# Two decades of land cover mapping in the Río de la Plata grassland region: the MapBiomas Pampa initiative

Baeza, S.[1]*; Vélez-Martin, E.[2]; De Abelleyra D.[3]; Banchero, S.[3]; Gallego, F.[4]; Schirmbeck, J.[2]; Veron, S.[3, 5]; Vallejos, M.[6]; Weber, E.[7]; Oyarzabal, M.[5]; Barbieri, A.[8]; Petek, M.[3]; Guerra Lara M.[9]; S. Sarrailhé, S.[3]; Baldi, G.[10]; Bagnato. C.[11]; Bruzzone, L.[4]; Ramos, S.[8]; Hasenack, H.[12,]

[1] Departamento de Sistemas Ambientales, Facultad de Agronomía, UdelaR. Montevideo 12900, Montevideo Uruguay; sbaeza@fagro.edu.uy

[2] GeoKarten Consultoria em Tecnologia da Informação Ltda. Roca Sales 95735-000, Rio Grande do Sul, Brasil; evelezmartin@gmail.com , schirmbeck.j@gmail.com

[3] Instituto de Clima y Agua, Instituto Nacional de Tecnología Agropecuaria (INTA) Hurlingham 1686, Buenos Aires, Argentina; deabelleyra.diego@inta.gob.ar, banchero.santiago@inta.gob.ar, veron@agro.uba.ar, ssarrailhe@agro.uba.ar, mpetek@agro.uba.ar

[4] Instituto de Ecología y Ciencias Ambientales, Facultad de Ciencias, UdelaR. Montevideo 11400, Montevideo Uruguay; fgallego@fcien.edu.uy , lolibruzzone@gmail.com

[5] Departamento de Métodos Cuantitativos y Sistemas de Información, LART, IFEVA, Facultad de Agronomía, UBA/CONICET. Buenos Aires 1417, Buenos Aires, Argentina; oyarzabal@agro.uba.ar

[6] Programa de Investigación en Producción y Sustentabilidad Ambiental, Instituto Nacional de Investigación Agropecuaria. El semillero 70006, Colonia, Uruguay; mvallejos@inia.org.uy

[7] Departamento Interdisciplinar e Programa de Pós-Graduação em Sensoriamento Remoto, Universidade Federal do Rio Grande do Sul, Campus Litoral Norte. Tramandaí 95590-000, Rio Grande do Sul; eliseu.weber@ufrgs.br .

[8] Departamento de Geografía, Facultad de Ciencias, UdelaR. Montevideo 11400, Montevideo Uruguay; abarbieri@fcien.edu.uy , sebastianramos897@gmail.com

[9] Instituto de Matemática Aplicada San Luis, Universidad Nacional de San Luis y CONICET. San Luis 5700, San Luis, Argentina; guerralara@agro.uba.ar

[10] Instituto de Matemática Aplicada San Luis, Universidad Nacional de San Luis and CONICET. San Luis 5700, San Luis, Argentina; baldi@unsl.edu.ar

[11] IRNAD, UNRN, CONICET, San Carlos de Bariloche 8400, Río Negro, Argentina.; bagnato@agro.uba.ar

[12] Departamento de Ecologia, IB e Programa de Pós-Graduação em Agronegócios, CEPAN, Universidade Federal do Rio Grande do Sul. Porto Alegre 91501-970, Rio Grande do Sul, Brasil; hhasenack@ufrgs.br

* Correspondence: sbaeza@fagro.edu.uy

## Abstract

The Río de la Plata Grasslands (RPG) region is the largest area of the temperate humid and sub-humid grasslands biome in South America and one of the largest in the world. The region is located on fertile soils, generally very suitable for agricultural development, so it is undergoing an intense land cover change process. Our knowledge of these changes remains incomplete. Most regional-scale studies have been conducted over specific periods, limited subsets of the RGP, coarse resolution and, in general, used land cover classes that are not readily compatible. In this work we described and analyzed the land cover changes in the entire RPG region for the first two decades of the 21st century, especially those related to grasslands loss. We generated annual land cover maps with 30-meter resolution that discriminate between 8 categories: native woody formation, forest plantation, swampy areas and flooded grassland, grassland, farming, non-vegetated area, water and non-observed. The map series was evaluated for the years 2001 and 2018 using a completely independent dataset, selected by stratified randomized sampling. Overall accuracy was 73.5% and

77.8% for 2001 and 2018, respectively, with user and producer accuracies that varied between classes and years. In 20 years, RPG region lost, at least, 2.4 million ha of grassland (9% of the remaining grassland area in 2001). Most of these losses are concentrated in Brazil and Uruguay and are associated with new agricultural or forestry areas that increased by 5% and 100%, respectively. Our maps allow a comprehensive understanding of the transformation processes that RPG are undergoing and provide the context on which to explore a large set of hypotheses related to ecosystem structure and functioning. It will also contribute to improving decision-making at both the regional and national levels.

**Keywords:** Land use change, Landsat, Time series, Grasslands, Classification

## 1. Introduction

The disruption of ecosystem structure and functioning is a ubiquitous feature of the interaction between people and nature and it is generally referred to as land use or land cover change. An increasing number of studies show that human transformative land cover practices have impacted on carbon, nitrogen and hydrologic balance, biodiversity and climate (Hansen et al. 2013, Steffen et al. 2015) across multiple spatio-temporal scales (Ellis et al. 2021). In addition, land cover changes are triggered by a complex and bundled set of driving forces –from population increase, social inequality, market forces, infrastructure development, and individual responses to economic or technological opportunities which are in turn mediated by institutional factors (Lambin et al. 2001)-, which defy simplifications and require local or regional approaches to improve our understanding and assist decision making.

The RPG, also known as "Campos" or "Pampas"", is the largest temperate grassland region in South America and one of the largest in the world, with an area of more than 70 million hectares, covering the great plain of central-eastern Argentina, Uruguay and the south of Brazil (Soriano, 1991). They are renowned for their rich and productive vegetation mainly composed of grasses and herbs (Andrade et al. 2018; Lezama et al. 2019) and for providing habitat to a diverse and specific biota, including 109 species of grassland birds (Azpiroz et al. 2012). However, these grasslands are among the most altered ecoregions of the world as less than 1% of their area is subject to any kind of use restriction (Henwood 1998, Hoekstra et al. 2005, Watson et al. 2016). Thus, over the last 200 years large tracts of native grasslands have been mainly replaced by sown pastures, crops, and tree plantations (Baeza & Paruelo, 2018; Hall et al. 1992; Viglizzo et al. 2001). Together with the economic benefits brought about by the international trade of grain, meat, and other primary goods, public concerns on the sustainability and conservation of the RPG have intensified (Rotolo et al. 2015). The expansion of agriculture has significant impact on biodiversity (Staude et al. 2018), biological invasions (Guido et al. 2016), and carbon (Caride et al. 2012; Guershman et al. 2003), nitrogen (Austin et al. 2006) and hydrologic cycles (Noseto et al. 2012). The replacement of grasslands by Eucalyptus plantations have been documented to reduce soil pH, increase evapotranspiration, and may cause soil salinization (Jobbagy & Jackson, 2003; Nosetto et al. 2005). Moreover, cattle and sheep grazing have been shown to increase or decrease grasslands aboveground net primary production (Altesor et al. 2005; Rusch & Oesterheld, 1997) depending on the effects of changing species, plant functional type composition, biomass, and vertical distribution upon water and nutrient availability (Altesor et al. 2005).

Despite its importance, our understanding of the land cover changes and grassland conservation status in the RPG remains incomplete, coarse and fragmented. Most regional-scale studies have focused on the portion of the RPG limited to a given country and generally use official agricultural statistics aggregated at county level to characterize land cover changes (Baeza et al. 2014, Paruelo et al. 2006, Viglizzo et al. 2011). In turn, detailed studies have been conducted over specific periods, limited subsets of the RGP, coarse resolution and, in general, used land cover classes that are not readily compatible (Baeza & Paruelo, 2018, 2020; Baldi et al. 2008; Cordeiro & Hasenack, 2009; Graesser et al. 2015, Souza et al. 2020; Volante et al. 2015). Thus, while these studies have been instrumental to highlight the magnitude of the anthropogenic alteration of the RPG ecosystems, information on what remains and where, at what rates and over which type of land cover changes have been actively occurring is still lacking.

Our knowledge of the Earth's surface dynamics has increased in pace with remote sensing technological advances. Compared to conventional ground-based approaches, remote sensing is particularly advantageous to monitor large areas due to its synoptic and repetitive observations. The recent advent of Google Earth Engine (GEE) (Gorelick et al. 2017), together with easy access of global very high-spatial resolution images, the increased availability of digital tools to create and edit geographical data and crowdsourcing data collection protocols have opened the door for customized, periodic, and accurate land cover monitoring (Azzari & Lobell 2017). Indeed, the availability of long term (>20 years) annual time series of land cover maps over national, continental or global extents produced with an objective and reproducible methodology and consistent legends represents a giant step forward in our ability to characterize past, and predict future, land cover changes, its environmental and social impacts and enhance territorial planning (Souza et al. 2020).

The MapBiomas initiative (https://mapbiomas.org) was created to develop a methodology capable of generating annual land cover maps based on Landsat satellite imagery collection, in a concept of progressively evolving land cover map collections. Data is processed using machine learning algorithms at GEE and both, land cover maps and the algorithms used, are publicly available. The work is carried out by a network of interdisciplinary teams linked to universities, NGOs, technology companies and startups, operating in a collaborative environment. It involves methodological development as well as incorporates local knowledge on land cover to improve results. Started in Brazil (see Souza et al. 2020), the initiative has recently expanded to map land cover and its changes over time in different biomes, such as the Gran Chaco Americano (https://chaco.mapbiomas.org/; Banchero et al. 2020), Pan Amazonia (https://amazonia.mapbiomas.org/) or the Atlantic Forest (https://bosqueatlantico.mapbiomas.org/es).

Here we describe and analyze the land cover changes that occurred between 2000 and 2019 in the RPG using satellite based annual time series of land cover maps at 30 m resolution. To achieve this goal, we first developed and implemented a mapping framework – based on Landsat imagery and a GEE random forest classifier trained with visually interpreted samples- to produce a consistent land cover maps time series from the RPG biome. We then characterized the spatio-temporal pattern of land cover in the RPG focusing on the following questions: i) which is the present status of land cover types and how did they change in the last 20 years, ii) where have the rates of grassland –or other land cover conversion been highest, and iii) which have been the most frequent land cover transitions?

# 2 Materials and Methods

## *2.1 Study Area and land cover mapping approach*

The RPG occupies ca. 700000 km$^2$ (28°S–38°S, 50°W–61°W) (Soriano, 1991) and it ranges over 3 countries, central-eastern Argentina, Uruguay and part of southern Brazil. The mean annual temperature decreases from 20°C in the north to 13°C in the south, and the annual precipitation ranges from 1500 mm in the northeast to 400 mm in the southwest (Oyarzabal et al. 2020). Grasslands, formed by different combinations of C3 and C4 grasses and a broad set of herbs are the dominant vegetation (Andrade et al. 2018; Soriano 1991).

In this work, we focus only on the changes that have occurred within the RPG region. However, the total area mapped within the scope of the trinational MapBiomas Pampa initiative includes most of the RPG and also, parts of the neighboring phytogeographic regions of the Espinal and the Parana delta (Figure 1 ) to keep internal spatial continuity in the maps and with other

MapBiomas network initiatives. Results for the entire area covered by MapBiomas Pampa Collection 1 can be found on the project website ([https://pampa.mapbiomas.org/](https://pampa.mapbiomas.org/)).

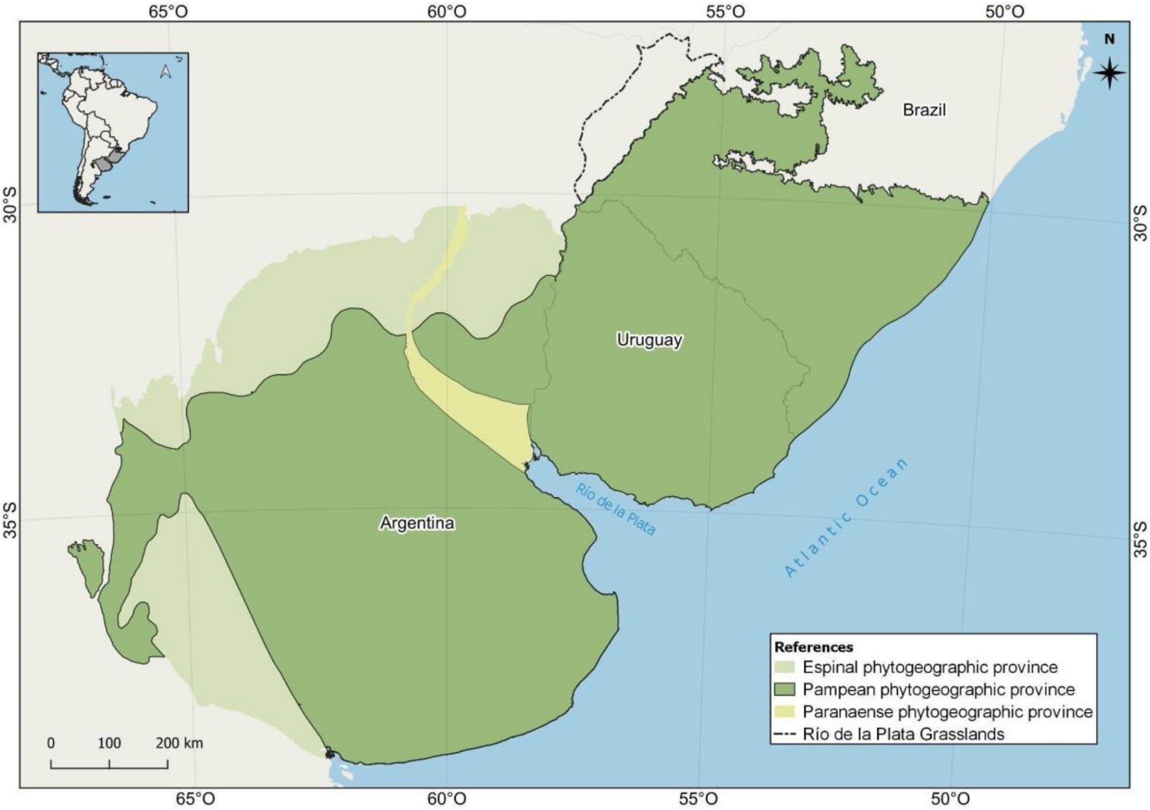



Figure 1: Region of interest mapped in the MapBiomas Pampa initiative, including the typical areas of the Pampa, Espinal, and Paraná river Delta.

The workflow of the classification process of Collection 1 in the MapBiomas Pampa initiative is shown in Figure 2. Having the study area defined, a legend with nine classes, a zonification of the area, with the definition of homogeneous sub-regions, and annual Landsat mosaics were generated. Visual interpretation samples for each class were obtained within each zone. The samples were generated using spectral data, vegetation indices and their temporal metrics. These were divided into training samples and testing samples and used only to perform a pre-classification with the random forest algorithm. From the pre-classification maps, then a new set of training stable samples (i.e. samples obtained from sites with the same class along the study period) was established and used as a basis for the final classification using the random forest algorithm again. To improve the classification within each sub-region, a set of complementary training stable samples was collected *ad hoc* and through visual interpretation. The post-processing of the classification consisted of a set of spatial, temporal and frequency filters. The results of this methodology were annual maps of the study area together with statistics regarding area and annual land cover transitions. The classifications were validated through a review process for the years 2001 and 2018, with a set of independent samples.

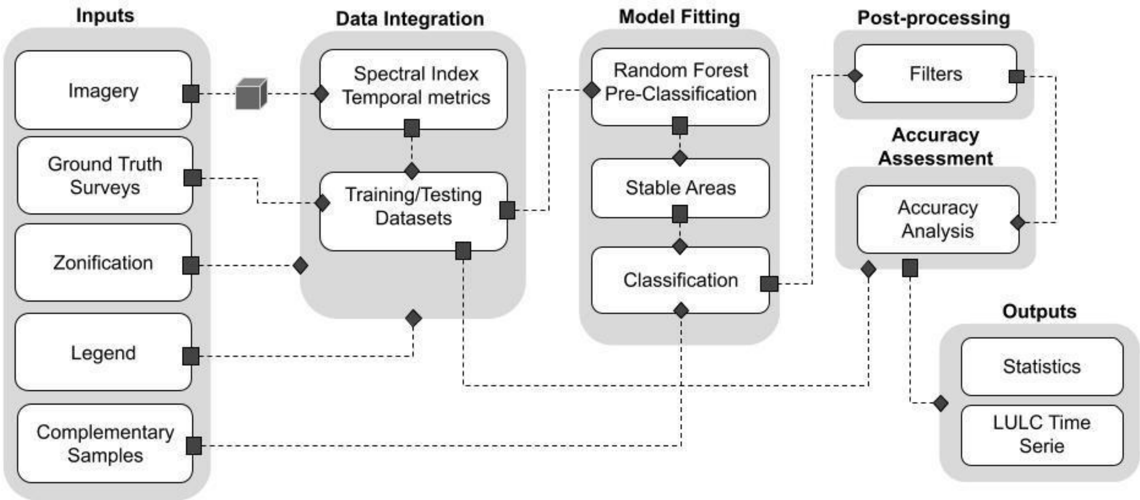



Figure 2: Workflow implemented for the classification process of Collection 1 of the MapBiomas Pampa initiative.

### *2.2 Inputs*

#### 2.2.1 Zonification

The classification process was carried out in 23 homogeneous sub-regions, nine in Argentina, seven in Brazil and seven in Uruguay (Figure S1, Supplementary material). These units correspond to relatively homogeneous areas established to perform the classifications independently, avoiding the use of samples from other sub-regions. Thus, each subregion is a geographical classification unit.

Zonification was based on different sources of information depending on each country: in Argentina, were included vegetation indices, cropland, rivers and water bodies density maps and climate information. In Uruguay, zonification was based on geomorphology criteria (Panario et al. 2014) and in Brazil, through a combination of soils, geomorphology and vegetation (Hasenack 2017).

### 2.2.2 Imagery

The imagery dataset used was obtained from the Landsat sensors Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS), on board of Landsat 5, Landsat 7 and Landsat 8, respectively. The Landsat imagery collections with 30 m pixel resolution were accessible via Google Earth Engine, and were provided by National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS). The imagery dataset used had Tier 1 from USGS and surface reflectance (SR), also had radiometric calibration and orthorectification correction based on ground control points and digital elevation model to account for pixel co-registration and correction of displacement errors. For the selection of Landsat scenes a threshold of 90% of cloud cover was applied (i.e., any available scene with up to 90% of cloud cover was accepted). This limit was established based on a visual analysis, after many trials observing the results of the cloud removing/masking algorithm.

Selected Landsat scenes were merged and clipped within standardized cells for data processing, hereafter called 'charts', based on the grid of the World International Chart to the Millionth, at the 1:250,000 scale level. Each chart sets the geographical limits (2° x 1.5° size) to build up the temporal and spatial Landsat annual mosaics These mosaics were generated by the composition of pixels in each set of images , based on the median pixel value over a given period (a growing season or a year). These medians are constructed with all valid pixels, i.e.: without error (e.g.: data gaps on Landsat 7 SLC-off images) or cloud masked values. The periods of the year in which the images were selected varied by country and resulted from the balance between the probability of maximizing the differences in classes' spectral behavior and the availability of cloud-free images. In Uruguay and Brazil, the considered period was from September to November of each year while in Argentina from May to July. The three-months periods were extended for some years and charts when the availability of cloud-free images was low. To proceed with digital classification, all charts from the same year were merged and clipped by the boundary of the corresponding sub-region.

### 2.2.3 Legend

The legend of the MapBiomas Pampa initiative included nine land cover classes (see Table S1-Supplementary material for a detailed description of each class): native woody formation, forest plantation, swampy areas and flooded grassland, grassland, farming, non-vegetated area, water, and non-observed. Native woody vegetation can be divided only in Argentina into two classes, closed forest and open forest. To maintain internal consistency, this division is not taken into account in this work and the maps and statistics reported reflect what happened with the entire native woody vegetation class.

### 2.2.4 Training data for Pre-Classification

Training samples of each class were obtained by visual interpretation of images and time series of vegetation indices. For this, backdrops of false-color Landsat mosaics for all the 20 years as well as graphs showing the temporal behavior of spectral indices per pixel were used to create stable land cover class samples (i.e. areas where the class was the same during the 20-year period). The sampling was done drawing small polygons (less than 200 pixels) using GEE Code Editor. On average, 10 polygons per chart and per class were digitized. A total of 4,189 polygons were digitized for Argentina and 1,703 for Uruguay. These samples were used for the pre-classification process. In the Brazilian portion there was no sample collection once the pre-classification process followed an alternative approach (see below).

*2.3 Data integration*

Landsat imagery was used to generate the feature space (i.e. variables) used as input of the random forest classifier. For each chart we calculated different aggregation metrics to reduce all observations within the selected period and produce temporal annual mosaics. Each mosaic has spectral bands and index, fractions and index from spectral mixture analysis, temporal index (based on median, minimum, amplitude and standard deviation reducers), and textural index. Each year was divided into quartiles by the Normalized Difference Vegetation Index values to define the higher and lower periods of photosynthetic activity. The median values of the highest quartile were defined as the high activity image and the lowest ones as the low activity image. This criterion was applied over spectral bands and indices to generate the high and low version of the descriptor (Table S2-Supplementary material). We obtained a total of 107 bands that allow us to describe the temporal and spectral dynamics between 2000 and 2019.

Training samples were used to generate the training and calibration sets to fit a random forest classifier. We extracted the values from the mosaics and shuffled the samples following a holdout strategy, with 70% and 30% to train and validate respectively.

*2.4 Model fitting*

2.4.1 Pre-classification

A subset between 200 and 700 pixels per class and per zone were randomly selected from the pixels of the on-screen-digitized polygons (randomly selected too) and used as training areas for the classification algorithm. Classification was performed zone by zone, year by year, using the Smile Random Forest algorithm (Breiman, 2001) available in Google Earth Engine, running 40 iterations (random forest trees) with 4 variables per split and minimum leaf size of 25. For Argentina and Uruguay, a total of 20 yearly preliminary classifications were obtained and the frequency with which a pixel was classified to the same land cover class was calculated to define the temporal stable areas.

In Brazil, an existing classification for these 20 years (results of MapBiomas Brazil collection 4.1, launched in 2019) was used to define the temporal stable areas for each class, making it unnecessary to produce a pre-classification. The first map collections for this specific region were made using decision trees based on Spectral Mixture Modeling (MME) variables as is described in Souza Jr. et al. (2005).

### 2.4.2 Stable areas samples

Each pixel classified with the same land cover class for at least a minimum number of years in the period 2000-2019 is considered as stable. The frequency thresholds depend on the class and the subregion (e. g. forest plantations for pulp mills usually have a 12-year cycle in Uruguay and a 18-year cycle in Argentina). The layer of stable areas was generated by those thresholds from which pixels were extracted for the classification (2,000 samples for each subregion). The selection was random and stratified based on the class cover percentage. The data set was balanced, rare classes that did not reach a land cover of at least 10% of the region area had a minimum of 200 samples. The data set was divided in two categories, training and testing. 60% of the subset, labeled as training pixels, were used as training samples for the classification algorithm.

### 2.4.3 Complementary data

The need for complementary training samples was evaluated by visual inspection comparing the output of the preliminary classification with both Landsat and high-resolution (< 1m) images available as base maps in GEE (typically WorldView, GeoEyes or Ikonos imagery) . Complementary samples were obtained by checking the false-color composites of the Landsat mosaics for all the 20 years during the polygon drawing to ensure class stability. Complementary samples were a minority (1.4 % of the total samples) and were used in some categories to solve specific classification problems. For example, wet lowlands grasslands classified as agricultural areas or confusion between Forest plantations and native woody vegetation in hilly areas, etc.

2.4.4 Classification

The final classification was performed for all subregions and years with stable and complementary samples with the algorithm used in the pre-classification (Random Forest, with 40 trees, 4 variables per split and minimum leaf size of 25). All years used the same subset of samples, but trained using the specific mosaic of the year being classified.

*2.5 Post-processing*

The results of the final classification were improved through a sequence of filters, to correct missing data, "salt-and-pepper" classification errors and, specially, cases of misclassification.

The "gap" filter was applied to fill the no-data pixels. The no-data values are replaced by the temporally nearest valid classification. In this procedure, if no "future" valid position was available, then the no-data value was replaced by its previous valid class. Therefore, gaps should only exist if a given pixel has been permanently classified as no-data throughout the entire temporal domain.

The spatial filter avoids unwanted modifications to the edges of the pixel groups, a spatial filter was built based on the "connectedPixelCount" function. Native to the GEE platform, this function locates connected components (neighbors) that share the same pixel value. Thus, only pixels that did not share connections to a predefined number of identical neighbors were considered isolated. In this filter, at least six connected pixels were needed to reach the minimum connection value. Consequently, the minimum mapping unit is directly affected by the spatial filter applied, and it was defined as 6 pixels (~0,5 ha).

The temporal filter uses the information from the previous year and the later year to identify and correct a pixel misclassification, considered as cases of invalid transitions. In the first step, the filter looks at any natural cover (3, 4, 11, 12, 33) that is not this class in 2000 and was kept unchanged in 2001 and 2002 and then corrects the 2000's value to avoid any regeneration in the first year. In the second step, the filter looks at a pixel value in 2019 that is not 14 (Farming) but is equal to 14 in 2017 and 2018. The value in 2019 is then converted to 14 to avoid any regeneration in the last year.

The third process looks in a 3-year moving window to correct any value that changed in the middle year and returns to the same class next year.

To correct classification problems associated with some classes in specific regions, frequency filters were applied to use the temporal information available for each pixel to correct cases of false positives. The general logic of the frequency filter is to search for each pixel a specific combination of classes throughout the 20 years producing a subset of pixels considered eligible for correction. Then the filter detects and overwrites only those years where cases of false positives are present using a fixed class value, that usually is the mode of classifications detected along the temporal range.

### *2.6 Accuracy assessment*

We used an independent validation dataset to assess the accuracy of our land cover maps. To avoid temporal filter effects at the beginning and end of the study period (see above) we selected for the accuracy analysis the years 2001 and 2018. We followed the sampling scheme proposed by Olofsson et al. (2014) whereas 2,330 pixels were selected by means of a stratified random design. Thus, the common accuracy assessment sample consisted of seven strata (one per class) based on the 2010 land cover map for the entire area covered by MapBiomas Pampa Collection 1. The allocation of samples to each stratum was slightly shifted from proportional as we fixed a minimum and maximum number of samples for the rarest and for the most frequent classes. Each of the 2330 samples was evaluated by at least 2 different interpreters (and a third evaluation was required when initial interpretations disagreed) involving up to 16 interpreters from 3 countries. Interpreters could access an RGB visualization of a Landsat composite from 2001 and from 2018, a NDVI time-series plot, and the catalog of very high-resolution images available in Google Earth Pro.

Accuracy assessment was performed by comparing the land cover maps with the independent reference points and calculating non-normalized and normalized error matrices (Congalton 1991, 2009). From them, we computed a set of commonly used accuracy measures, comprising producer’s and user’s accuracy, omission and commission errors, and overall accuracy.

Additionally, we computed quantity disagreement (QD) and allocation disagreement (AD), which decompose the overall disagreement in its components of quantity and allocation (Pontius and Millones, 2011).

These measures were preferred instead of kappa taking into account criticisms about the meaning and usefulness of the latter in the literature (Foody, 2020; Olofsson et al. 2014; Pontius & Millones 2011; Stehman et al. 2021). While kappa measures how much the agreement is better than random, quantity disagreement and allocation disagreement measure how much the agreement is less than perfect, providing additional information that helps to explain the error. Allocation disagreement and quantity disagreement provide measures of discordance due to the imperfect spatial allocation of class pixels and due to the incorrect extent of classes, respectively. Quantity disagreement measures the amount of difference between the reference data and the classification map that is due to the less than perfect match in the proportions of the categories. Allocation disagreement measures the amount of difference between the reference map and the estimated map that is due to the less-than-optimal match in the spatial allocation of the categories, given the proportions of the categories in the reference data and in the classification (Pontius & Millones 2011).

### *2.7 Outputs*

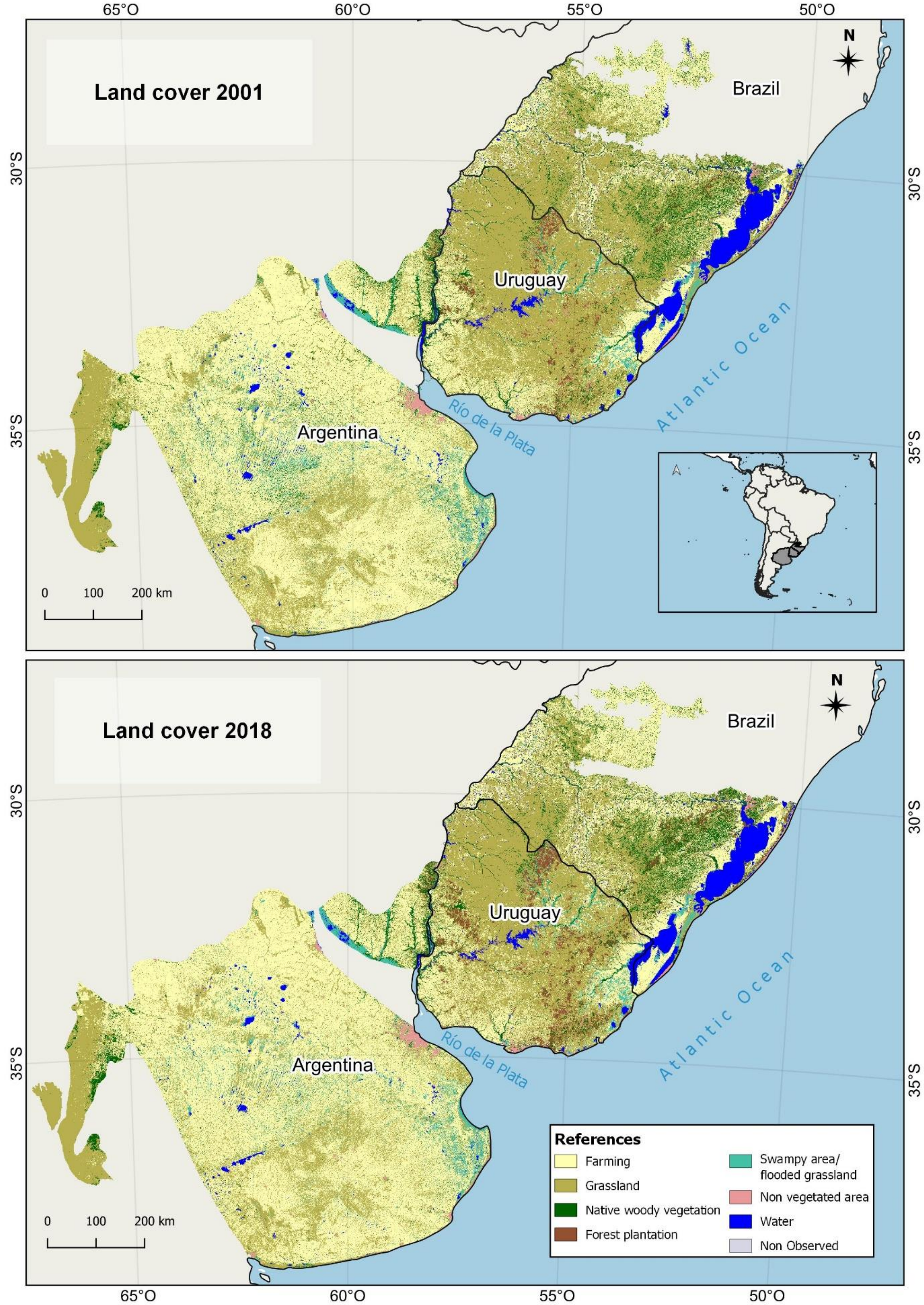
The area for each class in the annual maps was calculated from the number of pixels. The statistics were made for different spatial units: biomes, countries, and, in the website, for provinces and districts. Also, land cover changes occurring in a given period were calculated. In the same way as in the accuracy analysis, land cover transition for each pixel was calculated for 2001 and 2018, in order to avoid temporal filter effects. This data is available as spreadsheets, maps and Sankey diagrams respectively, in the MapBiomas Pampa web-platform. All GEE codes used in the classification process are available on GitHub https://github.com/schirmbeckj/mapbiomas-pampa-trinacional).

## 3 Results

Farming and grassland were the most abundant land cover classes in 2001 and 2018 for the whole region. Native woody vegetation was the third more abundant class, and swampy and flooded grassland the fourth one. The rest of the classes were relatively scarce (Figures 3 and 4). This general pattern integrated different individual patterns at country level in 2001 and 2018. In Argentina, farming was three times more abundant than grassland (Figures 3 and 4). In contrast, in Uruguay, grassland was three times more abundant than farming (Figures 3 and 4). In Brazil, farming and grassland were equally abundant, and native woody vegetation was more abundant than in Argentina and Uruguay (Figures 3 and 4).

Forest plantation class relatively increased 100% for the whole region between 2001 and 2018, while farming increased 5% and grassland and native woody vegetation decreased 8-9% (Figure 4). These general relative changes between 2001 and 2018 integrated different individual changes at country level. In Argentina, native forest decreased 30%, while forest plantation and swampy and flooded grassland decreased 7% (Figure 4). In Brazil, forest plantation increased 200%, farming 25% and native forest 5%, while grassland decreased 25% and swampy and flooded grassland 3% (Figure 4). In Uruguay, forest plantation increased 100%, swampy and flooded grassland 12% and farming 3%, while grassland area decreased 10% (Figure 4).

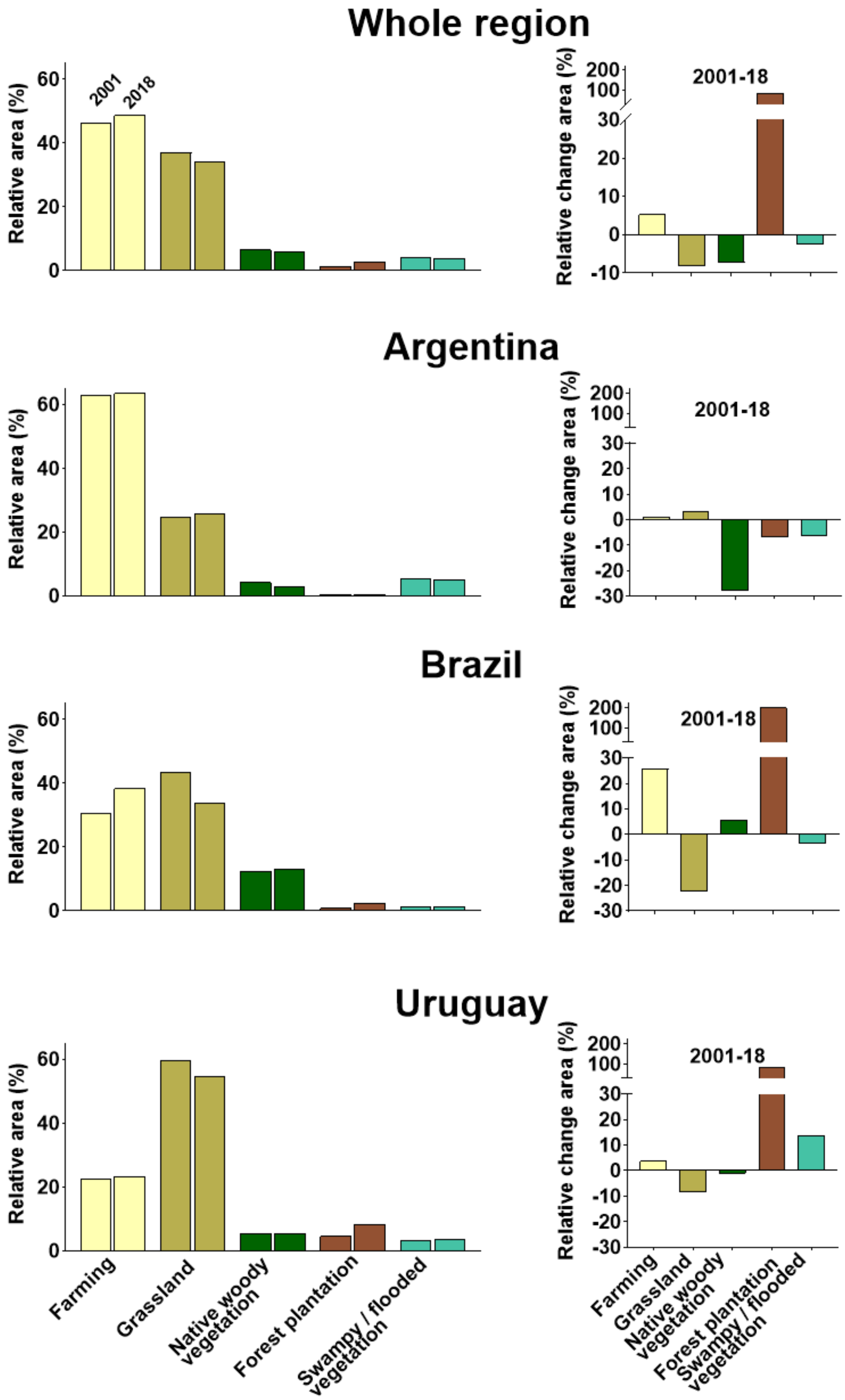
For the whole region the net loss of grassland was approximately 2.4 million hectares (Mha). This change includes the loss of 6.2 Mha (21% relative to grassland area in 2001), mainly due to replacement with farming, and the gain of 4.5 Mha of new grassland areas, mostly from farming. The transitions between the other classes were smaller and involved less than 0.9 Mha (Figure 5). At country level, Argentina has a net gain of grassland of 0.3 Mha, resulting for the transition from grassland to farming (2.8 Mha), from farming to grassland (2.7 Mha) and, to a lesser extent, from native woody vegetation and swampy area/flooded vegetation to grassland. Loss of native woody vegetation was around 0.6 Mha mainly for conversion to farming. In Brazil, net grassland loss was 1.9 Mha resulting for the transition from grassland to farming (2.1 Mha) and native woody vegetation (0.4 Mha) and the transition from farming to grassland (0.6 Mha). Uruguay has a net grassland loss of 0.9 Mha resulting for the transition from grassland to farming (1.4 Mha) and forest plantation (0.6 Mha) and the transition from farming to grassland (1.1 Mha). The rest of the transitions were less important and involved, all together, the change of category of 0.4, 0.2 and 0.2 Mha in Argentina, Brazil and Uruguay, respectively (Figure 5).



65°O
60°O
55°O
50°O
30°S
35°S
Land cover 2001
Brazil
Uruguay
Argentina
Río de la Plata
Atlantic Ocean
N
0
100
200 km
Land cover 2018
References
Farming
Grassland
Native woody vegetation
Forest plantation
Swampy area/
flooded grassland
Non vegetated area
Water
Non Observed

376 Figure 3: Land cover map for Rio de la Plata Grasslands during 2001 (top) and 2018 (bottom). Black

377 lines indicate international boundaries.




378

Figure 4: Relative area (%) of land cover main vegetated classes for the whole RPG region and each country between 2001 and 2018 (left), and relative change area (%; right). Relative change area was calculated as: (area 2018 - area 2001)/area 2001. For better readability, only two labels are shown in the first top left graphic.

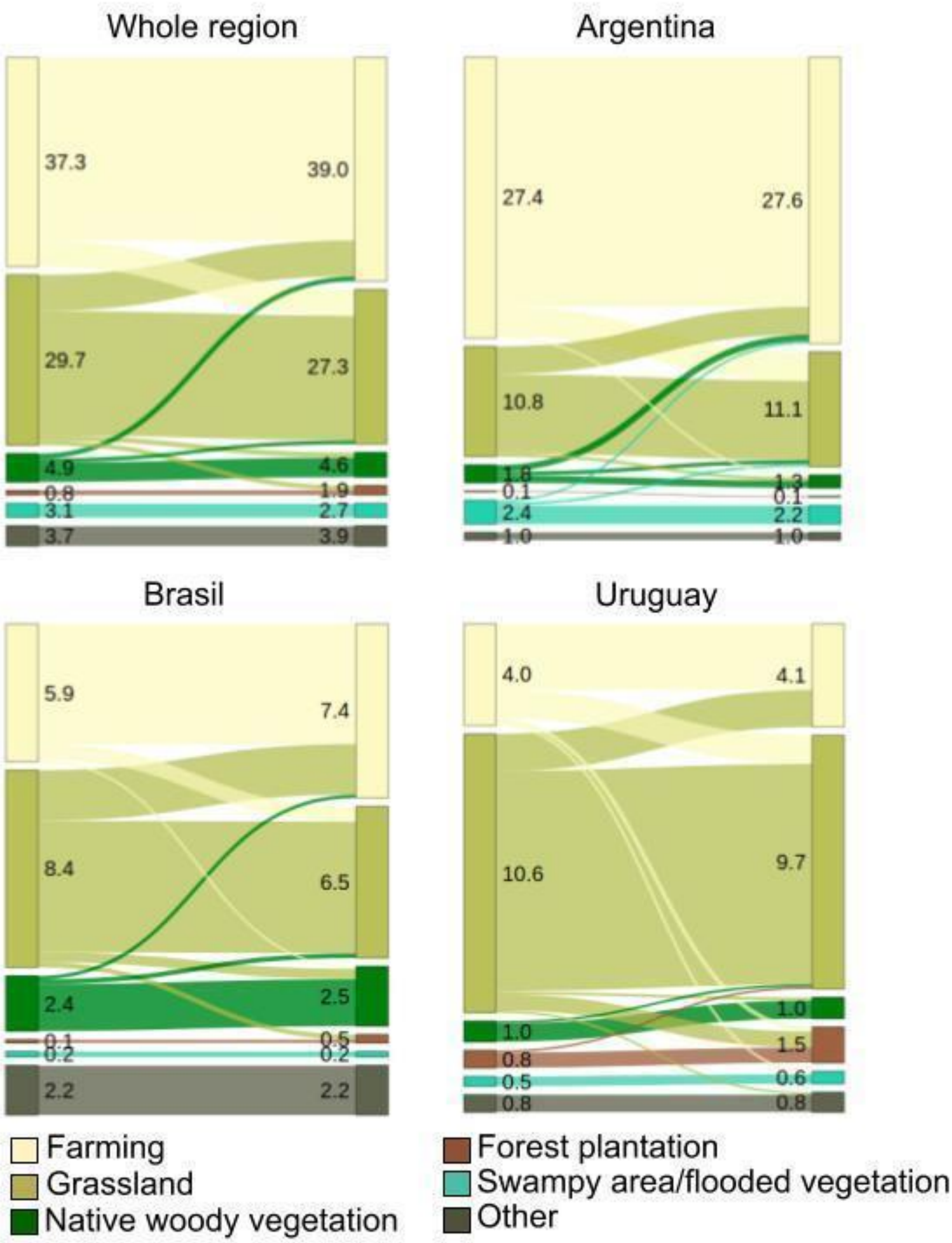


Figure 5: Transitions of land cover classes for the whole RPG region and each country between 2001 (left) and 2018 (right). Transitions with less than 0.5% of the total area were removed for visual purposes. In each panel, numbers indicate the area of each class (in million ha).

### *3.1 Accuracy Assessment*

Overall accuracy (OA) was 74% for 2001 and 78% for 2018. In 2001, user and producer´s accuracies were maximum for farming and water, and minimum for forest plantations. In 2018, both accuracies were also maximum for farming and water, user's accuracy was minimum for non-vegetated area while producer´s one was minimum for swampy area/flooded vegetation (Figure 6). Regarding the nature of disagreements, in both land cover maps, allocation disagreement (AD) was the major component of discordance with 24.3% in 2001 and 13.1% in 2018. Quantity disagreement (QD) in 2001 was 2.3% and in 2018, 1.31% (Table S3, Supplementary material). Summing overall agreement and allocation disagreement gives an indicator of area agreement which equals 97.7% in 2001 and 90.9% in 2018.

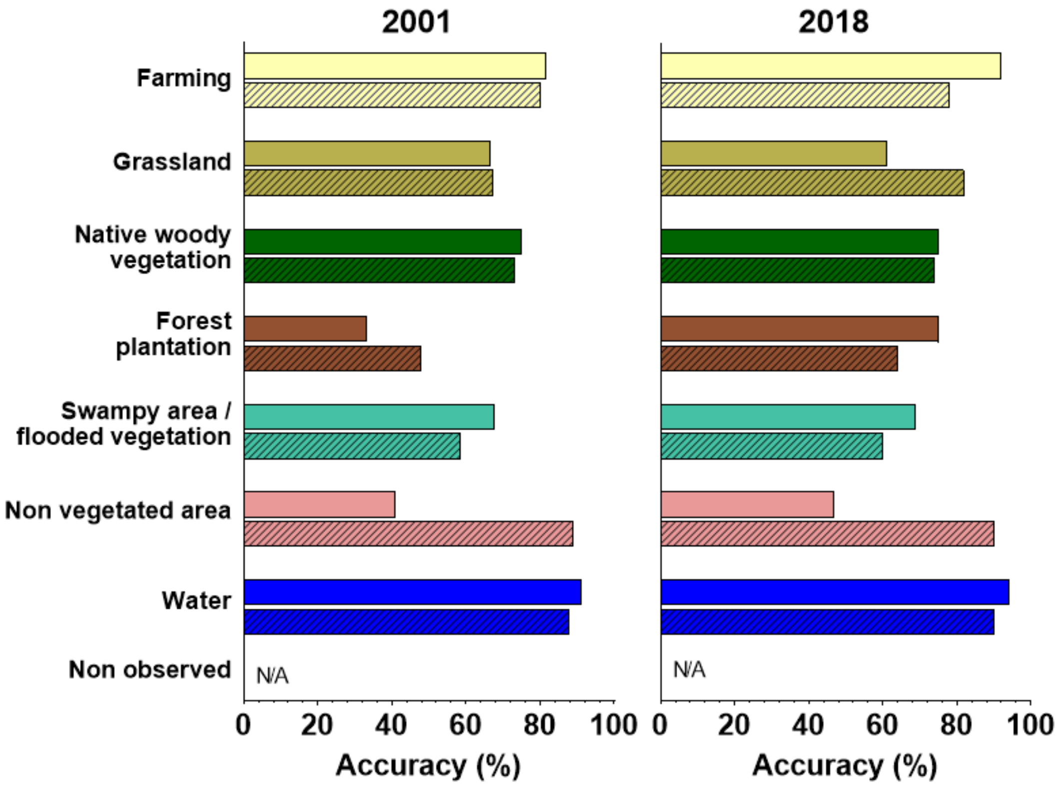



Figure 6: User´s (empty bars) and producer´s (scratched) accuracy of land cover maps in 2001 and 2018.

## 4 Discussion

Our work reports land cover and its changes over time for the entire RPG region with unprecedented spatial and temporal resolutions (20 years of 30 m annual maps). The MapBiomas Pampa initiative summarizes the collaborative effort of three countries and several public and private institutions incorporating local knowledge in the construction of maps. RPG region has lost at least 8 % of its natural grassland area in the last 20 years mainly due to farming and forest plantation expansion. These losses were greatest in the Brazilian portion of the study area, where grasslands lost almost 30% of their area. Wall to wall (entire region) maps allow a global understanding of the transformation processes that RPG are undergoing and provide the context in which to explore a large set of hypotheses related to the distribution of plant and animal species, effects of habitat loss and fragmentation on biodiversity, biological invasions or ecosystem functioning. Moreover, our maps can help to define cooperation on supranational management policies (e.g. planning of road infrastructure for cargo transport, estimating the final volume of raw materials in different ports, etc.) or to assess the effect of different land management policies at the national level.

Our maps presented accuracies comparable to those reported in other works that map land cover over large areas and reflect the complexity of mapping natural grasslands. For example, Buchorn et al. (2020), for Copernicus Global Land Cover - Collection 2, reported a global accuracy around 80%, accuracies around 70% for herbaceous vegetation and 50-60 % for wetlands and shrublands. Stheman et al. (2021), reported somewhat higher precision for the annual map series of the U.S. Geological Survey Land Change Monitoring, with an average overall accuracy of 82.5% but highly variable in space; for example, the grass/shrub class had user accuracies of 36 and 48% and producer accuracies of 15 and 11% for east and central-east regions, respectively. Wickham et al. (2021) analyzed the accuracy of the National Land Cover Database, a Landsat based land cover maps for the conterminous US, and reported global accuracies of around 72% and user and producer accuracies of 65 and 67% for grasslands, respectively. The accuracy of our maps was also similar to that of other map collections from the MapBiomas initiative. For example, Souza et al. (2020) for annual land cover maps of MapBiomas Brazil - Collection 3, reported overall accuracies ranging from 95 to 73%, depending on the biome considered, with high omission and commission errors for grassland class. In the Brazilian Cerrado, a particularly complex biome subjected to an intense process of land cover change, Alencar et al. (2020) mapped native vegetation with overall accuracies from 67 to 74% and higher errors in grasslands. For MapBiomas Chaco initiative, Banchero et al. (2020) reported overall accuracies around 74% but do not report the error distribution of the different mapped classes. In a direct antecedent that mapped RPG biome, Baeza and Paruelo (2020) used information on vegetation phenology derived from NDVI-MODIS time series to generate annual maps for the period 2000-2014. This work had higher accuracy (around 95% at regional level) but lower conceptual resolution (grouped natural grasslands with sown pastures and native forests with commercial afforestation), lower spatial resolution (250 m) and covered a shorter period of time than MapBiomas Pampa Collection 1 maps.

The accuracy analysis shows coincidences with other works and particular characteristics of our study area and the approach used. Overall accuracy (and producer / user accuracies) was higher in 2018 than in 2001, which is expected given the lower availability of high-resolution imagery at the beginning of the map series, which generates higher uncertainties in both training and evaluation sample generation. This trend of increasing accuracy of maps from more recent years was also reported in other works of MapBiomas initiative (Alencar et al. 2020, Souza et al. 2020).

A detailed analysis of the confusion matrices including omission and commission errors, allocation disagreement (AD) and quantity disagreement (QD), and their partial calculus, allows to identify the main problems of the maps and to infer which classes tend to have their extent overestimated or underestimated (Table S3, Supplementary material). One of the biggest challenges in the context of this work is the discrimination of grasslands from other land covers. Grasslands are mainly confused with farming, probably with sown pastures (included in farming class). The high physiognomic similarity and the intra class heterogeneity of the spectral response of both natural grasslands (different communities, landscape positions, location in the study area) and sown pastures (different species, sowing dates, pasture age, etc.) generate an overlapping of the spectral signatures of these coverages, which makes it difficult to discriminate between them. Additionally, and unlike other temperate grasslands where the herbaceous vegetation dries up or is covered with snow for part of the year, RPGs have photosynthetically active vegetation throughout the year, making it difficult to discriminate based on phenology. This difficulty for correctly discriminating grasslands has been reported before in several works and is reflected in the greater confusion of this category in the land cover works discussed above. For our study area, Rios et al. (2022) reported this problem for grasslands in southeastern Uruguay, Souza et al. (2020) for South Brazilian grasslands, Baeza et al. (2019) and Baeza and Paruelo (2020) for Uruguayan grasslands. Baeza and Paruelo (2020) dealt with this grassland-pasture confusion by merging the classes into a single category of perennial forage resources. Contrary, in our work, pastures were mapped together with crops in a single Farming class, leaving natural grasslands, the main natural vegetation formation of the biome, as an independent class.

### *4.1 Grassland loss and main Land Use Changes.*

In 20 years, RPG region lost almost 2.4 million ha of grassland (9% of the remaining grassland area in 2001). Most of these losses are concentrated in Brazil and Uruguay and are associated with new agricultural or forestry areas. Similar trends were previously reported in other works that cover partially (Baldi & Paruelo; 2008; Cordeiro and Hasenack, 2009; Kuplich et al. 2018; Oliveira et al. 2017; Volante et al. 2015) or totally (Baeza et al. 2020; Graesser et al 2015; Potapov et al. 2021) de study area. Song et al. (2021) recently reported that most of the expansion of the soybean area in South America occurred at the expense of grassland areas in the RPGs where the area with this crop practically doubled in the last 20 years. In Argentina, the area with natural grasslands remained practically unchanged, probably because most of the sites suitable for agriculture had already been transformed prior to the period analyzed and/or the new agricultural areas come from areas previously occupied with sown pastures. Baldi & Paruelo (2008) and Viglizzo et al. (2011) reported that the agriculturalization process in most of the Argentine pampas predates the year 2000. Baeza and Paruelo (2020) reported changes from perennial forage resources to crops in the Argentine pampas after 2000. These changes probably respond to an agricultural intensification process with a shift from sown pastures or pasture-agriculture rotation to continuous annual crops; both land cover categories fall into the farming class in our classification scheme, which would explain why our maps do not capture these changes.

Another important land cover change process that has occurred in the last two decades is the increase of forest plantation, which doubled the area occupied compared to 2001. This increase was particularly important in Uruguay and Brazil, where the forested area doubled and tripled, respectively. In Uruguay, the expansion of forest plantation is associated with political and economic incentives and the installation of the cellulose industrial complex (Baeza et al. 2006; Baeza and Paruelo, 2020; Baldi & Paruelo, 2008; Paruelo et al. 2006). In Brazil, it results from private investments made by large national and international companies to expand the pulp and paper supply chain within a framework of strong globalization, centralization of assets and concentration of industrial production (Benetti 2008). A similar process was documented for Argentina, but was mainly located in North Entre Ríos and Corrientes provinces (Baldi & Paruelo, 2008), areas not included in this study.

Although the accuracy of the maps is moderate, the analysis of the confusion matrix and the metrics proposed by Pontius and Millones (2011), shows that most of the error is associated with the allocation and not to quantity disagreement. This increases the map accuracy for area calculation (Overall accuracy + Allocation disagreement), reaching 98 and 91 % for 2001 and 2018 respectively, increasing confidence in the loss of grassland areas reported. Moreover, error-corrected area estimates (Table S4-Supplementary material) show that these grassland losses are surely even greater. Grassland area was slightly overestimated in 2001 and strongly overestimated in 2018, so the net loss is probably much higher than calculated from the maps. The opposite occurs with the two main grassland replacements; Farming underestimation was lower in 2001 than in 2018, from which it is reasonable to assume that expansion was larger than shown by the maps. Forest plantations were slightly overestimated in 2001 and considerably underestimated in 2018, implying that net gain was quite larger than that reported on the maps.

The decrease in grassland area coincides with what happened in other grasslands around the world (Bond and Parr, 2010; Lark et al. 2015; Neke and Du Plais, 2004; Veldman et al. 2015) and alerts about the conservation status of this biome, often forgotten in the conservation agenda (Hoekstra et al. 2005; Overbeck et al. 2007; Silveira et al. 2020; Watson et al. 2016). According to Oyarzabal et al. (2020) there are 99 protected areas in RPG , which cover between 3.7% and 6.8%

of the biome extent, depending on the considered regional limits. Most of these protected areas have been implemented on public lands of generally low-economic importance, regardless of their conservation values (Baldi et al. 2017, 2019; Oyarzabal et al 2020). The availability of regional (semi)natural vegetation maps with good spatial and temporal resolution therefore becomes central for defining efficient conservation and/or restoration policies (Buisson et al. 2021; IPCC, 2019). Our maps allow  systematically identifying both grassland remnants in highly transformed areas and large grassland patches within landscapes with low fragmentation suitable for conservation programs.

### *4.2 Limitations and next steps*

There are a number of aspects to consider when interpreting the results of this work, evaluating the scope of generated maps and improving future map collections. The results presented in this article do not contemplate the entire study area since the maps of MapBiomas Pampa-Collection 1 also incorporate portions of other neighbor biomes (see methods). However, the evaluation of the maps was carried out from a stratified sampling that contemplates the entire mapped area and not exclusively the RPG. This implies that the error estimation and area correction presented might be slightly different if the stratification and sampling had been done exclusively within the RPG limits.

Future work will require improvements in class differentiation, conceptual resolution (larger number of classes) and extension of the time period under study. Discrimination improvements depend on the class to map. In our region, the grasslands confusion discussed above, fundamentally with sown pastures, could be partially corrected through several mechanisms: improvements in the quantity and quality of training data; extension of the feature space; use of the historical map series to discriminate grasslands sites that were previously other land cover. Recently, Rios et al (2022) used an agricultural mask (sites that had agriculture in at least one of the last 12 years) to discriminate grasslands from other herbaceous covers (sown pastures, post-agricultural fields with different stages of vegetal succession) in the southeastern Uruguay. Another class with which grasslands are confused is native woody vegetation, particularly with open woody / savanna formations, a frequent confusion in systems with variable density of woody cover (Alencar et al. 2020; Sano et al. 2010). Incorporating, at least for the most recent maps, information that accounts for vegetation structure, such as radar images (see for example: Heckel et al. 2020; Lopes et al. 2020; Zhang et al. 2019,) or Lidar technology (Ferraina et al. 2022; Ferreira et al. 2011; Zimbres et al. 2020), could also improve the discrimination of open woody covers and reduce their mixing with grasslands.

The improvements in conceptual resolution fundamentally imply the separation of the farming class between crops and sown pastures and, within crops, between annual and perennial crops, expanding the potential uses of generated maps (see below). The extension of the studied period will allow to improve the description of land cover change processes and the analysis of its causes and consequences. In the RPGs, for example, much of grassland losses, mainly in the Argentine portion of the study area, occurred before the year 2000 and are not captured in the map collection presented here. The extension of the map series up to 1985 from the historical Landsat 5 archive has already been successfully used in other works such as MapBiomas Brazil (Souza et al. 2020) or the Land Change Monitoring Assessment and Projection (LCMAP) in the United States (Brown et al. 2020; Stehman et al. 2021).

Due to time and budget constraints, the evaluation of the map collection accuracy was carried out exclusively for two years, at the beginning and end of the series. An evaluation of the entire map collection would allow a correct quantification of the rates of change for the different classes, with more stable trends, enabling the possibility of correcting erroneous transitions.

### *4.3 The MapBiomas platform and its potential uses*

Wall to wall (entire region) RPG maps allow for a comprehensive view of a number of core aspects linked to ecosystem structure and functioning. They allow to, for example, assess the biodiversity conservation status and conservation/restoration priorities; model species distribution and design management strategies based on their habitat requirements; assess the role of habitat loss and fragmentation in biological diversity and/or exotics invasion processes; analyze exchanges of matter and energy and their influence on the regional climate; or define supranational management policies. On the other hand, the results allow the comparison of the land use planning policies of the three countries involved and the evaluation of their effect on the landscape conformation and its changes over time. For example, the law for the promotion of forestry activities in Uruguay (law 15939) and the installation of 3 large pulp mills, promoted the expansion of forestry plantations observed in our maps.

Previous products from other MapBiomas initiatives, such as MapBiomas Brazil maps' collections have been used in numerous works. For example, Rosa et al. (2021) quantified native forest cover dynamics in the Brazilian Atlantic Forest and related them to restoration programs and Nunes et al. (2020) analyzed the extension and carbon gains of secondary vegetation in the Brazilian Amazon. Several works also model the impact of land cover changes on energy flows and water cycle (dos Santos et al. 2022; Laipelt et al. 2021; Rosan et al. 2021) or animal diversity and distribution (Camana et al. 2020; Alvarenga et al. 2021, Galan Acedo et al. 2021)

MapBiomas Pampa land cover maps are conceived as successive evolving collections where all the products, methods and tools are freely and publicly available on internet (https://pampa.mapbiomas.org/). We hope that the successive maps collection of MapBiomas Pampa initiative contribute to the development of knowledge and the improvement of decision-making at both the regional and national levels

**Supplementary Materials:** Figure S1: Region of interest mapped in the MapBiomas Pampa initiative showing the limits of relatively homogeneous areas used to perform independent classifications, Table S1: Legend description of the MapBiomas Pampa Collection 1, Table S2: Feature space (107 variables) used in the digital classification of Landsat image mosaics in the MapBiomas Pampa Collection 1 (2000-2019), Table S3: Contingency matrices between classification results and independent validation dataset, Table S4: Area estimates corrected from the analysis of the contingency matrices

**Acknowledgements:** We would like to thank all the team involved in the MapBiomas Collections and particularly to Tasso Azevedo (general coordinator) and Marcos Rosa (technical coordinator) from MapBiomas for promoting and supporting the entire Pampa Trinational initiative. We gratefully acknowledge the USGS and NASA for the courtesy of the Landsat images. We are also grateful to Google for providing access to the Google Earth Engine platform that enables the processing of all data. We also thank Fundación Vida Silvestre Argentina for operating arrangements. This work has been partially funded by MapBiomas Brasil through Arapyaú Institute. MapBiomas is supported by a network of funders including Children's Investment Fund Foundation (CIFF), Climate and Land Use Alliance (CLUA), Global Wildlife Conservation (GWC), Good Energies Foundation, Gordon & Betty Moore Foundation, Iniciativa Internacional de Clima e Florestas da Noruega (NICFI), Instituto Arapyaú, Instituto Clima e Sociedade (ICS), Instituto Humanize, OAK Foundation, Quadrature Climate Foundation (QCF), Walmart Foundation (USA), Wellspring Philanthropic Fund (WPC). This work has been also partially funded by ANII INNOVAGRO projects FSA_PI_2018_1_149022 and FSA_PI_2018_1_148811; CSIC I+D 2020_358, FMV_3_2020_1_162279, and FMV_1_2021_1_167032

## References

Alencar, A., Z Shimbo, J., Lenti, F., Marques, C.B., Zimbres, B., Rosa, M., ... & Barroso, M. (2020). Mapping three decades of changes in the brazilian savanna native vegetation using landsat data processed in the google earth engine platform. *Remote Sensing*, *12*(6), 924.

Altesor, A., Oesterheld, M., Leoni, E., Lezama, F., & Rodríguez, C. (2005). Effect of grazing on community structure and productivity of a Uruguayan grassland. Plant Ecology, 179(1), 83-91.

Alvarenga, G. C., Chiaverini, L., Cushman, S. A., Dröge, E., Macdonald, D. W., Kantek, D. L. Z., ... & Kaszta, Ż. (2021). Multi-scale path-level analysis of jaguar habitat use in the Pantanal ecosystem. *Biological Conservation*, *253*, 108900.

Andrade, B. O., Marchesi, E., Burkart, S., Setubal, R. B., Lezama, F., Perelman, S., ... & Boldrini, I. I. (2018). Vascular plant species richness and distribution in the Río de la Plata grasslands. Botanical Journal of the Linnean Society, 188(3), 250-256.

Austin, A. T., Piñeiro, G., & Gonzalez-Polo, M. (2006). More is less: agricultural impacts on the N cycle in Argentina. *Biogeochemistry* 79: 45–60.

Azpiroz, A. B., Isacch, J. P., Dias, R. A., Di Giacomo, A. S., Fontana, C. S., & Palarea, C. M. (2012). Ecology and conservation of grassland birds in southeastern South America: a review. *Journal of Field Ornithology*, *83*(3), 217-246.

Azzari, G. & Lobell, D. B. (2017). Landsat-based classification in the cloud: An opportunity for a paradigm shift in land cover monitoring. Remote Sensing of Environment 202: 64–74.

Baeza, S. Baldassini, P., Bagnato, C., Pinto, P., Paruelo, J. M. (2014). Caracterización del uso/cobertura del suelo en Uruguay a partir de series temporales de imágenes MODIS. Agrociencia Uruguay, 18 2:95-105.

Baeza S. & Paruelo J. 2018. Spatial and temporal variation of Human Appropriation of Net Primary Production in the Rio de la Plata Grasslands. ISPRS Journal of Photogrammetry and Remote Sensing. 145: 238 – 249

Baeza, S., & Paruelo, J. M. (2020). Land use/land cover change (2000–2014) in the Rio de la Plata grasslands: an analysis based on MODIS NDVI time series. Remote Sensing, 12(3), 381.

Baeza, S., Paruelo, J. M., & Altesor, A. (2006). Caracterización funcional de la vegetación del Uruguay mediante el uso de sensores remotos. *Interciencia*, *31*(5), 382-388.

Baeza S.; Rama G. & Lezama F. 2019. Cartografía de los pastizales en las regiones geomorfológicas de Uruguay predominantemente ganaderas. Ampliación y actualización. En Altesor A, López-Mársico L y Paruelo J (Eds.). Bases ecológicas y tecnológicas para el manejo de pastizales II., pp. 27-47

Baldi, G., Paruelo, J.M. (2008). Land-Use and Land Cover Dynamics in South American Temperate Grasslands. Ecology and Society 13: 6.

Baldi, G., Schauman, S., Texeira, M., Marinaro, S., Martin, O. A., Gandini, P., & Jobbágy, E. G. (2019). Nature representation in South American protected areas: country contrasts and conservation priorities. *PeerJ*, *7*, e7155.

Baldi, G., Texeira, M., Martin, O. A., Grau, H. R., & Jobbágy, E. G. (2017). Opportunities drive the global distribution of protected areas. *PeerJ*, *5*, e2989.

Banchero, S., De Abelleyra, D., Veron, S. R., Mosciaro, M. J., Arevalos, F., & Volante, J. N. (2020, March). Recent Land Use and Land Cover Change Dynamics in the Gran Chaco Americano. In 2020 IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS) (pp. 511-514). IEEE.

Benetti, M. (2008) Indicadores da formação de uma plataforma exportadora de celulose no Rio Grande do Sul. Indicadores Econômicos FEE, Porto Alegre, v. 35, n. 3, p. 21-28.

Bond, W. J., & Parr, C. L. (2010). Beyond the forest edge: ecology, diversity and conservation of the grassy biomes. *Biological conservation*, 143(10), 2395-2404.

Breiman, L. Random Forests. *Machine Learning* 2001, 45, 5–32.

Brown, J. F., Tollerud, H. J., Barber, C. P., Zhou, Q., Dwyer, J. L., Vogelmann, J. E., ... & Rover, J. (2020). Lessons learned implementing an operational continuous United States national land change monitoring capability: The Land Change Monitoring, Assessment, and Projection (LCMAP) approach. *Remote Sensing of Environment*, *238*, 111356.

Buchhorn M, Lesiv M, Tsendbazar N E, Herold M, Bertels L and Smets B 2020 Copernicus global land cover layers-collection 2. Remote Sensing 12: 1–14.

Buisson, E., Fidelis, A., Overbeck, G. E., Schmidt, I. B., Durigan, G., Young, T. P., ... & Silveira, F. A. (2021). A research agenda for the restoration of tropical and subtropical grasslands and savannas. *Restoration Ecology*, *29*, e13292..

Camana, M., Dala-Corte, R. B., Collar, F. C., & Becker, F. G. (2020). Assessing the legacy of land use trajectories on stream fish communities of southern Brazil. *Hydrobiologia*, 1-16.

Caride, C., Piñeiro, G., & Paruelo, J. M. (2012). How does agricultural management modify ecosystem services in the argentine Pampas? The effects on soil C dynamics. Agriculture, ecosystems & environment, 154, 23-33.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment*, *37*(1), 35-46.

Congalton, R. G. (2009). Accuracy and error analysis of global and local maps: Lessons learned and future considerations. *Remote Sensing of Global Croplands for Food Security*, *441*, 47-55.

Cordeiro, J. L. P., & Hasenack, H. 2009. Cobertura vegetal atual do Rio Grande do Sul. Em: Pillar, V. D..; Müller, S. C.; Castilhos, Z. M. S. & Jacques, A. V. A. [Eds.]. Campos Sulinos–conservação e uso sustentável da biodiversidade. Brasília: Ministério do Meio Ambiente, Brasil, 285-299.

dos Santos, V. J., Calijuri, M. L., & de Assis, L. C. (2022). Land cover changes implications in energy flow and water cycle in São Francisco Basin, Brazil, over the past 7 decades. *Environmental Earth Sciences*, *81*(3), 1-24.

Ellis, E. C., Gauthier, N., Goldewijk, K. K., Bird, R. B., Boivin, N., Díaz, S., ... & Watson, J. E. (2021). People have shaped most of terrestrial nature for at least 12,000 years. *Proceedings of the National Academy of Sciences*, *118*(17).

Ferraina, A., Baldi, G., de Abelleyra, D., Grosfeld, J., & Verón, S. (2022). An insight into the patterns and controls of the structure of South American Chaco woodlands. Land Degradation & Development, 33( 5), 723– 738.

Ferreira, L. G., Urban, T. J., Neuenschawander, A., & De Araújo, F. M. (2011). Use of orbital LIDAR in the Brazilian Cerrado Biome: Potential applications and data availability. *Remote Sensing*, *3*(10), 2187-2206.

Foody, G. M. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sensing of Environment*, *239*, 111630.

Galán-Acedo, C., Spaan, D., Bicca-Marques, J. C., de Azevedo, R. B., Villalobos, F., & Rosete-Vergés, F. (2021). Regional deforestation drives the impact of forest cover and matrix quality on primate species richness. *Biological Conservation*, 263, 109338.

Graesser, J.; Aide, T. M.; Grau, H. R. & Ramankutty, N. 2015. Cropland/pastureland dynamics and the slowdown of deforestation in Latin America. Environmental Research Letters, 10(3), 034017

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment 202: 18-27

Guerschman, J. P., Paruelo, J. M., & Burke, I. C. (2003). Land use impacts on the normalized difference vegetation index in temperate Argentina. *Ecological applications*, *13*(3), 616-628.

Guido, A., Vélez-Martin, E., Overbeck, G. E., & Pillar, V. D. (2016). Landscape structure and climate affect plant invasion in subtropical grasslands. *Applied Vegetation Science*, *19*(4), 600-610.

Hall, A.J., Rebella, C.M., Ghersa, C.M., Culot, J.P. Field crop systems of the Pampas. In *Field Crop Ecosystems*; Pearson, C.J., Ed.; Elsevier: Amsterdam, The Netherlands, 1992; pp. 413–450.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... & Townshend, J. (2013). High-resolution global maps of 21st-century forest cover change. science, 342(6160), 850-853.

Hasenack, H. Determinantes biofísicos e geopolíticos do uso da terra no estado do Rio Grande do Sul, Brasil. 2017. 70 f. Tese (Doutorado) - Universidade Federal do Rio Grande do Sul, Centro de Estudos e Pesquisas em Agronegócios, Programa de Pós-Graduação em Agronegócios, Porto Alegre, BR-RS.

Heckel, K., Urban, M., Schratz, P., Mahecha, M. D., & Schmullius, C. (2020). Predicting forest cover in distinct ecosystems: The potential of multi-source Sentinel-1 and-2 data fusion. *Remote Sensing*, *12*(2), 302.

Henwood, W. D. (1998). An overview of protected areas in the temperate grasslands biome. *Parks*, *8*(3), 3-8.

Hoekstra, J.M.; Boucher, T.M.; Ricketts, T.H. & Roberts, C. 2005. Confronting a biome crisis: global disparities of habitat loss and protection. Ecology letters, 8, 23-29.

IPCC, 2019: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. In press.

Jobbágy, E. G., & Jackson, R. B. (2003). Patterns and mechanisms of soil acidification in the conversion of grasslands to forests. *Biogeochemistry*, *64*(2), 205-229.

Kuplich, T. M., Capoane, V.; Costa, L. F. F. O avanço da soja no bioma Pampa. Boletim Geográfico do Rio Grande do Sul, Porto Alegre, n. 31, p. 83-100, jun. 2018

Lark, T. J., Salmon, J. M., & Gibbs, H. K. (2015). Cropland expansion outpaces agricultural and biofuel policies in the United States. *Environmental Research Letters*, *10*(4), 044003.

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., ... & Xu, J. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global environmental change*, *11*(4), 261-269.

Laipelt, L., Kayser, R. H. B., Fleischmann, A. S., Ruhoff, A., Bastiaanssen, W., Erickson, T. A., & Melton, F. (2021). Long-term monitoring of evapotranspiration using the SEBAL algorithm and Google Earth Engine cloud computing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *178*, 81-96.

Lezama, F., Pereira, M., Altesor, A., & Paruelo, J. M. (2019). Grasslands of Uruguay: classification based on vegetation plots. Phytocoenologia, 211-229.

Lopes, M., Frison, P. L., Durant, S. M., Schulte to Bühne, H., Ipavec, A., Lapeyre, V., & Pettorelli, N. (2020). Combining optical and radar satellite image time series to map natural vegetation: savannas as an example. *Remote Sensing in Ecology and Conservation*, *6*(3), 316-326.

Neke, K. S., & Du Plessis, M. A. (2004). The threat of transformation: quantifying the vulnerability of grasslands in South Africa. *Conservation Biology*, *18*(2), 466-477.

Nosetto, M. D., Jobbágy, E. G., Brizuela, A. B., & Jackson, R. B. (2012). The hydrologic consequences of land cover change in central Argentina. Agriculture, Ecosystems & Environment, 154, 2-11.

Nosetto, M. D., Jobbágy, E. G., & Paruelo, J. M. (2005). Land-use change and water losses: the case of grassland afforestation across a soil textural gradient in central Argentina. *Global Change Biology*, *11*(7), 1101-1117.

Nunes, S., Oliveira, L., Siqueira, J., Morton, D. C., & Souza, C. M. (2020). Unmasking secondary vegetation dynamics in the Brazilian Amazon. *Environmental Research Letters,* 15(3), 034057.

Oliveira, T. E. D.; Freitas, D. S. D.; Gianezini, m.; Ruviaro, C. F.; Zago, D.; Mércio, t. Z.; Dias, E. A.; Lampert, V. D. N.; barcellos, J. O. J. Agricultural land use change in the Brazilian Pampa Biome: The reduction of natural grasslands. *Land Use Policy*, v. 63, p. 394-400, 2017/04/01/ 2017.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote sensing of Environment*, *148*, 42-57.

Overbeck, G. E., Müller, S. C., Fidelis, A., Pfadenhauer, J., Pillar, V. D., Blanco, C. C., ... & Forneck, E. D. (2007). Brazil's neglected biome: the South Brazilian Campos. *Perspectives in Plant Ecology, Evolution and Systematics*, *9*(2), 101-116.

Oyarzabal M, Andrade B, Pillar VD, Paruelo JM. 2020. Temperate subhumid grasslands of southern South America. Pp 1-17. In: Di Paolo, D. Encyclopedia of the World's Biomes. Elsevier, Países Bajos. ISBN 978-0-12-816096-1.

Panario, D., Gutiérrez, O., Sánchez Bettucci, L., Peel, E., Oyhantçabal, P., & Rabassa, J. (2014). Ancient landscapes of Uruguay. In *Gondwana landscapes in southern South America* (pp. 161-199). Springer, Dordrecht.

Paruelo, J. M., Guerschman, J. P., Piñeiro, G., Jobbagy, E. G., Verón, S. R., Baldi, G., & Baeza, S. (2006). Cambios en el uso de la tierra en Argentina y Uruguay: marcos conceptuales para su análisis. *Agrociencia, 10*, 47-61.

Pontius Jr, R. G., & Millones, M. (2011). Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing*, *32*(15), 4407-4429.

Potapov, P., Turubanova, S., Hansen, M. C., Tyukavina, A., Zalles, V., Khan, A., ... & Cortez, J. (2021). Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. Nature Food, 1-10.

Rios, C., Lezama, F. Rama, G., Baldi, G. & Baeza, S. (2022). Natural grassland remnants in dynamic agricultural landscapes: identifying drivers of fragmentation. *Perspectives in Ecology and conservations*. https://doi.org/10.1016/j.pecon.2022.04.003

Rotolo, D., Hicks, D., & Martin, B. R. (2015). What is an emerging technology?. *Research policy*, *44*(10), 1827-1843.

Rosa, M. R., Brancalion, P. H., Crouzeilles, R., Tambosi, L. R., Piffer, P. R., Lenti, F. E., ... & Metzger, J. P. (2021). Hidden destruction of older forests threatens Brazil's Atlantic Forest and challenges restoration programs. *Science advances*, *7*(4), eabc4547.

Rosan, T. M., Goldewijk, K. K., Ganzenmüller, R., O'Sullivan, M., Pongratz, J., Mercado, L. M., ... & Sitch, S. (2021). A multi-data assessment of land use and land cover emissions from Brazil during 2000–2019. *Environmental Research Letters*, *16*(7), 074004.

Rusch, G. M., & Oesterheld, M. (1997). Relationship between productivity, and species and functional group diversity in grazed and non-grazed Pampas grassland. *Oikos*, 519-526.

Sano, E. E., Rosa, R., Brito, J. L., & Ferreira, L. G. (2010). Land cover mapping of the tropical savanna region in Brazil. *Environmental monitoring and assessment*, *166*(1), 113-124.

Silveira, F. A., Arruda, A. J., Bond, W., Durigan, G., Fidelis, A., Kirkman, K., ... & Buisson, E. (2020). Myth-busting tropical grassy biome restoration. *Restoration Ecology*, *28*(5), 1067-1073.

Song, X. P., Hansen, M. C., Potapov, P., Adusei, B., Pickering, J., Adami, M., ... & Tyukavina, A. (2021). Massive soybean expansion in South America since 2000 and implications for conservation. *Nature sustainability*, *4*(9), 784-792.

Soriano, A. Rio de la Plata Grasslands. In Natural Grasslands; Coupland, R.T., Ed.; Elsevier: Amsterdam, The Netherlands, 1991; pp. 367–407.

Souza, C.M., Jr., Z. Shimbo, J., Rosa, M.R., Parente, L.L., A. Alencar, A., Rudorff, B.F.T., Hasenack, H., Matsumoto, M., G. Ferreira, L., Souza-Filho, P.W.M., de Oliveira, S.W., Rocha, W.F., Fonseca, A.V., Marques, C.B., Diniz, C.G., Costa, D., Monteiro, D., Rosa, E.R., Vélez-Martin, E., Weber, E.J., Lenti, F.E.B., Paternost, F.F., Pareyn, F.G.C., Siqueira, J.V., Viera, J.L., Neto, L.C.F., Saraiva, M.M., Sales, M.H., Salgado, M.P.G., Vasconcelos, R., Galano, S., Mesquita, V.V., Azevedo, T. Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. Remote Sensing 2020: 12, 2735

Souza, C.M., Jr.; Roberts, D.A.; Cochrane, M.A. Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment*. 2005, 98, 329–343.

Staude, I. R., Vélez-Martin, E., Andrade, B. O., Podgaiski, L. R., Boldrini, I. I., Mendonca Jr, M., ... & Overbeck, G. E. (2018). Local biodiversity erosion in south Brazilian grasslands under moderate levels of landscape habitat loss. *Journal of Applied Ecology*, *55*(3), 1241-1251.

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., ... & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. Science, 347(6223).

Stehman, S. V., Pengra, B. W., Horton, J. A., & Wellington, D. F. (2021). Validation of the US Geological Survey's Land Change Monitoring, Assessment and Projection (LCMAP) Collection 1.0 annual land cover products 1985–2017. *Remote Sensing of Environment*, *265*, 112646.

Veldman, J. W., Overbeck, G. E., Negreiros, D., Mahy, G., Le Stradic, S., Fernandes, G. W., ... & Bond, W. J. (2015). Where tree planting and forest expansion are bad for biodiversity and ecosystem services. *BioScience*, *65*(10), 1011-1018.

Viglizzo, E. F., F. Lértora, A. J. Pordomingo, J. N. Bernardos, Z. E. Roberto, and H. Del Valle. 2001. Ecological lessons and applications from one century of low external-input farming in the pampas of Argentina. *Agriculture, Ecosystems and Environment*, 83: 65-81.

Viglizzo, E. F., Frank, F. C., Carreño, L. V., Jobbagy, E. G., Pereyra, H., Clatt, J., ... & Ricard, M. F. (2011). Ecological and environmental footprint of 50 years of agricultural expansion in Argentina. *Global change biology*, *17*(2), 959-973.

Volante, J., Mosciaro, J., Morales Poclava, M., Vale, L., Castrillo, S., Sawchik, J., ... & Paruelo, J. (2015). Expansión agrícola en Argentina, Bolivia, Paraguay, Uruguay y Chile entre 2000-2010: Caracterización espacial mediante series temporales de índices de vegetación. *RIA. Revista de investigaciones agropecuarias*, *41*(2), 179-191.

Watson, J. E., Jones, K. R., Fuller, R. A., Marco, M. D., Segan, D. B., Butchart, S. H., ... & Venter, O. (2016). Persistent disparities between recent rates of habitat conversion and protection and implications for future global conservation targets. Conservation Letters, 9(6), 413-421.

Wickham, J., Stehman, S. V., Sorenson, D. G., Gass, L., & Dewitz, J. A. (2021). Thematic accuracy assessment of the NLCD 2016 land cover for the conterminous United States. *Remote Sensing of Environment*, *257*, 112357.

Zhang, W., Brandt, M., Wang, Q., Prishchepov, A. V., Tucker, C. J., Li, Y., ... & Fensholt, R. (2019). From woody cover to woody canopies: How Sentinel-1 and Sentinel-2 data advance the mapping of woody plants in savannas. *Remote Sensing of Environment*, *234*, 111465.

Zimbres, B., Shimbo, J., Bustamante, M., Levick, S., Miranda, S., Roitman, I., ... & Alencar, A. (2020). Savanna vegetation structure in the Brazilian Cerrado allows for the accurate estimation of aboveground biomass using terrestrial laser scanning. *Forest Ecology and Management*, *458*, 117798.