The MapBiomas Uruguay initiative to monitor annual land use and land cover changes from 1985 to 2023

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ABSTRACT

1. Land use and land cover change has been identified as one of the most significant drivers of the Earth system. In this context, the production of accurate, detailed and long-term maps is essential.

2. Here, we present Collection 2 of MapBiomas Uruguay, which provides annual land use and land cover maps for the country spanning the period from 1985 to 2023. The maps were generated using Landsat imagery (30 m) and a supervised classification approach based on the Random Forest algorithm. Eight land use and land cover classes were mapped and validated: Native woody vegetation, Forest plantations, Swampy areas / flooded vegetation, Grasslands, Sown pastures, Annual crops, Non-vegetated areas and Water bodies.

3. We observed a substantial decline in natural grasslands (-21.4%), primarily replaced by annual crops (+77.4%) and forest plantations (+857%).

4. Forest plantations expanded mainly in the east, northeast and central-west regions, while annual crops increased predominantly in the central-southern region. The central-northern region retains the highest proportion of natural grasslands in the country.

5. The overall accuracy of the maps exceeded 80% for the analysed years.

6. Implications. These maps represent an important step in mapping and tracking land use and land cover changes across Uruguay's temperate and subtropical grasslands, offering an unprecedented combination of spatial and temporal resolution. Our platform, which provides access to annual maps and statistics, is publicly available online for consultation and download. This open-access tool serves as a valuable resource for territorial planning, land use regulation and the formulation of public policies that support the sustainability of productive systems.

[Keywords: remote sensing, Landsat, open-access data, transitions, Rio de la Plata grasslands]

RESUMEN. La iniciativa MapBiomas Uruguay para monitorear los cambios anuales en el uso y cobertura del suelo entre 1985 y 2023

1. El cambio en el uso y la cobertura del suelo ha sido identificado como uno de los impulsores más significativos del sistema terrestre. En este contexto, es fundamental producir mapas precisos, detallados y de largo plazo.

2. Aquí presentamos la Colección 2 de MapBiomas Uruguay, que proporciona mapas anuales del uso y la cobertura del suelo para el país, desde 1985 hasta 2023. Los mapas se generaron utilizando imágenes Landsat (30 m) y un enfoque de clasificación supervisada basado en el algoritmo Random Forest. Se mapearon y validaron ocho clases de uso y cobertura del suelo: Vegetación leñosa nativa, Plantaciones forestales, Áreas pantanosas / vegetación inundada, Pastizales, Pasturas sembradas, Cultivos anuales, Áreas no vegetadas y Cuerpos de agua.

3. Observamos una disminución sustancial de los pastizales naturales (-21.4%), reemplazados, sobre todo, por cultivos anuales (+77.4%) y plantaciones forestales (+857%).

4. Las plantaciones forestales se expandieron principalmente en las regiones este, noreste y centro-oeste; los cultivos anuales aumentaron sobre todo en la región centro-sur. La región centro-norte conserva la mayor proporción de pastizales naturales del país.

5. La precisión general de los mapas superó el 80% para los años analizados.

6. Implicancias. Estos mapas representan un paso importante en la cartografía y seguimiento de los cambios en el uso y la cobertura del suelo en los pastizales templados y subtropicales de Uruguay, ofreciendo una combinación sin precedentes de resolución espacial y temporal. Nuestra plataforma, que brinda acceso a mapas y estadísticas anuales, está disponible públicamente en línea para consulta y descarga. Esta herramienta de acceso abierto constituye un recurso valioso para la planificación territorial, la regulación del uso del suelo y la formulación de políticas públicas que apoyen la sostenibilidad de los sistemas productivos.

[Palabras clave: sensores remotos, Landsat, datos de acceso abierto, transiciones, pastizales del Río de la Plata]

Introduction

The conversion of land for food production represents one of the most significant drivers of global environmental change (Turner II et al. 1993; Lambin and Geist 2008; Ellis et al. 2013; Winkler et al. 2021). Over the past six decades, human activities have transformed ecosystems at an unprecedented rate and scale, posing critical risks to future generations (Steffen et al. 2015; Richardson et al. 2023). Land use and land cover changes accelerate biodiversity loss (Jaureguiberry et al. 2022; Keck et al. 2025) and alter the interactions between ecosystems and the atmosphere. Specifically, these changes influence climate through biogeochemical (e.g., alterations in nutrient cycles) and biogeophysical (e.g., modifications in albedo) processes (Vitousek 1994; Foley et al. 2005), which, in turn, impact radiation fluxes, heat distribution, and evapotranspiration, with consequences at both local and regional scales (Pielke et al. 2002; Pielke 2005; Ellis et al. 2013; Luo et al. 2024). Recognizing the importance of land use and land cover changes as a key environmental indicator, both the United Nations Framework Convention on Climate Change (UNFCCC) and the Sustainable Development Goals (SDGs) emphasize the need for its systematic monitoring to support climate change mitigation, land degradation prevention, and overall human well-being (UNCC 2025; UN-SDG 2025). In this context, accurate land use and land cover change mapping is essential for effective natural resource management and evidence-based decision-making (Paruelo et al. 2006; O'Connor et al. 2020).

Satellite-borne sensors have revolutionized the capacity to characterize land use and cover across extensive spatial scales (Townshend et al. 1991; Rufin et al. 2025). The synoptic and temporally consistent coverage provided by satellite imagery has made remote sensing an indispensable tool for land use and land cover mapping (Cabello and Paruelo, 2008; Paruelo 2008; Chaves et al. 2020). Differentiation among land cover types relies on the spectral response of surface materials in different portions of the electromagnetic spectrum (Curran 1985). Furthermore, the availability of time-series satellite data has enabled the analysis of vegetation phenology, offering insights into seasonal dynamics (Zhang et al. 2003). With the recently increased accessibility to free cloud-based satellite data processing tools, the capacity to generate high-resolution land use and land cover maps at local, regional

and global scales has been significantly enhanced (Gorelick et al. 2017).

At a global scale, substantial efforts have been made to map land use and land cover changes. Notable examples include global land cover maps derived from MODIS imagery at a 500 m resolution (Friedl et al. 2010) and the European Space Agency's land cover dataset, which employs Sentinel-2 imagery (10-m resolution) and artificial intelligence models (Zanaga et al. 2021). At the regional scale, Eva et al. (2004) produced a land use and land cover map for South America (1 km resolution). More recently, Graesser et al. (2022) used Landsat imagery to estimate land cover changes across the Southern Cone from 1999 to 2018, while Baeza and Paruelo (2020) analysed land use and land cover dynamics in the Río de la Plata grasslands from 2000 to 2014 using MODIS-derived time series. Although these studies provide valuable references, limitations in spatial, temporal, and conceptual resolution (i.e., the level of detail or number of land cover classes), update frequency, data availability, or adaptability to local conditions often restrict their applicability for regional-scale decision-making.

At the national level, several efforts have been undertaken to map Uruguay's land use and land cover changes. Baeza et al. (2014) generated a land use/land cover map of Uruguay for the 2011-2012 agricultural year using phenological information (derived from the Normalized Difference Vegetation Index obtained from the MODIS sensor) and decision trees. Also, Baeza et al. (2011, 2019) analysed the spatial distribution of natural grasslands across four geomorphological regions of Uruguay using supervised classifications of Landsat images. The Ministerio de Ganadería, Agricultura y Pesca has also generated land use and land cover maps for 2017/18 and 2020/21 by integrating data from multiple sources (DGRN-MGAP, 2021). However, these maps were derived from heterogeneous methodologies and datasets, lack validation, and are insufficient for comprehensive accuracy assessment. More recently, Álvarez et al. (2024) applied the Land Cover Classification System (Di Gregorio and Jansen 1998) to classify Uruguay's land cover at some particular years —2000, 2008, 2011, 2015, 2019/2020 and 2021/2022— using Landsat, for the first four years, and Sentinel, for the last. Despite these advances, Uruguay still lacks a long-term, cost-effective, standardized, and reproducible system for generating annual

land use and land cover maps at the national scale. Existing approaches represent important methodological progress, but they have not yet been implemented to produce a continuous, year-by-year historical series covering multiple decades. These limitations render them unsuitable for medium- and long-term analyses of land use and land cover changes.

The MapBiomas initiative (mapbiomas.org) was developed to facilitate the traceability and the annual monitoring of land use and land cover changes, offering a comprehensive understanding of territorial transformations. Initially launched for the Brazilian territory (Souza et al. 2020), the initiative has expanded to map the land use and land cover, and its changes, over time in different biomes, such as the Gran Chaco Americano, Pan Amazonia or the Atlantic Forest. In a recent work, Baeza et al. (2022) presented the results of the MapBiomas Pampa initiative (pampas.mapbiomas.org), analysing the land use and land cover changes in the Rio de la Plata Grasslands region between 2000 and 2019. In the last few years, MapBiomas expanded and focused on covering all South American countries, including Uruguay. In this sense, MapBiomas Uruguay (uruguay.mapbiomas.org) aims to generate annual, country level, land use and land cover maps to support environmental monitoring and policy development. Recently, MapBiomas Uruguay released its Second Collection of Annual Land Use and Land Cover Maps, covering the period 1985-2023 at a 30-m spatial resolution with eight classification categories. This collection represents a significant advancement in Uruguay's historical land use and land cover mapping, offering an unprecedented level of spatial and temporal detail while ensuring transparency and methodological rigor through robust validation techniques. Furthermore, the data are freely available and open-source, ensuring their replicability and long-term continuity. In this work, we present the initiative and provide an analysis of the main land use and land cover changes in Uruguay between 1985 and 2023 (39 years). We provide an accessible platform for diverse stakeholders, including policymakers, producers, researchers, and civil society, to explore and use this valuable information for informed decision-making.

Materials and Methods

Study area

The study area covers the entire continental territory of Uruguay (~17.6 M ha), located between latitudes 30°-35° S and longitudes 53°-58° W. Characterized by a slightly undulating topography, Uruguay has an average annual precipitation of 1295 mm/year and an average annual temperature of 17.7 °C, considering the period 1991-2020 (INUMET 2025). It is completely immersed within the Río de la Plata Grasslands region, one of the most significant natural grassland areas worldwide and the main one in South America (Soriano et al. 1991; Oyarzabal et al. 2020). Therefore, the original natural vegetation of Uruguay corresponds to natural grasslands, which present an exceptional floristic diversity (Lezama et al. 2019) and have been used, historically, as a forage resource for extensive livestock activity (Modernel et al. 2016; Gutiérrez et al. 2020). Currently, agriculture and forestry have gained greater economic relevance, with cellulose, beef, soybean and dairy products being the main export items in 2024 (Uruguay XXI 2025).

For a more detailed analysis that considers the distinctive features of the study area, the territory was subdivided into seven units following the geomorphological regions proposed by Panario et al. (2014): Basaltic Cuesta (BC), Gondwanic Sediment Basin (GWB), Lagoon Merin Graben (LMG), Eastern Hills (EH), Santa Lucía Graben (SLG), Crystalline Shield (CS), and Western Sediment Basin (WSB) (Supplementary Material 1). Each unit show relative homogeneity in terms of soils, topography, and predominant land uses.

Land use and land cover classification

We classified land use and land cover annually in Uruguay from 1985 to 2023 using 30-m resolution Landsat imagery acquired from the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS) sensors, onboard the Landsat 5, Landsat 7 and Landsat 8 satellites, respectively. We used Collection 2, Tier 1 surface reflectance (SR) images, radiometrically calibrated and orthorectified based on ground control points and digital elevation models. These data were accessed via the Google Earth Engine platform (Gorelick et al. 2017) from National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS).

To ensure optimal spectral separability of land cover classes, we generated annual

mosaics for each year (1985-2023), using images from September to November (Baeza et al. 2022). This period corresponds to the spring growing season in Uruguay, when vegetation conditions enhance spectral contrast between classes, such as grasslands, annual crops, sown pastures, forest plantations and native woody vegetation (Baeza et al. 2014). We masked clouds and cloud shadows at the pixel level using the QA_PIXEL band, following the approach of Goodwin et al. (2013). Eight land use and land cover classes were mapped: Native woody vegetation (NWV), Forest plantation (FP), Swampy areas/flooded vegetation (SAFV), Grasslands (G), Sown pasture (SP), Annual crops (AC), Non-vegetated areas (NVA), and Water bodies and rivers (WB) (see conceptual class definitions in Supplementary Material 2). The classification workflow was applied independently within each geomorphological region, and the resulting regional maps were subsequently merged to produce the annual national land use and land cover maps.

We generated training samples via visual interpretation of representative stable areas, defined as areas where the land use and land cover class remained unchanged throughout the 39 years. This was done using false-colour composite mosaics (infrared-red-green) and Normalised Difference Vegetation Index time series. Approximately, 250 polygons per class (fewer than 200 pixels) were digitalized in Google Earth Engine for Uruguay. These stable training samples were used to generate preliminary classifications (called pre-classifications) for each year, using a set of 107 variables, including spectral bands, spectral indices, spectral decoupling bands, temporal indices (e.g., median, minimum, amplitude, standard deviation) and texture indices (see Supplementary Material 3).

To improve sample representativeness across Uruguay's geomorphological regions and land use and land cover classes, a set of randomly selected stable pixels was selected from the pre-classifications based on a minimum temporal frequency criterion. This criterion requires that each pixel maintain the same land cover class for a minimum number of years within the temporal series, in order to ensure its reliability for training purposes. For instance, in the case of forest plantations, a pixel was considered stable if it was classified as forest for at least 8 out of 10 years, allowing for possible harvesting events without excluding relevant areas. We classified each stable sample under the same

land use and land cover class across four sub-periods (1985-1994, 1995-2004, 2005-2014 and 2015-2023). We stratified the selection by class, geomorphological region and sub-period from a pool of 2000 potential pixels per class, and balanced sample numbers relative to class area over time using simple linear models to estimate class area over time based on the pre-classifications. A minimum of 50 and a maximum of 2000 samples per class were defined, and sampling was conducted independently for each year. We adjusted model intercepts when necessary to correct under and over-estimations, based on ancillary data (e.g., previous collection maps, Landsat mosaics, or other crop maps). To improve classification accuracy, we added complementary training samples, when necessary, by visually identifying stable pixels across the time series and cross-validating them with high-resolution imagery (e.g., WorldView, GeoEye, Ikonos) available in Google Earth Engine. This step was guided by the analysis of classification outputs to identify areas with systematic errors, which were then corrected by incorporating additional, reliably classified pixels into the training dataset. The number of samples per year, class and geomorphological region is provided in Supplementary Material 4.

We performed a supervised classification using the Random Forest algorithm, based on the training samples, with 40 trees, 4 variables per split and a minimum leaf size of 25. The same training set of stable and complementary samples was used for all years, and we used the specific set of 107 variables corresponding to each year to yearly classify land use and land cover classes. We iteratively repeated yearly classifications using additional complementary training samples until visual errors were solved in all annual maps. This process involved qualitative evaluations through visual analysis, with errors analysed and discussed by a group of local experts familiar with the territory.

An important advancement in MapBiomas Uruguay Collection 2, with respect to the first Collection, was the disaggregation of Annual crops (AC) and Sown Pastures (SP), previously grouped as a single class called Farming (see Collection 1 in Baeza et al. 2022). To separate these classes, we used the final classification from the previous process, which identified pixels under the Farming, and we conducted a dedicated classification using agricultural-year mosaics (July to June) and the median

of all reflectance bands in 3-month windows to optimize spectral contrast. Additionally, we used four spectral indices in the same 3-month windows: NDVI —which is closely related to vegetation cover (Running 1990)—, GNDVI (Green NDVI) —which is more sensitive to chlorophyll variation (Gitelson et al. 1996)—, NDMI (Normalized Difference Moisture Index) —which estimates vegetation water content (Hardisky et al. 1983)— and NBR (Normalized Burn Ratio) —which is more sensitive to vegetation change (Key and Benson 1999). This process followed the methodology proposed by Baldassini et al. (2024) for mapping crop types and cropping systems using Sentinel imagery. To optimize data quality, pixel-level filters were applied to remove cloud and shadow artefacts (Goodwin et al. 2013) using the F-Mask algorithm information in the QA_PIXEL band. Landsat 5, 7, and 8 collections were harmonised using Roy's method (Roy et al. 2016) to ensure comparability across sensors. To support Random Forest training, we used auxiliary data provided by farmers, including field-level crop type information for the 2011-2022 period. Based on this, three climatically contrasting years (2015: average; 2016: wet; 2020: dry) were selected to train a generic classification model applied to the full 1985-2023 period.

Finally, to reduce classification artefacts (e.g., temporal inconsistencies, spatial noise), we applied a set of post-classification filters, including: gap-filling filters to address missing data, temporal filters to ensure consistency across years, spatial filters to smooth isolated pixel errors, and frequency/incidence filters to reduce improbable transitions (see Supplementary Material 5 for a detailed description of these filters). These filters were tailored to the characteristics of each sub-region and applied in two stages: a) the first stage targeted the annual classifications, including the Farming class, and b) the second stage was applied after dividing the Farming class into Annual Crops (AC) and Sown Pastures (SP), focusing exclusively on these two classes.

Maps evaluation

We followed the sampling protocol proposed by Olofsson et al. (2014) to evaluate the classification accuracy. Independent validation samples were obtained by visual interpretation of points selected using a stratified random design. We did not use temporally stable pixels for validation, as doing so would compromise the independence of the accuracy assessment by evaluating model performance on samples that are, by definition, easier to classify due to their persistent spectral behavior. Between 430 and 490 pixels were analysed for eight reference years: 1986, 1991, 1996, 2001, 2006, 2012, 2018 and 2022. We calculated the overall accuracy, in addition to the omission and commission errors, using a contingency matrix. Validating each of the 39 annual maps independently was not feasible due to the substantial effort required to visually interpret a very large number of samples. Therefore, following standard practice for long time series, we adopted a reference-year approach that provides robust and representative accuracy estimates across the full classification period.

Seven land use and land cover classes were assessed during the validation process: Native woody vegetation (NWV), Forest plantation (FP), Swampy areas/flooded vegetation (SAFV), Grassland (G), Farming (including Annual crops and Sown pasture), Non-vegetated area (NVA) and Water bodies (WB). Due to the lack of reliable and detailed information, Annual crops (AC) and Sown pasture (SP) could not be assessed separately. For each point and year evaluated, Landsat mosaics, spectral signatures, and high-resolution imagery (when available) were reviewed to assign the most appropriate class. If the pixel was located in a transition zone between two classes or showed a mixed cover, it was labelled as 'not applicable' and excluded from evaluation.

Validation was conducted independently by two reviewers to minimize interpretation bias. In cases of disagreement regarding class assignment or edge condition, a third reviewer conducted a new assessment. If discrepancies persisted, a fourth evaluation was performed by at least three reviewers, who discussed the class assignment until consensus was reached. Once the validation process was complete and reference points established, we performed an accuracy assessment by comparing our land use and land cover maps with the independent reference data and generating non-normalized and normalized error matrices (Congalton 1991, 2004). Non-normalized matrices report raw counts of agreement and disagreement between map classifications and reference data, while normalized matrices express these values as proportions, facilitating comparison across classes and datasets.

Results

At the national level, Uruguay´s current land use and land cover configuration is predominantly characterized by grasslands (G), followed by annual crops (AC) and forest plantations (FP). In 2023, grasslands covered over half of the national territory, amounting to 9977563 ha (56.6%). Annual crops occupied 2857937 ha (16.2%), while Sown Pastures (SP) and Forest Plantations accounted for 1715940 ha (9.7%) and 1220486 ha (6.9%), respectively.

Native Woody Vegetation (NWV) covered 913869 ha (5.2%). Regarding aquatic and wetland ecosystems, Swampy areas/flooded vegetation (SAFV) represented 2.6% of the area (454139 ha), and Water bodies (WB) —including rivers and lakes— covered 270258 ha (1.5%). Lastly, Non-vegetated areas (NVA) comprised 206892 ha, equivalent to 1.2% of the national territory (Figure 1, Figure 2A).

From 1985 to 2023, Uruguay experienced substantial shifts in land use and land cover
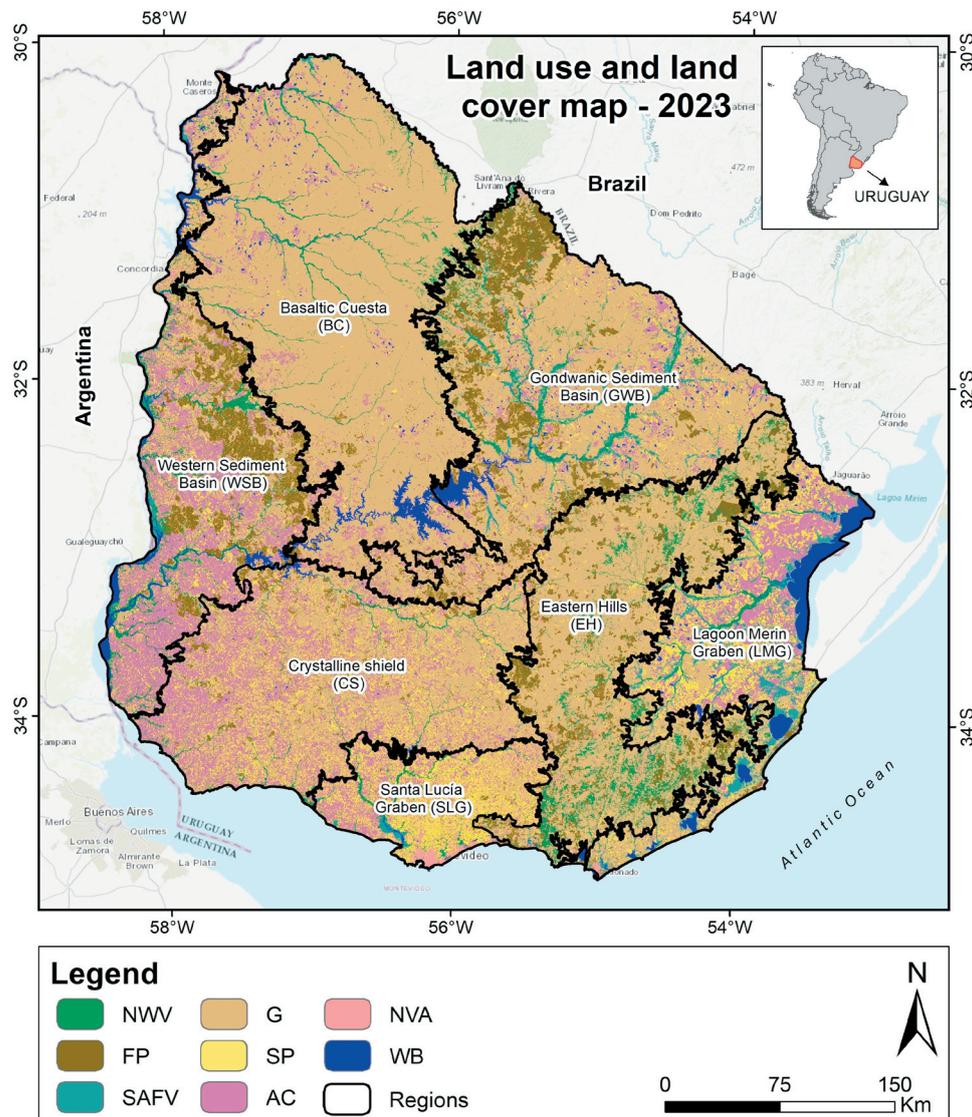

Figure 1. Land use and land cover map for Uruguay for the year 2023. Black lines on the map indicate the boundaries of geomorphological units (according to Panario et al. 2014). Land use and land cover classes: NWV: Native woody vegetation. G: Grassland. NVA: Non-vegetated area. FP: Forest plantation. SP: Sown pasture. WB: Water body. SAFV: Swampy areas/flooded vegetation. AC: Annual crops.

Figura 1. Mapa de uso y cobertura del suelo de Uruguay para el año 2023. Las líneas negras en el mapa indican los límites de las unidades geomorfológicas (según Panario et al. 2014). Clases de uso y cobertura del suelo: NWV: Vegetación leñosa nativa. G: Pastizal. NVA: Área no vegetada. FP: Plantación forestal. SP: Pastura sembrada. WB: Cuerpo de agua. SAFV: Zonas pantanosas/vegetación inundable. AC: Cultivos anuales.
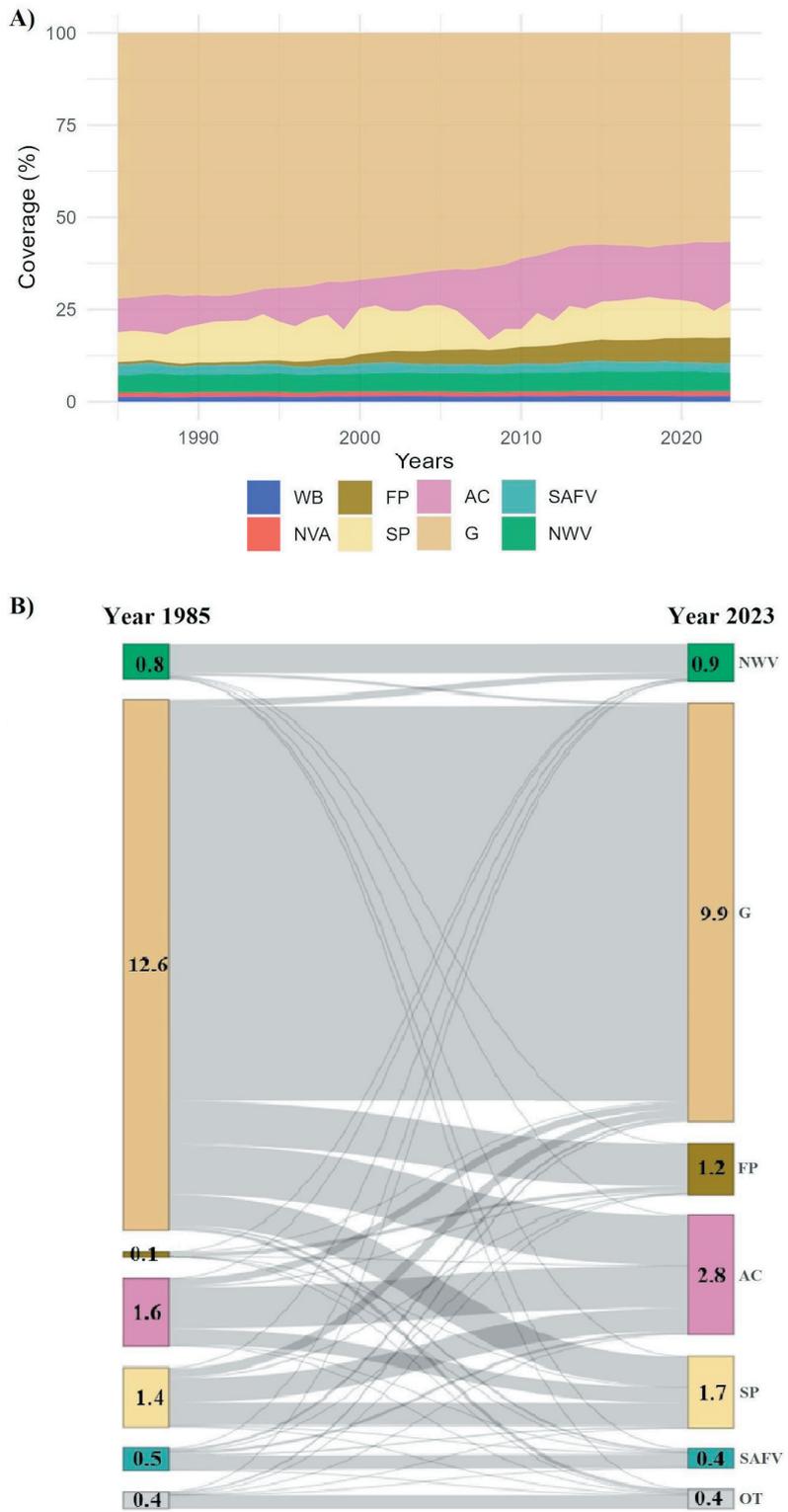
A)

B)

Figure 2. A) Annual land use and land cover dynamic from 1985 to 2023. B) Land use and land cover classes transitions in Uruguay between 1985 (left) and 2023 (right). Land use and land cover classes: WB: Water body. NVA: Non-vegetated area. FP: Forest plantation. SP: Sown pasture. AC: Annual crops. G: Grassland. SAFV: Swampy areas/flooded vegetation. NWV: Native woody vegetation. In panel B, land use and land cover classes with fewer transitions were grouped under 'Others'.

Figura 2. A) Dinámica anual del uso y cobertura del suelo desde 1985 hasta 2023. B) Transiciones de clases de uso y cobertura del suelo en Uruguay entre 1985 (izquierda) y 2023 (derecha). Clases de uso y cobertura del suelo: WB: Cuerpo de agua. NVA: Área no vegetada. FP: Plantación forestal. SP: Pastura sembrada. AC: Cultivos anuales. G: Pastizal. SAFV: Zonas pantanosas/vegetación inundable. NWV: Vegetación leñosa nativa. En el panel B, las clases con menos transiciones se agruparon en 'Otros'.

classes. Forest Plantations (FP) showed the largest relative expansion (+857.3%), equivalent to an increase of ~+1.27 M ha (~33500 ha/year). This was followed by Annual crops (AC), which expanded by 77.4%, equivalent to an increase of ~+1.24 M ha (~49000 ha/year). Moderate increases were observed in Sown pastures (SP) (+20.5%; +291000 ha), Water bodies (WB) (+19.3%; +43800 ha), Native woody vegetation (NWV) (+10.8%;

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+89200 ha), and Non-vegetated areas (NVA) (+7.8%; +15000 ha). In contrast, Grasslands (G) experienced the largest absolute decline (-21.4%; -2.7 M ha, ~-83500 ha/year), while Swampy areas/flooded vegetation (SAFV) showed a smaller, but consistent, reduction (-13.5%; -71000 ha) (Figure 2A). Land use and land cover transitions between 1985 and 2023 revealed both persistence and significant change across classes. Grasslands retained 9.97 M ha in 2023, although they also experienced substantial conversions to Annual crops (1.19 M ha), Forest plantations (1.02 M ha), and Sown pastures (733000 ha). Native woody vegetation (NWV) remained relatively stable in extent and experienced a net increase over the study period. Although NWV lost area to Grasslands (69800 ha) and Forest Plantations (12800 ha), these losses were outweighed by gains from other classes, resulting in an overall expansion of ~10%. Annual crops exhibited a mix of persistence and change: 996000 ha remained under cultivation, while 358000 ha transitioned to Sown pastures and 34000 ha to Forest plantations. Swampy areas/flooded vegetation declined notably, with conversions to Grasslands (59800 ha), Annual crops (65600 ha) and Sown pastures (35700 ha). Sown pastures were among the most dynamic classes, showing considerable losses to Annual crops (574000 ha) and Grasslands (205000 ha). Finally, Non-vegetated areas and Water bodies remained relatively stable over the study period (Figure 2B).

At the level of geomorphological regions, distinct patterns of land use and land cover change were observed. In both the Gondwanic Sediment Basin and Eastern Hills, similar trends emerged, with the predominant transformation involving the conversion of Grasslands (G) to Forest plantations (FP). In the Gondwanic Sediment Basin, approximately 397000 ha of Grasslands were converted, mainly to Forest plantations (~292000 ha). A comparable pattern occurred in the Eastern Hills, where 434000 ha of Grasslands were transformed, with an increase of 281000 ha in Forest plantations. In contrast, the Crystalline Shield exhibited a different dynamic, where the conversion of 644000 ha of Grasslands was mainly driven by the expansion of Annual crops (AC). In the Western Sediment Basin, grassland replacement followed a more diversified trajectory, involving Forest plantations (401000 ha), Annual crops (77000 ha), and Sown pastures (SP) (268000 ha). The remaining three regions exhibited relatively

stable patterns over time. The Basaltic Cuesta stood out as the region with the highest natural cover, mainly dominated by Grasslands. Conversely, the Lagoon Merín Graben and the Santa Lucía Graben had already undergone significant transformations prior to the study period (1985) and were characterised by a high relative presence of Annual crops and Sown pastures (Figure 3).

Overall accuracy for the eight years analysed was always above 80%. The year with the lowest overall accuracy was 1986 (80%), while the highest was in 2012 (91%). On average, commission errors ranged from 4% to 54% across classes, with the lowest values observed in Grasslands (4%) and Water bodies (0%), and the highest in Non-vegetated areas (54%) and Forest plantations (38%). Omission errors varied more widely, from 0% in Water bodies to 42% in Swampy areas/flooded vegetation and 38% in Forest plantations. Natural classes, such as Grasslands, consistently exhibited the lowest omission and commission errors, with values below 10% in most years. In contrast, classes such as Forest plantations and Non-vegetated areas showed higher error rates, particularly in earlier years. Farming showed moderate omission rates (average 20%) and variable commission errors (22%). In general, both omission and commission errors tended to decrease in more recent years, especially from 2012 onward, reflecting improvements in classification consistency (see Figure 4 and Supplementary Material 6).

Discussion

Our results show a 21.4% decline in natural grasslands over a nearly 40-year study period, primarily driven by the expansion of annual crops and forest plantations. However, land use and land cover changes were not spatially homogeneous across the country. Grasslands were predominantly replaced by Forest plantations in the Eastern and Central-Western regions, whereas conversions to Annual crops were concentrated mainly in the Central-Southern region. A consistent and systematic description of land use and cover, as well as their temporal dynamics, is a key element for the sustainable management of natural resources and informed decision-making in the agricultural sector (Paruelo et al. 2006; O'Connor et al. 2020; Paruelo and Sierra 2023). Our maps have direct and practical applications, including agricultural forecasting (i.e., predictive models —such
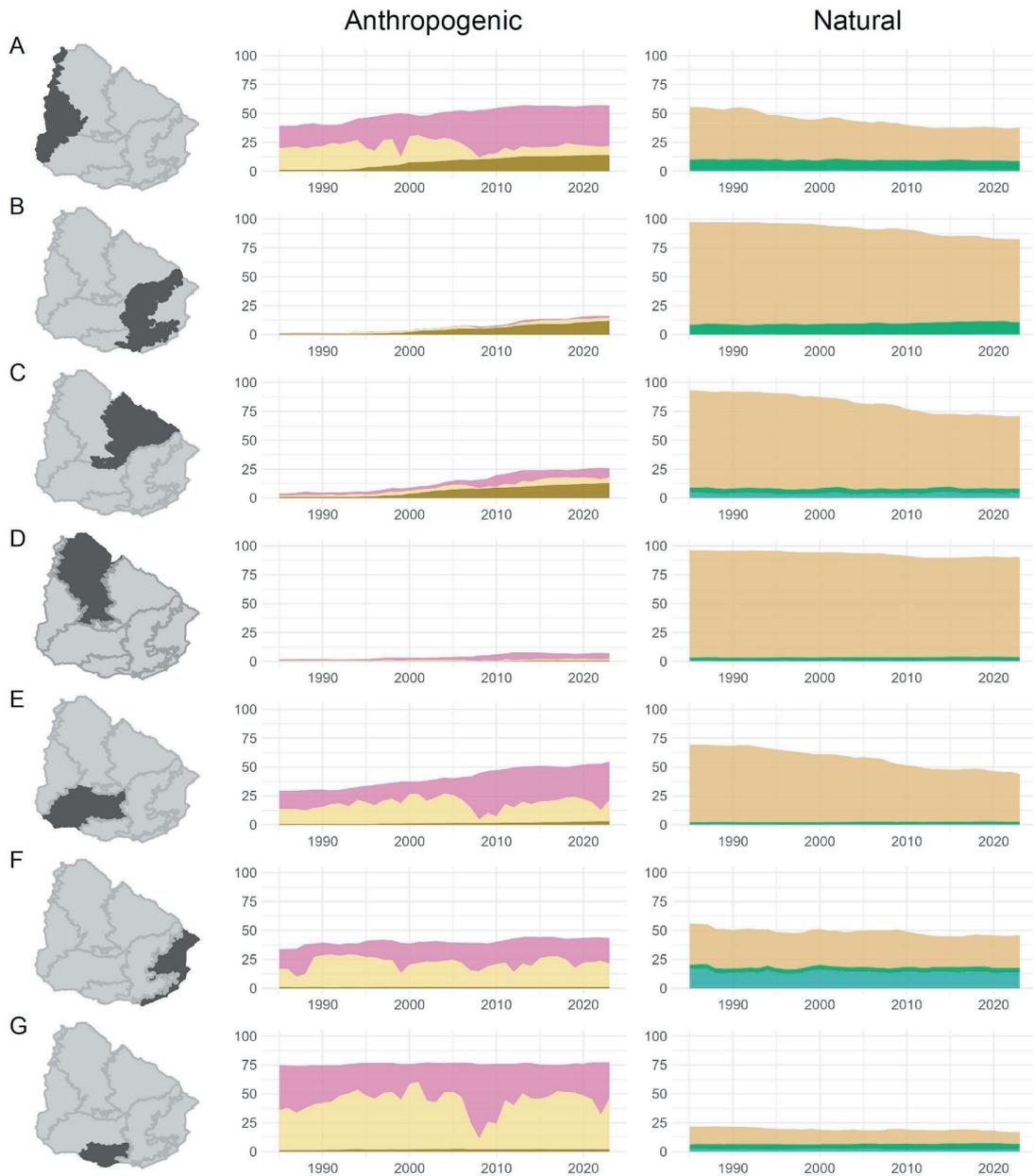
Figure 3. Annual land use and land cover dynamic from 1985 to 2023 by geomorphological regions. A) Western Sediment Basin. B) Eastern Hills. C) Gondwanic Sediment Basin. D) Basaltic Cuesta. E) Crystalline Shield. F) Lagoon Merín Graben. G) Santa Lucía Graben. Only a subset of land cover classes is shown: Annual crops (AC), Sown pasture (SP) and Forest plantation (FP) for anthropogenic land uses, and Grassland (G), Native woody vegetation (NWV) and Swampy areas/flooded vegetation (SAFV) for natural covers.

Figura 3. Dinámica anual del uso y cobertura del suelo desde 1985 hasta 2023 por regiones geomorfológicas. A) Cuenca Sedimentaria Occidental. B) Sierras del Este. C) Cuenca Sedimentaria Gondwánica. D) Cuesta Basáltica. E) Escudo Cristalino. F) Graben de la Laguna Merín. G) Graben del Santa Lucía. Solo se muestra un subconjunto de clases de cobertura: Cultivos anuales (AC), Pastura sembrada (SP) y Plantación forestal (FP) para usos antrópicos del suelo, y Pastizal (G), Vegetación leñosa nativa (NWV) y Zonas pantanosas/vegetación inundable (SAFV) para coberturas naturales.

as Markov-chain-based approaches— to explore future agricultural expansion scenarios [e.g., Vega et al. 2009 or Gallego et al. 2025]), land use regulation, the promotion of conservation measures, and monitoring compliance with land management plans. In addition, they have proven particularly valuable for evaluating the environmental
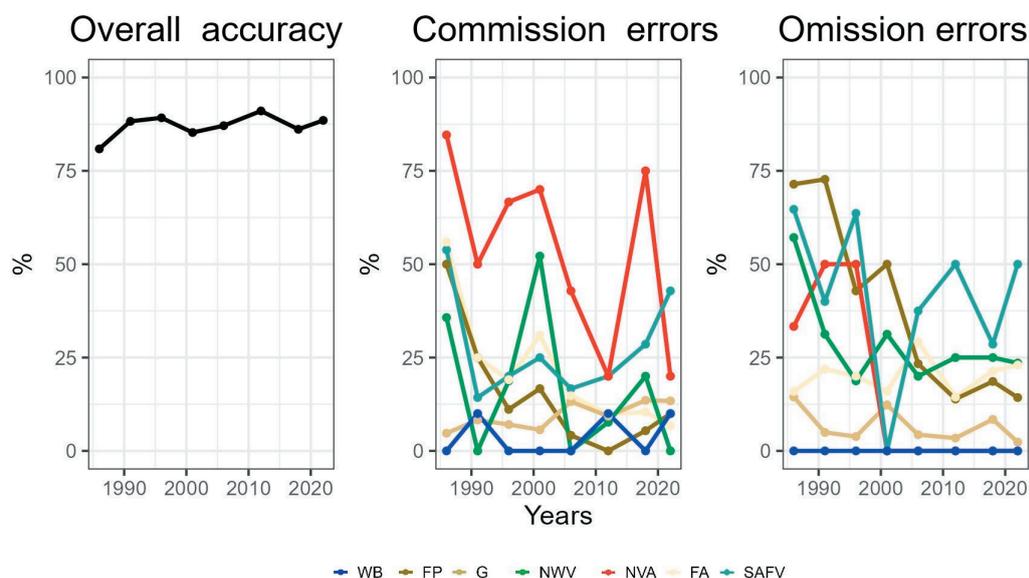
Overall accuracy   Commission errors   Omission errors

Figure 4. Overall accuracy, commission and omission errors of land use and land cover maps for 1986, 1991, 1996, 2001, 2006, 2012, 2018 and 2022. WB: Water body. FP: Forest plantation. G: Grassland. NWV: Native woody vegetation. NVA: Non-vegetated area. FA: Farming (including Annual Crop and Sown pasture). SAFV: Swampy areas/flooded vegetation.

Figura 4. Precisión global, errores de comisión y omisión de los mapas de uso y cobertura del suelo para los años 1986, 1991, 1996, 2001, 2006, 2012, 2018 y 2022. WB: Cuerpo de agua. FP: Plantación forestal. G: Pastizal. NWV: Vegetación leñosa nativa. NVA: Área no vegetada. FA: Uso agropecuario (incluye Cultivo anual y Pastura sembrada). SAFV: Zonas pantanosas/vegetación inundable.

performance of productive systems (Paruelo et al. 2024) and for assessing the influence of the configuration and composition of landscapes on the ecosystem services supply (Camba Sans et al. 2024).

One of the main contributions of this study, compared with the first Collection of MapBiomas Uruguay, is the disaggregation of the Farming class into Annual crops and Sown pastures classes, allowing for a more accurate analysis of the temporal dynamics of productive systems in Uruguay. The results show a good general agreement with official agricultural statistics (R²=0.55; P<0.001) (Supplementary Material 7) provided by the Dirección de Estadísticas Agropecuarias del Ministerio de Ganadería, Agricultura y Pesca (DIEA-MGAP 2025). To date, there are no known precedents in Uruguay for land cover mapping that distinguishes these classes separately. To our knowledge, even at the regional level, available studies are limited and typically operate at small spatial and temporal scales. For instance, Baldassini et al. (2024) produced a map for the department of Junín, Buenos Aires, Argentina (covering an area of 44000 km²) corresponding to a single agricultural year (2020/2021).

Our analysis of land use and land cover trends in Uruguay reveals a sustained loss of natural Grasslands, alongside an expansion of Annual crops, Sown pastures and Forest plantations. This pattern is consistent with trends observed not only regionally (Baldi and Paruelo 2008; Graesser et al. 2018; Baeza and Paruelo 2020; Baeza et al. 2022; Graesser et al. 2022), but also globally (Ramankutty and Foley 1999; Winkler et al. 2021), where productive systems are expanding into natural ecosystems, with consequences for biodiversity and the supply of ecosystem services (Foley et al. 2005; Ceballos et al. 2015; Newbold et al. 2015; IPBES 2019; Hasan et al. 2020; Paruelo et al. 2022). In this context, land use and land cover changes have been identified as one of the most important drivers of the Earth system (Campbell et al. 2017).

The 857% increase in forest plantations in Uruguay is particularly significant. Although the forestry sector contributes substantially to the national economy (Uruguay XXI 2025), it also exerts considerable influence on landscape structure, biodiversity, watershed hydrology and soil characteristics (Farley et al. 2005; Jobbágy et al. 2006; Silveira et al. 2006, 2011, 2016; Silveira and Alonso 2009;

Cano et al. 2023). This transformation has been especially marked in the Gondwanic Sediment Basin and Eastern Hills, where natural grasslands were systematically converted. The notable expansion of this sector is likely driven by a combination of political, economic and market-related factors. From a political standpoint, the enactment of Law N°15939 in 1987 established a regulatory framework for forestry development, including incentives such as tax exemptions and preferential credit schemes (OPYPA 2021), as well as the designation of priority forestry areas, which now extend over nearly 4 M ha. From an economic and market perspective, the establishment and growth of the pulp industry (Wright et al. 2000; Oyhantcabal 2005; Altesor et al. 2008) have also played a decisive role. Today, pulp is Uruguay's leading export commodity, generating a total of U$S 2.545 billion (Uruguay XXI 2025).

Another major land use change captured by our maps is the significant expansion of Annual crops, particularly since the mid-2000s. Unlike forestry, this transformation did not rely solely on converting natural grasslands but also included the replacement of Sown pastures. This trend was most prominent in the Crystalline Shield, Santa Lucía Graben and Western Sediment Basin. Multiple factors contributed, including rising global demand and prices for cereals, the adoption of technologies such as no-till farming, economic crises in neighbouring countries (e.g., Argentina) and the spread of genetically modified organisms (GMO), particularly soybeans (Paruelo et al. 2006; Redo et al. 2012; Vassallo 2013; Terradas et al. 2016; Gorosábel et al. 2020). Historically, soybeans played a minor role in Uruguay's agriculture, but between 2000 and 2008, the area planted with soy expanded rapidly, surpassing wheat, which had previously dominated the landscapes (FAOSTAT 2025). Economically, this production boom coincided with a 193% increase in international prices (from U$S157 to U$S462/t). Today, soybean production reaches 3 M t and generates over US$1199 billion in exports to China and Argentina (Uruguay XXI 2025).

The overall accuracy of the maps exceeded 80% for all years analysed, indicating a high level of reliability (Shao and Wu 2008). However, omission and commission errors varied across classes and years, reflecting both detection limitations and methodological challenges. The accuracy obtained for the

eight reference years also shows some degree of interannual variability, which is expected given that spectral conditions may differ between years due to factors such as residual cloud contamination, phenological changes, climatic variability —such as differences in precipitation, temperature or drought intensity— or scene availability. Although it was not feasible to validate each of the 39 years independently, the use of multiple reference years distributed throughout the time series ensures that this variability is adequately represented. Forest plantation and Swampy areas/flooded vegetation classes showed the highest omission errors, particularly in earlier years (1986 and 1991), likely due to seasonal variability (e.g., water level fluctuations in wetlands; Henderson and Lewis 2008; Gallant 2015) and spectral similarity with other classes such as Native woody vegetation (Nery et al. 2019). In contrast, the Grassland class showed consistently low omission errors, indicating more reliable detection. For commission errors, the Non-vegetated area class showed the highest overestimation, likely due to misclassified pixels from sparse grasslands (Lezama et al. 2019; Baeza et al. 2019) or temporarily bare croplands and plantations. These discrepancies highlight the need to improve classification criteria and incorporate auxiliary data (e.g., field observations) to reduce class confusion, particularly in heterogeneous landscapes. Moreover, field-based validation would help assess classification accuracy for the Sown pasture and Annual crop classes, which were not evaluated in this study.

A methodological aspect that represents both an innovation and a potential limitation in our approach is the use of temporally stable pixels for selecting training samples. The use of temporally stable pixels helps ensure label reliability, but it may also introduce a potential bias by favouring land cover types or locations with more persistent dynamics. This could, theoretically, underrepresent rapidly changing areas or short-duration land cover states. However, several elements of our sampling design contribute to mitigate this effect: 1) stability thresholds adapted to each class (e.g., accounting for plantation harvest cycles); 2) stratified samples by land cover class, geomorphological region, and sub-period, which were randomly selected each year, for a better capture of spatial and temporal variability, and 3) independent validation did not show disproportionate errors in highly dynamic classes.

A comparison between MapBiomas Uruguay and other national studies reveals important differences in the classes with the largest extent: Grassland, Farming (including Annual crops and Sown pastures) and Forest plantations (Table 1). For Grassland, discrepancies are particularly notable between the Ministerio de Ganadería, Agricultura y Pesca (MGAP) data —based on livestock declarations (Livestock Control Office, DICOSE; SNIG-MGAP 2023)— and land cover maps produced by the Dirección General de Recursos Naturales (DGRN; DGRN-MGAP 2021). While MapBiomas Uruguay reports 56.6% grassland cover, DGRN estimates 69.5%. Interestingly, this difference reverses for Farming: MapBiomas estimates 26%, while DICOSE reports 14.9%. For Forest plantations, estimates are more consistent, ranging from 5.5% to 7.9%, suggesting that this class is more easily delineated, possibly due to its distinct remote sensing signature and official records. Discrepancies are less pronounced for minor land cover classes. Overall, differences largely stem from the diverse methodologies and classification criteria adopted by each source, which result in significant variation in surface estimates for each class.

While Uruguay has a valuable history of land use and cover mapping, the MapBiomas Uruguay initiative advances in improving the accuracy and reliability of maps, the transparency of classification processes and the development of user-friendly platforms for data queries and downloads (uruguay.mapbiomas.org). This represents a key comparative advantage, as the availability of open data fosters information use, particularly in the development of environmental and agricultural policies. MapBiomas Uruguay is designed to produce new collections that expand temporal coverage, incorporate new land use and land cover classes, and enhance classification accuracy.

Conclusions

MapBiomas Uruguay initiative in Collection 2 reveals considerable land use and land cover changes over nearly four decades, with a marked decline in natural grasslands and a significant expansion of annual crops and forest plantations. These patterns, which varied across the territory, reflect transformations driven by political, economic and technological factors, and align with regional and global trends in which productive systems expand into natural ecosystems, with consequences for biodiversity and the provision of ecosystem services.

Despite the methodological limitations identified —such as omission errors in certain classes or the lack of field validation for some land uses—, the MapBiomas Uruguay maps represent a significant technical and conceptual advance in national land monitoring. Their spatial (30 m) and temporal (annual from 1985-2023) resolution, along with open access availability, position them as a strategic tool for territorial planning, land use regulation and the design of public policies aimed at the sustainability of productive systems.

Table 1. Percentage of land use and land cover classes by data source. MA: Ministerio de Ambiente (OAN 2022). MVOT: Ministerio de Vivienda y Ordenamiento Territorial (DINOT-MVOT 2022). DGRN-MGAP: Dirección General de Recursos Naturales (DGRN-MGAP 2021). DICSOE-MGAP: Livestock Control Office (SNIG-MGAP 2023). MB Uy: MapBiomas Uruguay.

Tabla 1. Porcentaje de las clases de uso y cobertura del suelo según la fuente de datos. MA: Ministerio de Ambiente (OAN 2022). MVOT: Ministerio de Vivienda y Ordenamiento Territorial (DINOT-MVOT 2022). DGRN-MGAP: Dirección General de Recursos Naturales (DGRN-MGAP 2021). DICOSE-MGAP: Oficina de Control de la Producción Agropecuaria (SNIG-MGAP 2023). MB Uy: MapBiomas Uruguay.

Land-use and Land-cover classes	MA (2021/2022)	MVOT (2021/2022)	DGRN-MGAP (2021)	DICOSE-MGAP (2023)	MB Uy (2023)
Non vegetated areas	0.8	1.8	1.0	-	1.2
Water bodies	2.3	2.1	1.6	-	1.5
Grasslands	61.3	58.0	69.5	68.8	56.6
Farming	23.0	21.8	15.3	14.9	26.0
Swampy/flooded vegetation	2.4	2.9	1.9	-	2.6
Native woody vegetation	4.4	5.5	4.6	-	5.2
Forest plantations	5.9	7.9	6.1	5.5	6.9

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