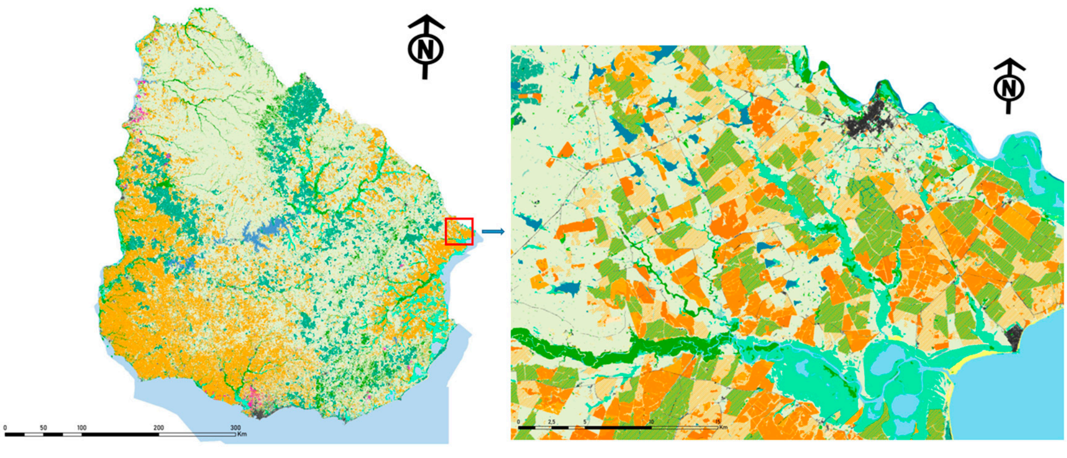


Figure 4. Workflow of the new mapping procedure for the second stage.



(**a**) (**b**)

Figure 5. (**a**) Land cover map of Uruguay for 2021/2022, classified using the 14 land cover classes from the second-stage 7/14/30 legend. At this scale, the main land cover classes that dominate Uruguay's landscape can be observed, including grasslands (pale green), croplands (orange), forest plantations (dark green), native forests (light green), and water bodies (blue). The red square highlights a complex, diverse region in eastern Uruguay with multiple land uses. (**b**) A zoomed-in view of a this area, classified into 30 land cover categories from the second-stage 7/14/30 legend, demonstrating a higher level of detail. For example, different shades of orange are used to distinguish variations in crop types, such as winter, summer, and double-cropping systems.

A. Construction of the LCCS Legend

The new stage of land cover mapping began with the creation of an updated legend (Figure 4), derived from previous ones but adapted to meet the new requirements and capabilities offered by modern remote sensing tools. A detailed description of the new legend is provided in Section 2.3.2.

B. Creation of Sentinel-2 Image Mosaic

For each study period, a cloud-free Sentinel-2 image mosaic was produced using the SEPAL platform (System for Earth Observation Data Access, Processing, and Analysis for Land Monitoring). This platform utilizes Google Earth Engine (GEE) to merge images pixel by pixel, enhancing data quality and ensuring temporal consistency [16–18].

C. Segmentation and Generation of Objects/Polygons

The image mosaic was segmented using eCognition software, applying a multi-resolution algorithm that groups pixels into spectrally and spatially homogeneous objects. The resulting segmentation was exported in vector format, with the objects represented as polygons.

D. Data Download and Analysis in Google Earth Engine (GEE)

The data obtained from GEE included spectral and temporal information from Sentinel-1 (VV and VH polarizations), Sentinel-2 (bands 2, 3, 4, 8, and 11; quarterly NDVI), and SRTM (Shuttle Radar Topography Mission, providing height and slope data) [17–19,26,27]. These statistics were calculated for each polygon and downloaded for integration with the vector tables.

E. Classification using Machine Learning

Training polygons were manually defined using the LCCS3 Basic Coder in QGIS and reviewed in two stages to minimize classification errors. Final classification was carried out in RStudio using the Random Forest algorithm, which efficiently handles large datasets and produces a robust model for automatic classification (Figure 5) [20–23,28–30].

F. Accuracy Assessment

An accuracy assessment was performed by generating random sample points, which were verified through visual interpretation of high-resolution images and Sentinel-2 products, ensuring the reliability and quality of the results.

2.3. Evolution of the LCCS Land Cover Legend in Uruguay

The legend is the core component of the database, as it contains all the information used to define the land cover classes. Uruguay's land cover legend was developed to systematically categorize land cover classes at the national level, ensuring consistency and standardization throughout the classification process.

By adopting the LCCS's parametric approach, Uruguay created a land cover map legend specifically adapted to its national context. Each class within the legend clearly defines landscape elements using explicit, quantifiable parameters. This method avoids ambiguities and overlaps between categories, ensuring consistency and semantic interoperability across different scales or levels of detail. The legend is adaptable to Uruguay's specific needs while also complying with the ISO 19144-2 LCML (Land Cover Meta Language) standard model, which enhances its ability to integrate with both local and global datasets, promoting harmonization and interoperability [10–12].

The LCCS legend in Uruguay has evolved in response to the country's growing mapping needs and technological capabilities (Figure 1). This evolution also aligns with global efforts to standardize land cover datasets, as emphasized in international initiatives like the land cover legend registry (LCLR), which promotes interoperability and supports the achievement of the UN's Sustainable Development Goals (SDGs) [7,31,32].

Two distinct stages mark this evolution, corresponding to the development of different LCCS products. This process culminated in the Land Cover Reference System (LCRS), the final standardized product of Uruguay's national legend.

2.3.1. Initial LCCS Legend: 7/17/46 Classes

During the first phase of the project, an initial land cover legend for Uruguay (Table 1) was developed using the LCCS methodology and LCCS2 software. In 2005, efforts began to develop this preliminary legend, adapted to Uruguay's specific context. This process involved consulting experts from various disciplines, including technicians from key government institutions [11].

Building on national data, the interdisciplinary expertise of the project team, and the preliminary legend developed in 2005, a 46-class legend was first created in 2008. The project team included experts from the Ministry of Housing and Territorial Planning (MVOT), Ministry of Environment (MA), and Ministry of Livestock, Agriculture, and Fisheries (MGAP). FAO's LCCS2 software was used to build the classification, which followed two phases: first, a dichotomous phase that identified eight main land cover types; then, a hierarchical modular phase, where classifiers and their hierarchical arrangement were adapted to each major land cover type [1].

Table 1. Initial land cover legend of Uruguay (2000–2015).

Groups	17 Classes	46 Classes
A11 Cultivated and Managed Terrestrial Areas	Irrigated Crops > 4—5 ha	Irrigated Crops > 4–5 ha
		Sugar Cane
		Rice Plantation > 4–5 ha
		Sugar Cane or Rice > 4–5 ha
	Rainfed Crops > 4—5 ha	Rainfed Crops > 4–5 ha
	Small Crops < 4—5 ha	Rainfed Crops < 4–5 ha
		Irrigated Crops < 4–5 ha
	Forest Plantation > 5 ha	Forestry Plantation > 5 ha
		Planted Coastal Forest
		Eucalyptus Plantation > 5 ha
		Pine Forestry Plantation > 5 ha
		Shelter and Shade Woods < 5 ha
		Urban Park
	Fruit Trees Plantation	Citrus Plantation
		Fruit Tree Plantation
A12 Natural and Semi—natural Vegetation	Natural Herbaceous	Natural Grassland
		Psammophilic Herbaceous
		Natural Grassland with Scattered Palm Groves (1–15%)
		Herbaceous with Rocky Outcrop
	Shrubs	Shrub and Natural Grassland
	Native Forest	Native Hill and Ravine Forest
		Gallery Native Forest
		Native Forest
		Natural Park Forest
	Palm Groves	Palm Groves
A24 Natural and Semi-natural Aquatic or Regularly Flooded Vegetation	Flooded Natural Areas	Permanently Flooded Herbaceous (Marsh)
		Seasonally Flooded Herbaceous

Table 1. *Cont.*

Groups	17 Classes	46 Classes
B15 Artificial Surfaces and Associated Areas	Urban Equipment	Airports
		Airfields
		Sports Facilities
		Industrial Areas
		Port Areas
	Urban Area	Urban Area
	Dispersed Urban Areas	Dispersed Urban and Crops
		Dispersed Urban and Natural Grassland
		Dispersed Urban and Forestry Plantation
	Quarries, Sand Pits, Open-Pit Mines	Quarries, Sandpits, Open-Pit Mines
B16 Uncovered or Bare Areas	Bare Areas	Beach Sand
		Dunes
		Consolidated Rock
		Bare Soil
B27 Artificial Bodies of Water, Snow, and Ice	Artificial Water Bodies	Canals
		Lakes, Reservoirs, and Dams
B28 Natural Bodies of Water, Snow, and Ice	Natural Water Bodies	Lagoons
		Watercourses
		Wet Soil and Seasonally Flooded

As new data and products became available, the legend was adjusted to address emerging needs and limitations in the classification process. Over time, the original 46-class legend was derived into a simplified 17-class legend, suitable for analyzing land cover changes over the years 2000 to 2015 [11].

2.3.2. Current LCCS Legend: 7/14/30 Classes

Advancements in geospatial technologies, along with improvements in temporal and spatial resolution, have enabled the creation of a more detailed and accurate land legend. In the 2019/2020 and 2021/2022 land cover datasets, the legend is organized into three levels of detail: macroclasses (7), classes (14), and subclasses (30) (Table 2) [33].

The macroclasses represent the seven main land cover types, aligning with the predefined categories established in the dichotomous phase of the LCCS. These macroclasses serve as the broadest categories within the system.

Next, the seven macroclasses are further divided into fourteen classes, providing a level of detail that facilitates direct comparisons with earlier land cover maps produced using the LCCS. This intermediate level enhances specificity while maintaining consistency with previous classifications.

Finally, these 14 classes are subdivided into 30 subclasses, offering even finer detail. This hierarchical structure allows for a more precise evaluation of different land cover types, improving the monitoring and analysis of land cover changes in Uruguay. The advances in geospatial technology have significantly improved the spatial and temporal resolution of land cover assessments, enhancing both the accuracy and reliability of the classification and expanding the number of distinct classes.

Table 2. Uruguayan Land Cover Legend (2019/2020–2021/2022).

Macroclass	Class	Subclass
Cultivated Land Areas	Crops	Rice Crops
		Sugar Cane Crops
		Winter Crops
		Winter and Summer Crops (Double Cropping)
		Summer Crops
		Small Crops
		Agricultural Grassland
	Forestry Plantation	Shelter and Shade Plantation
		Forest Plantation (Eucalyptus)
		Mixed or Unknown Forest Plantation
		Forest Plantation (Pine)
		New or Harvested Forest Plantation
	Fruit Trees	Fruit Trees
Natural and Semi-Natural Vegetation	Grassland	Grassland
		Grassland with Rocky Outcrop
		Wet or Periodically Flooded Grassland
	Native Forest	Native Forest
		Scattered Native Forest
	Palm Groves	Palm Groves
		Grassland and Palm Groves
	Shrubs	Shrubs
Natural and Semi-Natural Aquatic or Regularly Flooded Vegetation	Flooded Natural Area	Marshes/Wetlands
Artificial Surfaces and Similar Areas	Artificial Impervious Area	Impervious Area
	Dispersed Artificial Impervious Area	Scattered Impervious Area
	Quarry, Sand Pit, Open-pit Mine	Quarry, Sandpit, Open-pit Mine
Bare or Exposed Areas	Bare Area	Sand
		Consolidated Rock
		Bare Soil
Artificial Water Bodies, Snow, and Ice	Artificial Water	Artificial Water Body
Natural Water Bodies, Snow, and Ice	Natural Water	Natural Water Body

2.3.3. Land Cover Reference System (LCRS)

Lately, DINOT, in collaboration with FAO, has developed a new product, Uruguay's Land Cover Reference System (LCRS), marking a significant evolution from the legends used in previous land cover products. The LCRS is designed to provide a detailed and accurate representation of the various land cover types across Uruguay and aims to serve as a reference for harmonizing the various mappings carried out by multiple national institutions [33,34].

The LCRS offers several advantages over traditional legends. It provides a higher level of detail through its multi-tiered classification structure, it is flexible in terms of scale for different analyses, and its hierarchical design allows for updates and the disaggregation of categories to better reflect real-world conditions. Moreover, it is compatible with

Geographic Information Systems (GISs), making it easy to integrate into spatial analysis platforms and applications [34].

Developed using LCCS 3 software and based on the previous legend, each class within the system is enriched with additional parametric attributes such as coverage percentage, height, and water persistence. This results in a dynamic, adaptable land cover database that can evolve to meet future needs.

The system is initially divided into two main groups: vegetated and non-vegetated areas. Each branch is then further subdivided based on specific attributes relevant to Uruguay. For instance, vegetated areas include both natural vegetation (terrestrial and aquatic) and cultivated or managed vegetation (such as trees and crops), each categorized at multiple levels (Table 3). In the case of cultivated vegetation, herbaceous crops are detailed up to level 7, addressing specific needs identified by MGAP.

Table 3. Uruguayan national Land Cover Reference System.

Land Cover Classification Levels						
Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**	**Level 7**
Vegetated Area	Natural and semi-natural vegetation	Terrestrial	Dominated by trees	Dense natural forest	Native Serrano and Stream Forest	
					Gallery Forest	
					Palm Groves	
				Dispersed Natural Forest	Native Serrano and Stream Forest	
					Gallery Forest	
					Park Natural Forest	
					Palms	
			Dominated by shrubs	Shrubland		
				Shrubland with Grasses	Open Shrubland	
					Closed Shrubland	
			Dominated by Herbaceous Plants	Grassland/Praries	Grassland with Rocky Outcrops	
					Grassland with Palms	
				Psammophile Vegetation		
				Natural Vegetation Temporarily/Seasonally Waterlogged		
		Aquatic	Dominated by Herbaceous Plants	Permanent flooded natural vegetation		
	Cultivated Vegetation	Forestry crops	Forest plantation	Timber Plantation	Eucalyptus	
					Pine	
					Mixed or Unknown Plantation	Mixed Plantation
						Unknown Plantation
				Protection Forest	Shade and Shelter Forest	
					Coastal Plantation	
			Fruit plantations	Small-scale Crops	Citrus	
					Olive	
					Other Fruit Trees	
				Medium and Large-scale Crops	Citrus	
					Olive	
					Other Fruit Trees	

Table 3. *Cont.*

Land Cover Classification Levels						
Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**	**Level 7**
			Small-scale Crops			
		Herbaceous Crops	Medium and Large-scale Crops	Summer Crop	Irrigated	Rice
						Sugarcane
						Soybean
						Corn
						Sorghum
						Sunflower
						Other Crops
					Dryland	Soybean
						Corn
						Sorghum
						Sunflower
						Other Crops
				Winter Crop	Irrigated	Wheat
						Barley
						Rapeseed
						Other Crops
					Dryland	Wheat
						Barley
						Rapeseed
						Other Crops
				Winter and Summer Crop	Irrigated	Double Cropping
						Annual Green Manure
					Dryland	Double Cropping
						Annual Green Manure
				Perennial Crop	Pastures	
Non-vegetated Area	Terrestrial	Natural Surface	Bare Areas	Bare Soil		
				Consolidated Rock		
				Sand	Dunes	
					Beach Sand	
		Artificial Surface	Non-linear Built Area	Dispersed Urban	Dispersed Urban and Crops	
					Dispersed Urban and Grassland	
					Dispersed Urban and Plantations	
				Dense Urban		
				Infrastructure	Airport/Aerodrome	
					Sports Infrastructure	
					Industrial Areas	
					Ports	
			Linear Built Areas			
			Extraction Sites	Quarries		
				Mines		

Table 3. *Cont.*

Land Cover Classification Levels						
Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**	**Level 7**
	Water	Water Courses	Natural Water Courses	Rivers, Streams, and/or Gullies		
			Artificial Water Courses	Canals		
		Water Bodies	Natural Water Bodies			
			Artificial Water Bodies			

The Land Cover Reference System establishes a national framework that aims to ensure interoperability among existing classifications, facilitates comparisons with current classifications by clearly defining classes using objective criteria, and is sufficiently adaptable to evolve according to future needs.

3. Results: Implementation of LCCS in Uruguay

3.1. National Land Cover Database

As a result of applying the LCCS methodology, Uruguay has developed a detailed and standardized national land cover database (Figure 6). This database provides reliable information on land cover distribution, adapted to the country's specific needs while ensuring semantic interoperability with international standards. The national database consists of multiple land cover maps, generated for the years 2000, 2008, 2011, 2015, 2019/2020, and 2021/2022. Each map includes a corresponding legend, structured into hierarchical levels that categorize land cover types and spatial distribution across Uruguay. Additionally, the Land Cover Reference System (LCRS) has been created to evolve and harmonize these legends, providing a unified framework for integrating data from various national mapping efforts (Figure 6) [1,12,33,34].

Land cover Products

Legend

> Legend Uruguay 7/17/46 classes
> Legend Uruguay 7/14/30 classes
> Land Cover Reference System Uruguay

DBS

> LC 2000
> LC 2008
> LC 2011
> LC 2015
> LC 2019/2020
> LC 2021/2022

Change assessment

> Change assessment 2000—2015

Figure 6. Land cover products using LCCS in Uruguay.

3.1.1. Land Cover Distribution and Temporal Changes

Land cover mapping with LCCS in Uruguay showed that natural herbaceous areas dominate, covering over 50% of the country, followed by agricultural areas and forest plantations.

Over the past two decades, the analysis shows significant changes in these classes, with the most substantial transformations occurring between 2000 and 2015. During this period, natural herbaceous areas declined by 13% as they were converted primarily into rainfed crops and forest plantations [4]. This shift reflects a response to favorable market conditions and policy incentives that encouraged agricultural and forestry expansion [35]. The changes are most evident in the central-west, northeast, and southeast regions, where rainfed crops have expanded eastward and forest plantations have increased in the eastern, northwest, and central-west zones.

Although these trends continued beyond 2015, the pace of expansion slowed, reflecting shifts in commodity demand. These results align with agricultural census data, underscoring economic drivers and policy influences on land use and highlighting the need for balanced resource management [35,36].

3.1.2. Accuracy Improvement

The accuracy of land cover mapping in Uruguay has improved notably from the first stage (2000–2015) to the second stage (2019/2020 and 2021/2022), with overall accuracy increasing from approximately 85% to 95% [11,12,21]. However, this enhancement was not consistent across all classes. In the second stage, the inclusion of more detailed subclasses increased the complexity of classification, particularly at the subclass level. While broad categories like grasslands achieved high accuracy, more specialized classes, particularly those with smaller areas or more heterogeneous characteristics, faced challenges.

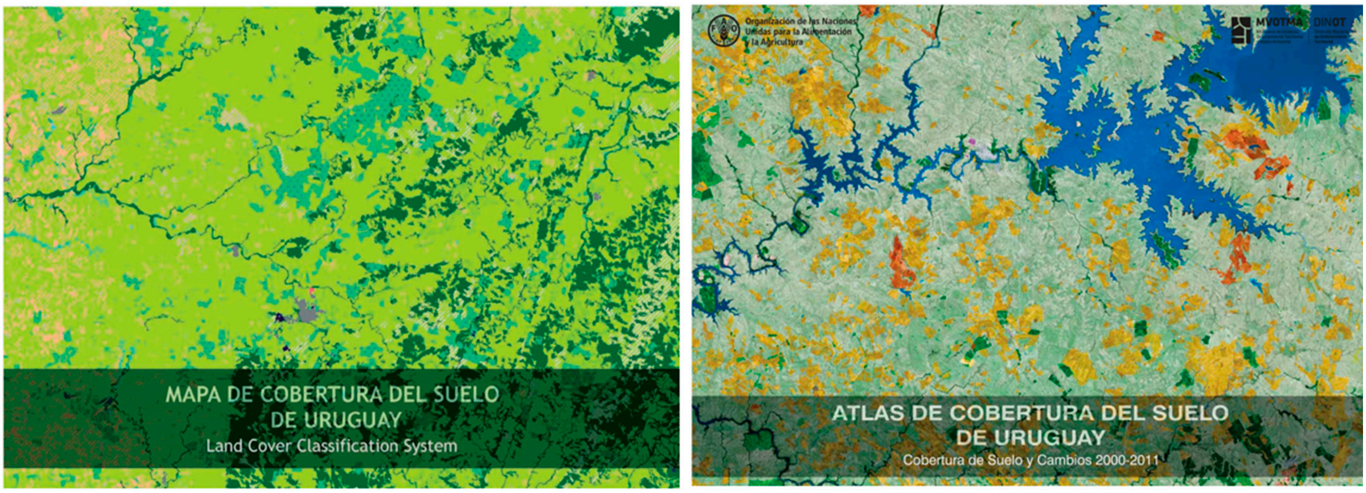
The accuracy also varied by the level of analysis. Macroclasses showed higher precision than subclasses, emphasizing the trade-off between more detailed classifications and the difficulty of maintaining high accuracy, particularly in areas with mixed land covers or complex environmental conditions. The increase in the number of subclasses led to more classification errors, particularly when distinguishing between visually similar land covers. For instance, differentiating between forest plantations (Eucalyptus, Pine, or Mixed Plantations) and fruit trees or between grassland and palm groves proved difficult due to their similar appearance in satellite imagery, especially in regions with heterogeneous vegetation. Similarly, the distinction between small crops and pastures or wetlands and flooded grasslands also presented challenges due to environmental variability and small-scale presence.

3.2. Official Publications

As an additional outcome of the LCCS implementation, two official publications were produced: the Mapa de Cobertura del Suelo de Uruguay (Uruguay Land Cover Map) (2008), which focused on the land cover classification for that year, and the Atlas de Cobertura del Suelo 2011-Cobertura del Suelo y Cambios 2000/2011 (Land Cover Atlas 2011—Land Cover and Changes 2000/2011) (Figure 7), which documented land cover data along with detected changes over the 2000–2011 period. These publications served to communicate Uruguay's advancements in land cover monitoring and the initial results of LCCS classification, highlighting both the land cover distribution and change detection across the country [11,12].

3.3. Online Land Cover Atlas of Uruguay

The Online Land Cover Atlas of Uruguay (Figure 8) is the result of the collaborative effort, initiated in 2005, between the Uruguayan government and the Food and Agriculture Organization of the United Nations (FAO). Hosted by the Ministry of Housing and Territorial Planning (MVOT) on the ArcGIS platform, this dynamic and interactive tool allows continuous consultation, comparison, and updates of land cover data. By maintaining up-to-date land cover information and conducting multitemporal analysis, the Atlas provides insights into the dynamics of the territory and enables the projection of different scenarios across various scales (global, national, departmental, and local). It also supports the download of geospatial data for specific analyses, offering reliable information to inform public policies for sustainable development [33].



(**a**) (**b**)

Figure 7. Covers of Uruguay's official land cover publications: (**a**) Uruguay Land Cover Map (2008) (**b**) Land Cover Atlas 2011—Land Cover and Changes 2000/2011.

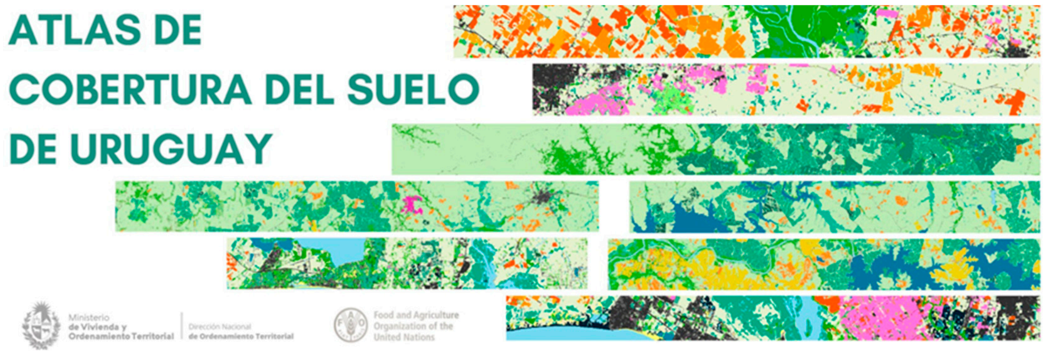


Figure 8. Online Land Cover Atlas of Uruguay.

The main objective of the web Atlas is to provide decision-makers, researchers, academics, and other stakeholders with updated land cover data, serving as a tool to interpret territorial dynamics and assess the impact of human activities on the landscape.

In addition, the Atlas serves as a key unifier for various national institutions engaged in land cover and land use mapping efforts. By centralizing and harmonizing data generated by these actors, the Atlas helps establish a common framework for analyzing and managing the country's natural resources. This unified vision promotes coherent decision-making and supports sustainable territorial planning.

3.4. Application of LCCS Products in Uruguay

Beyond their primary purpose of monitoring land cover and assessing changes, LCCS products serve several additional functions. Some notable examples include the use of land cover data for analyzing territorial dynamics and developing land use plans, as well as for evaluating progress toward the Sustainable Development Goals (SDGs) [2,7].

3.4.1. Land Use Planning

Land use planning for sustainable development is a strategic process where land use and natural resources are managed in a balanced manner, considering the current and future needs of society and the environment [7]. LCCS land cover maps play a crucial role in this process, as they provide a detailed and accurate representation of land use and territorial dynamics in a specific area.

In this context, the land cover database of Uruguay has become a fundamental input for the formulation of national and local land use plans, supporting evidence-based decision-making. The information it provides offers multitemporal and accurate data on land cover, helping to identify suitable areas for various land uses, such as urban expansion, agricultural development, ecological conservation, and other essential activities for sustainable development. This contributes to more effective and sustainable land management practices, such as promoting crops or afforestation in areas that present favorable conditions for agriculture, while vulnerable or critical zones can be protected to conserve biodiversity.

Uruguay currently has high levels of land use dynamisms (Figure 9) due to its nature of being a raw materials producer, based on agricultural exploitation: livestock/forestry/crops /industries/energy/drinking water/urban settlements [4,5].

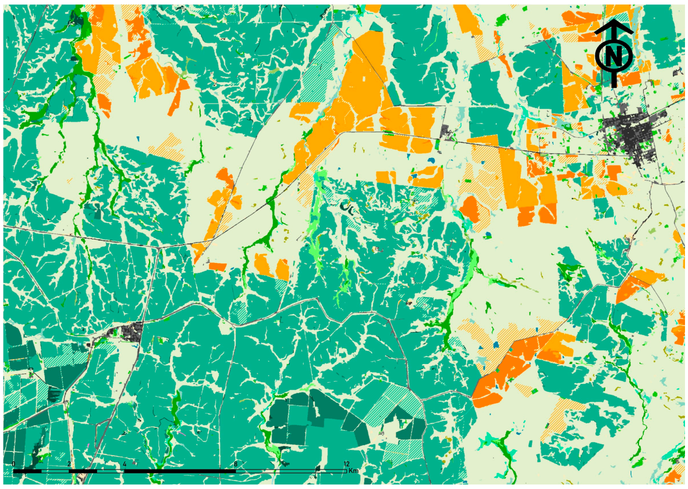


Figure 9. Land cover map of Uruguay 2019/2020, showing various land uses and cover types, such as forestry (green), urban areas (gray), native forest (light green), and croplands (orange). The map highlights the prevalence of forested areas near urban regions, illustrating the competition for land between agricultural and forestry activities alongside the demand for urban expansion. The image focuses on the localities of Guichón and Algorta, located on the border between the departments of Paysandú and Río Negro in western Uruguay.

Livestock continues to be the most important sector and occupies the largest area. However, it is losing relative weight because of the growth of other productive activities, such as, fundamentally, agriculture and forestry, but also energy generation, new kinds of urban settlements, etc. [3–5].

In addition, urban planning needs settlement classification and growth measurement to guarantee sustainable urbanization. The integration of Earth Observation data and geospatial approaches through LCCS data into planning processes ensures that decisions regarding land use are based on solid and updated information, promoting sustainable development and optimal resource use, resulting in more effective land management. This is a key aspect of addressing contemporary challenges such as population growth, climate change, and the preservation of natural resources. By encouraging optimal and balanced resource use, it contributes to the creation of more sustainable cities, resilient economies, and healthy ecosystems.

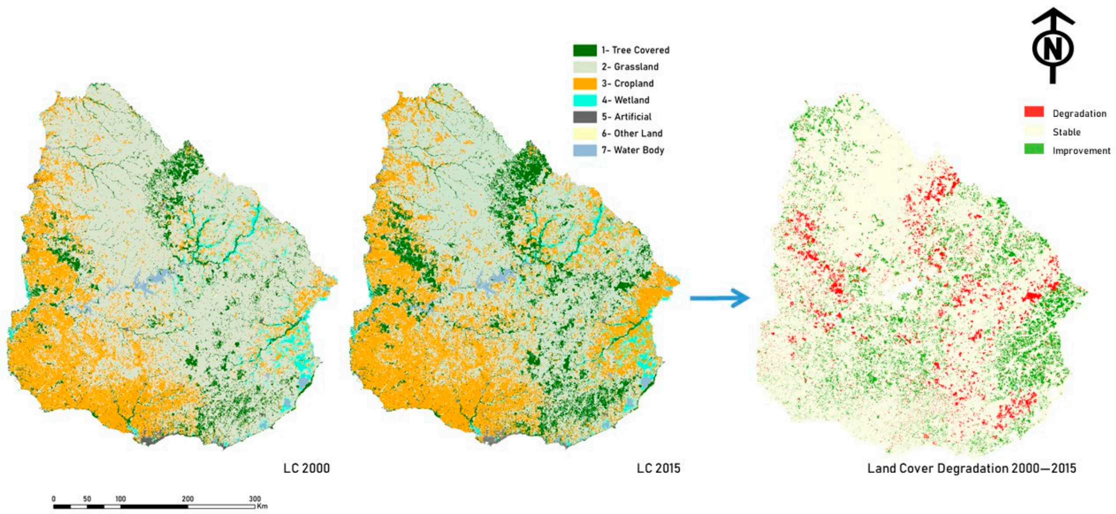
Therefore, territorial planning supported by LCCS land cover maps allows for informed decision-making oriented toward the long term, with a focus on sustainable development that prioritizes sustainability and overall well-being, promoting a balance between human development and environmental conservation.

3.4.2. Sustainable Development Goals (SDGs)

LCCS products play a crucial role in monitoring and reporting on Sustainable Development Goals (SDGs), particularly for indicators 15.3.1, 11.3.1, and 11.7.1 [7].

SDG 15.3.1

Indicator 15.3.1 measures the proportion of degraded land relative to the total land area, using three sub-indicators: land cover and land cover change, Soil Organic Carbon (SOC) stocks, and land productivity. In Uruguay, the sub-indicator land cover and land cover change has been assessed using products developed with the LCCS methodology, which were subsequently reclassified into the seven land cover classes defined by the IPCC (Intergovernmental Panel on Climate Change) for reporting purposes related to this indicator. These LCCS products provided a baseline for understanding the evolution of land cover, enabling the country to monitor and report on land degradation while supporting efforts to achieve the target of SDG 15.3.1 (Figure 10) [13].



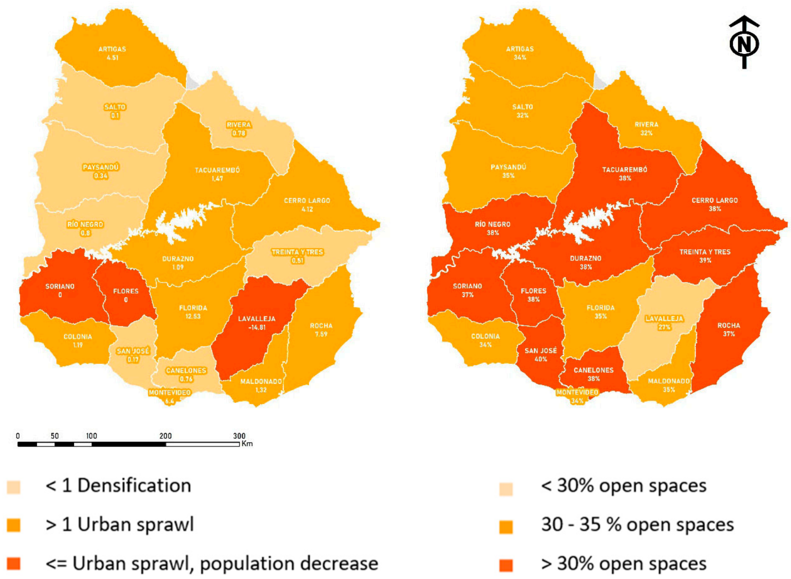
(**a**) (**b**) (**c**)

Figure 10. SDG 15.3.1—sub-indicator land cover and land cover change. (**a**) Land cover of Uruguay for the year 2000, reclassified using the IPCC's seven classes: tree covered, grassland, cropland, wetland, artificial, other land, and water body; (**b**) land cover of Uruguay for the year 2015, also categorized using IPCC's seven classes; and (**c**) land cover degradation from 2000 to 2015, calculated using the Trends.Earth tool [13].

SDG 11.3.1 and SDG 11.7.1

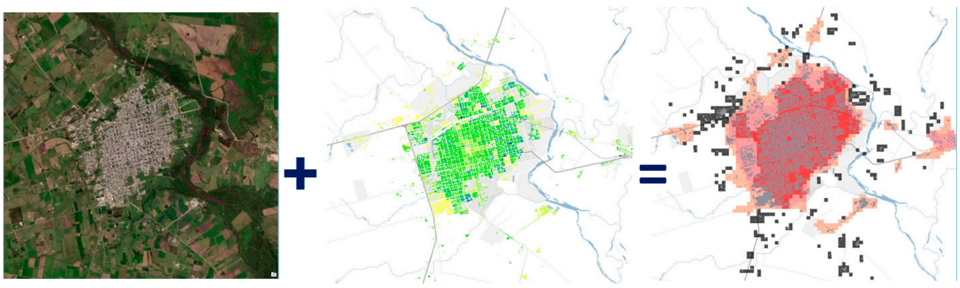
Indicators 11.3.1 and 11.7.1, part of SDG 11, aim to make 'cities and human settlements inclusive, safe, resilient, and sustainable' (Figure 11). LCCS land cover data have been instrumental in calculating these indicators [7]. These data enabled DINOT technicians to analyze urban expansion patterns, identify trends, pinpoint areas of concern, and facilitate improved land use planning [37].

Moreover, the global approach to defining and classifying urban and rural areas, Degree of Urbanisation (DEGURBA), is applied in Uruguay by using 'Urban' and 'Dispersed Urban' classes derived from land cover data generated with the LCCS (Figure 12) [9]. This integration of local land cover data with a global methodology allows for a consistent classification of urban and rural areas, ensuring that the spatial patterns of urbanization in Uruguay align with internationally recognized standards. This approach facilitates more accurate comparisons and data analysis both within the country and at a global level, which is essential for evidence-based policymaking and for measuring progress toward the Sustainable Development Goals in both urban and rural areas.



(**a**) SDG 11.3.1 (**b**) SDG 11.7.1

Figure 11. (**a**) SDG 11.3.1 indicator: Land consumption rate relative to population growth rate by department in Uruguay. Yellow tones (<1) represent urban densification, where land consumption grows slower than population. Orange tones (>1) indicate urban expansion, where land consumption grows faster than population. Red tones ($\leq$0) highlight urban expansion with population decline, suggesting potentially unsustainable growth. (**b**) SDG 11.7.1 indicator: Average share of the built-up area of cities that is open space for public use. This indicator highlights the differences among departments regarding the availability of accessible urban public spaces, with higher values representing a greater proportion of open public space in urban areas.



NAME	DENSITY inhab./ha	BUILT-UP AREA	POPULATION	DISTANCE
Major Urban Areas	>=15	>50%	>20,000	
Intermediate Urban Areas	>=15	>30%	5,000–20,000	
Minor Urbanized Areas	>=3	>15%	500–5,000	
Dispersed Urbanized Areas	>=0.5	>15%	50–500	
High-Density Periurban areas	>=15	>50%	5,000–20,000	<1 km to UA
Medium-Density Periurban Areas	>=3	>15%	>5,000	<1 km to UA
Low-Density Periurban Areas	>=0.5	>15%	50-500	<1 km to UA
Mostly Uninhabited Area	<0.5			

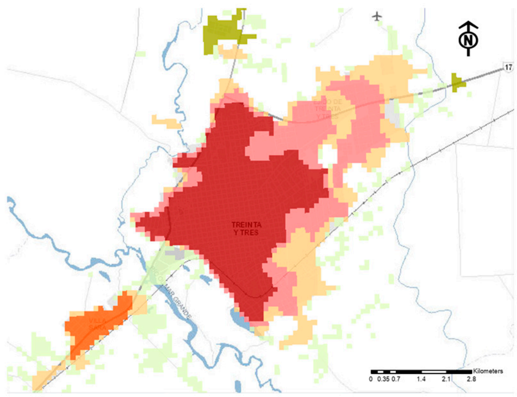


Figure 12. Locally adapted settlement classification in Uruguay based on DEGURBA methodology. The criteria combine population density, built-up area percentages (from LCCS products), population thresholds, and distance to urban areas.

4. Discussion

4.1. Critical Evaluation of Land Cover Product Quality

4.1.1. Methodological Improvements in Land Cover Classification

The second stage of land cover classification brought key improvements that significantly enhanced both the accuracy and efficiency of the process. One of the most notable advancements was the transition from Landsat to Sentinel-1 and Sentinel-2 images, offering higher resolution and improved accuracy. This allowed for more detailed and continuous analysis, even under adverse weather conditions [9]. Furthermore, the use of cloud-based platforms such as Google Earth Engine and SEPAL provided efficient access to, and processing of, large volumes of data, reducing analysis time.

Additionally, the adoption of machine learning techniques, particularly the Random Forest algorithm, automated classification processes, eliminating subjectivity, improving reproducibility, and enabling the handling of large datasets more effectively.

4.1.2. Challenges and Limitations in Data Comparison Between Stages

Comparing data from the first and second stages of the project presents a series of methodological and technical challenges (Table 4).

Table 4. Methodological differences between stages.

	2000 2008 2011 2015 **Landsat Satellite Images**	**Methodological Change**	**2019–2020** **Sentinel 1 (Radar) and 2 Satellite Images**
Spatial resolution	30 m		10 m
Temporal resolution	Every 16 days		Every 4–5 days
Image availability	Limited due to acquisition frequency and the presence of clouds		Greater availability of images, less affected by the presence of clouds due to radar's ability to penetrate clouds
Sensor type	Passive sensors (optical and thermal)		Passive (optical) and active (radar) sensors
Image acquisition dates	A single moment in the period, conditioned by image availability and the presence of clouds		Composites of images from the entire period are used, allowing better temporal coverage
Classification	Highly dependent on the operator's subjectivity		Semi-automatic, reducing dependence on subjectivity and facilitating reproducibility
Advantages	Information from optical and thermal sensors. Manual classification allows for the elimination of errors in spectrally similar classes.		Higher spatial and temporal resolution, with year-round information. Less dependence on cloud cover due to radar use. Semi-automatic classification reduces subjectivity
Disadvantages	Limited image availability due to acquisition frequency and the presence of clouds. High subjectivity in classification.		Requires greater processing capacity due to the larger amount of data

A major challenge arises from differences in spatial and temporal resolution between the images used, making it difficult to integrate results and ensure temporal continuity of land cover maps. Sentinel and Landsat imagery offer varying levels of detail, making it hard to compare maps across different periods. Areas previously classified as homogeneous with Landsat may now show variability in Sentinel images.

Another challenge lies in the types of sensors employed. During the first stage, only optical sensors (Landsat) were used, whereas the second stage incorporated both radar (Sentinel-1) and optical sensors (Sentinel-2). Radar technology helped overcome cloud cover issues but introduced new data variables, particularly regarding moisture detection. This variation means that land covers identified by different technologies are not directly comparable, creating uncertainties in both spatial and temporal analyses.

Differences in data availability between the stages also pose a significant limitation. Landsat images, with their lower capture frequency and greater susceptibility to cloud cover, provided limited data for analysis. In contrast, Sentinel images, with their higher temporal frequency, offer richer coverage, enabling continuous and more accurate monitoring. This improved temporal granularity could reveal changes that were not detectable in the first stage.

Despite these methodological differences, comparisons between the two stages are essential, necessitating harmonization efforts to ensure meaningful analysis. The three-level legend structure was designed to facilitate such comparisons with previous datasets. However, variations in methodology and technological advancements between stages still pose significant challenges.

To enable national-level comparisons, both land cover products were resampled to a common spatial resolution of 30 m. This resampling process addresses some of the discrepancies caused by the differences in the native resolutions of Landsat and Sentinel imagery, such as Sentinel-2's finer 10 m resolution versus Landsat's coarser 30 m resolution. By standardizing the spatial scale, this adjustment helps reduce certain errors, particularly those linked to varying spatial resolutions. Nevertheless, this approach does not completely eliminate challenges associated with comparing small, highly variable, or complex land cover types. For instance, small urban areas or heterogeneous vegetation types remain prone to misclassification even after resampling, as the resolution may still not adequately capture their intricate spatial patterns.

Moreover, resampling the data to 30 m sacrifices some of the advantages inherent in Sentinel's higher spatial precision. Fine details such as narrow linear features or fragmented vegetation patches, which are crucial for accurate classification in detailed land use planning, may be lost. This limitation highlights a trade-off between achieving comparability and preserving high-resolution detail, which is vital for nuanced analyses.

Additionally, as the classification relies on Object-Based Image Analysis (OBIA), segmentation accuracy becomes another critical factor. Differences in the native resolution of the input imagery can lead to segmentation discrepancies, complicating direct comparisons across datasets. To address these issues for classes requiring greater detail, manual methods such as polygon editing, reclassification, and incorporating supplemental information were employed to improve the accuracy of comparisons. These efforts underscore the complexities and methodological rigor involved in harmonizing land cover data while striving to retain as much spatial and thematic detail as possible.

4.1.3. Challenges in Class Comparison: Two Cases

A notable example of the challenges faced in comparing data between the two stages is the discrepancies in estimating forested areas and urbanized areas (Figure 13).

In the second stage, products generated with Sentinel images offer higher spatial and temporal resolution, enabling the identification of details that were previously indistinguishable, such as firebreaks, roads, or separation areas between forest plantations. In the first stage, these areas were grouped under the broad category of 'forest plantation' without differentiation, leading to an overestimation of the effective forested area. Figure 14 shows the percentages of the total forested area across the different LCCS mappings, where the 2015 mapping indicates a higher forested area compared to the subsequent mappings. However, this difference is not real but stems from the methodological variations mentioned, such as the lower resolution of satellite images used in the first stage.

This discrepancy highlights the challenges of relying on data with inconsistent methodologies, as it can lead to misinterpretations about land cover changes and their implications. Accurate and consistent information is crucial for land use planning, especially in regions with regulations on forest plantation surface areas. Misjudgments based on overestimated forested areas could result in ineffective or misaligned policies, potentially undermining sustainable land management and regulatory compliance. The methodological improvements introduced in the second stage ensure a more reliable foundation for decision-making and better support the development of informed forest policies.

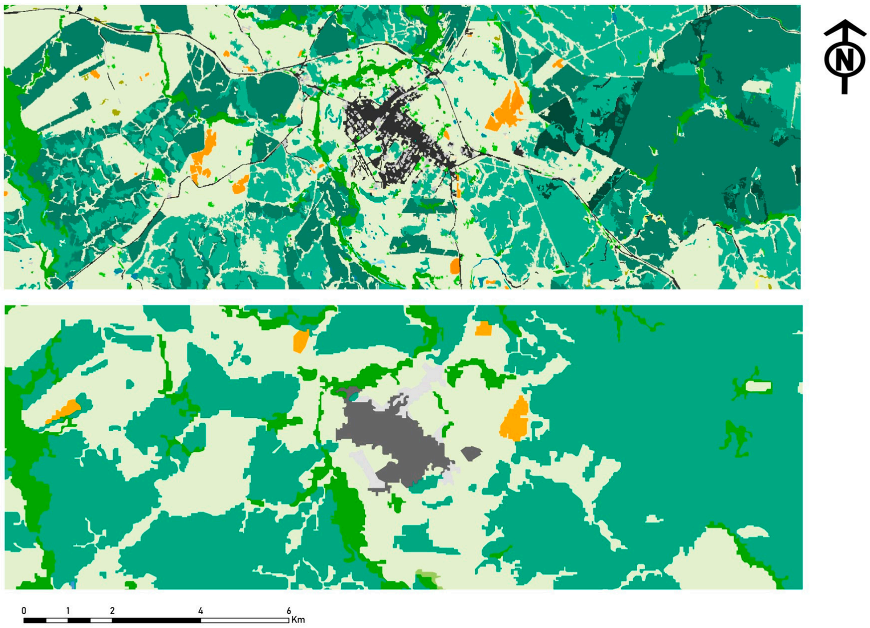


Figure 13. Comparison of resolution and precision between land cover maps from the first stage (2015, Landsat) and the second stage (2021/2022, Sentinel), focusing on urban and forest classes. The top image illustrates the city of Tranqueras, located in the department of Rivera, Uruguay, as mapped in 2021/2022. This map showcases higher resolution and improved precision in distinguishing land cover classes, such as consolidated urban (dark gray), dispersed urban (light gray), and forest plantation (dark green). The bottom image presents the same area using the 2015 land cover mapping, which, due to lower resolution, groups smaller features and lacks the detail evident in the Sentinel-based mapping.

Figure 14. Percentage of total forested area in Uruguay according to LCCS mappings.

Similarly, challenges also arise in estimating urban and dispersed urban areas. In the first stage, the lower spatial resolution of Landsat images led to less accurate classification, overestimating the extent of dispersed urban areas. The larger and less detailed polygons generated from Landsat imagery often included undeveloped or vegetated areas in urban classifications. In contrast, the higher resolution of Sentinel images now allows for distinguishing between consolidated urban areas, peri-urban zones, and dispersed settlements. This differentiation is vital for land use planning, as it informs the provision of services, infrastructure, and sustainable urban expansion.

Misinterpretations resulting from a direct comparison between products from the two stages can lead to misleading conclusions, which could significantly influence land use policies. These discrepancies, such as overestimating forest cover or underestimating urban expansion, may ultimately affect strategic decisions in land management and resource allocation.

4.2. Advantages of the Application of LCCS in Uruguay

4.2.1. Benefits of the LCCS Approach

The adoption of the LCCS methodology in Uruguay has provided numerous benefits for land cover mapping. The standardized classification system, combined with iterative improvements, has enabled a more comprehensive understanding of land cover dynamics. The flexibility of LCCS to use a wide range of satellite data—from Landsat to Sentinel—has enhanced the accuracy and relevance of land cover maps.

The use of the LCCS methodology, which combines high-resolution satellite data with advanced classification techniques for national land cover mapping, has demonstrated significant benefits. This approach has enhanced the accuracy, detail, and consistency of land cover data, providing a more comprehensive understanding of territorial dynamics. It has also facilitated better decision-making in areas such as land use planning, environmental monitoring, and sustainable development by offering reliable, up-to-date information that supports informed policy and management actions.

4.2.2. Impact on Policy and Planning

LCCS products have had a significant impact on land use planning and policy formulation in Uruguay. The detailed and accurate land cover information facilitates evidence-based decision-making for sustainable development. For example, the land cover assessment related to urban expansion contributes to better management of urban sprawl and supports sustainable city planning by identifying suitable areas for expansion while preserving green spaces and minimizing environmental impacts. Related to agricultural development, the LCCS database enables policymakers to oversee the balance between agricultural growth and environmental conservation. LCCS products help monitor the expansion of agriculture, assess soil health, and prevent overuse of resources, contributing to long-term land productivity. Therefore, LCCS products contribute to informed territorial planning and long-term decision-making with a focus on sustainable development.

Additionally, LCCS data have allowed Uruguay to monitor and report on Sustainable Development Goals (SDGs), including SDG 15.3.1 (land degradation) and SDG 11 (sustainable cities). LCCS products have supported Uruguay's efforts to achieve its sustainability targets and address critical challenges by identifying vulnerable ecosystems, improving natural resource management, and enhancing climate resilience. But, by leveraging LCCS products, Uruguay not only meets its own national sustainability goals but also strengthens its position within the international community. The compatibility of LCCS data with global standards enables Uruguay to share reliable information with international organizations and to contribute to global sustainability databases.

Overall, Uruguay's LCCS has proven essential for integrating environmental sustainability into the country's planning and policy formulation processes, aligning national development with sustainable land use practices, and fulfilling its commitments to global sustainability goals.

4.3. Future Applications and Improvements

4.3.1. Emerging Technologies

Advances in remote sensing technologies and classification techniques offer promising opportunities for the future of land cover mapping. Emerging sensors with superior spatial and temporal resolutions, combined with advanced machine learning algorithms, will enhance the precision and detail of land cover products. The incorporation of data from hyperspectral imagery and next-generation synthetic aperture radar (SAR) systems could provide deeper insights into land cover dynamics, further increasing the accuracy and reliability of future classifications.

4.3.2. Training and Resources

Ongoing training for technicians and professionals is critical to maximize the effectiveness of LCCS-based tools. Training in advanced geospatial techniques, data processing, and interpretation will help ensure that the products generated meet the highest precision standards. Strategic investments in training and technological infrastructure will strengthen the capacity to implement LCCS methodologies effectively, allowing Uruguay to address emerging challenges in land cover mapping and monitoring.

5. Conclusions

The Online Land Cover Atlas of Uruguay, as the culmination of the LCCS methodology application, represents a major achievement in land management and planning. Advances in classification methodologies and remote sensing technologies have enabled more accurate and up-to-date data collection, providing a vital tool for informed decision-making. Interinstitutional collaboration and the integration of multiple state initiatives have been key to the success of this project, contributing significantly to Uruguay's sustainable development.

The transition from Landsat images to Sentinel imagery, combined with advanced classification techniques such as machine learning, has substantially improved the quality and accuracy of land cover data. The efforts to create a unified Land Cover Reference System, embodied in the new Land Cover Atlas, address the challenges of harmonizing different datasets and methodologies, offering a cohesive framework for future territorial analysis.

However, Uruguay faces challenges in land cover mapping, particularly due to the lack of coordination among the various institutions conducting their own mapping efforts, which can lead to inconsistencies and duplication of work. While satellite image technology is advancing and becoming more accessible, the integration of data from different sources remains a significant challenge. This is where artificial intelligence (AI) can play a fundamental role: machine learning and deep learning techniques can automate the processing of large data volumes, improving both the speed and accuracy of land cover classification and enabling more frequent and detailed updates. This could help overcome institutional fragmentation and provide more robust tools for decision-making in key areas such as urban planning, agriculture, and biodiversity conservation.

As remote sensing technology and classification methods continue to advance, and with ongoing professional training, Uruguay will be well positioned to enhance its land management practices. This will provide more precise and detailed data to guide informed decision-making in areas such as urban planning, agriculture, and conservation. Additionally, ongoing training for professionals and fostering interinstitutional collaboration will strengthen the country's capacity to achieve sustainable development and ensure effective management of natural resources. By fostering collaboration and aligning with national and international sustainability frameworks, Uruguay can enhance land management practices, further its long-term sustainability goals, and improve its environmental stewardship.

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