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LAND-USE and land-cover change processes in Pampa biome and relation with environmental and socioeconomic data

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ABSTRACT

Pampa biome in the last years has gone through a process of change in land use, chiefly due to the conversion of grassland vegetation for agriculture of grains and silviculture. The main objective of this work is to analyze processes of Land-Use and Land-Cover (LUCC) in the Brazilian Pampa Biome, mapped from Multitemporal data of MODIS sensor, including the main processes of landscape transformation. The period studied was 2000 and 2014, and MODIS-EVI images and night DMSP-OLS images were used for generation of land use and cover maps, through decision tree classification. IBGE census sectors' limits were used. To investigate the processes of landscape transformation of Pampa Biome, environmental variables were used including geomorphometric data, landscape metrics and climate data and socioeconomic variables. Local (GWR) and global linear regression models were used in addition to procedures for spatial clustering (SKATER algorithm). Reduction of around 25% of grassland class in 15-year interval was verified, from 10,252,740 ha to 7,676,208 ha. On the other hand, agriculture areas like Soybean class obtained 145.56% increase in their total area, from 855,087 ha in 2000, to 2,099,837 ha in 2014. Silviculture class also presented increase of over 167% of its total area. The main factors in the global regression model that negatively contributed to grassland degradation process are: population density, height against the closest drainage (HAND Model) and degradation patches in the grassland. Factors that positively contributed are: population residing in domiciles, average of number of residents in domiciles, Soybean expansion patches and distance from Soybean expansion process. It was concluded that orbital data along with geoprocessing techniques provided tools for monitoring changes in land use and cover.

1. Introduction

The growing demand for land resources (food, water, fuel) along with unsustainable environmental practices resulted in growing environmental degradation of major natural ecosystems, threatening both the capacity to produce food and the ecologically fragile environments (Nellemann et al., 2009).

Agriculture is one of the major agents for land-use and land-cover (LUCC) (Cassman et al., 2005). Despite the importance of agriculture, because it is one of the main suppliers of food for human population (Smith & Mcdonald, 1998), agricultural expansion to natural ecosystems leads to the loss of ecosystem services, like necessary habitat to keep biodiversity, carbon storage, mitigation of floods, soil fertility, water quality, among others (Defries et al., 2004; Foley et al., 2005; Gibbs et al., 2010; Lambin & Meyfroidt, 2011). Therefore, understanding landscape transformations introduced by men provide reliable subsidies like, for example, monitoring of such activities over time, become essential for governmental entities' decision making.

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Pampa Biome, which includes a portion of the South of Brazil, the whole Uruguay territory and the northeast portion of Argentina, has an area of approximately 176.496 km^2 (Allen et al., 2011). It is one of the largest and richest pasture zones worldwide, with huge diversity of species and unique co-existence of several C_3 and C_4 plants with presence of characteristic grasses and presenting diversity of around 2200 species (Boldrini, 2009). Lately, however, a trend of change of land use in this biome has been observed, particularly through the conversion of grassland vegetation to grain agriculture (especially Soybean cultivation) and silviculture (Nabinger et al., 2009). In this Biome, therefore, studies on LUCC processes' dynamics and monitoring are important.

Studies from several parts of the world point to the feasibility of the use of satellite images for LUCC dynamics monitoring (Friedl et al., 2002; Liu et al., 2011; Zhou et al., 2013). In Brazilian biomes, some works are outstanding for using remote sensing and geoprocessing to analyze processes of land use transformations with focus on deforestation. Espindola et al. (2012) analyzed deforestation rates in Amazonia and assessed the factors that influenced such processes. Grecchi et al. (2014) used geotechnologies to assess the impacts of agricultural expansion over time in the Brazilian Cerrado and analyzed the influence of indicators of vulnerability to erosion. In upper Uruguay river basin, Freitas et al. (2013) analyzed the processes of land use and cover, linking environmental and socioeconomic variables from 2002 to 2008.

More specifically in the Brazilian portion of Pampa Biome, several remote sensing studies analyzed time series with high temporal resolution focusing on the agrometeorological relation of the system (Jacóbsen et al., 2003; Scottá & Fonseca, 2015; Wagner et al., 2013). Jacobsen et al. (2003) observed that the pattern of variation of NDVI values throughout the year are similar to that of availability of sun radiation and air temperature, presenting maximum values in summer and minimum values in winter. Wagner et al. (2013) observed the negative trends in time series MODIS-EVI and NDVI for the period from 2000 to 2011, associated to the combination of water deficit occurrence in shallow soil with overgrazing. Scottá & Fonseca (2015) associated aerial biomass data in local scale with data in regional scale of NDVI from SPOT/Vegetation sensor.

However, studies on the monitoring and dynamics of LUCC processes in the Brazilian Pampa Biome are still scarce, chiefly in the last two decades, where the landscape is suffering the process of conversion of grassland vegetation into agricultural areas, particularly Soybean cultivation. In this sense, the present work seeks to contribute to the advance of knowledge on the main processes of land use in Pampa Biome and identify which variables have more influence in landscape changes. The guiding hypothesis is that LUCC changes can be mapped using techniques for digital classification of images that express time variation in vegetation indices, and that there are variables that induce changes (socioeconomic, climatic, metric of landscape and geomorphometric), which can be described with local and global regression models.

The objective of this work is to analyze processes of land use and cover in the Brazilian Pampa biome and identify the main processes of landscape transformation and their driving factors. Seven processes of LUCC changes were studied in the study area (urbanization, regeneration, silviculture expansion, Soybean expansion, grassland degradation, forest degradation and intensification). The work comprised two stages: the first stage was LUCC classification with MODIS and DMSP-OLS images for years 2000 and 2014 and identification of main processes of landscape transformation. The second stage was the investigation of LUCC processes using environmental variables, which include geomorphometric data, landscape metrics, climate data and socioeconomic variables, made with global and geographically weighted regression (GWR), in addition to spatial clustering procedures (SKATER).

2. Methodology

2.1. Study area

The area studied comprises the limits of Pampa biome as defined by the Brazilian Institute of Geography and Statistics (IBGE), in Rio Grande do Sul state, located in the far south of Brazil, totaling an area of 16,579,332 ha and total population of 5,373,216 inhabitants, corresponding to 50.24% of Rio Grande do Sul state total population (Fig. 01).

According to Köppen classification (Alvares et al., 2013), in most Pampa Biome Cfa climate (rainy subtropical with hot summers) prevails and only Serra do Sudeste region, with higher altitudes (~400 m altitude), presents Cfb type climate (rainy subtropical with mild summers).

2.2. Classification of land use and cover change and data preparation

For the assessment of land use and cover change in Pampa biome, the period studied was 2000–2014. The year 2000 was chosen as reference because it was the period when MODIS sensor time series obtained its first images. To analyze changes in the studied area two land use maps were generated from TERRA satellite images, MODIS sensor, MOD13Q1 product, collection 6, containing compositions of images of 16 days as EVI vegetation indices, with spatial resolution of 250 m. For each year (2000 and 2014), 23 MODIS images were used.

Categories of land use and cover were listed in nine classes for Pampa Biome: Agriculture areas (rice, soybean and mosaic of cultures), forest, grassland, beaches and dunes, water, urban area and silviculture. The classification stage considered small differences and specific characteristics of each region, adopting a classifier exclusively trained to work on each of them.

The classifier used was Decision Tree (AD) for land use and cover classes (water, beaches and dunes, forest, silviculture and grassland), and MODIS time series filtered with *Timesat*, comprising 23 images of EVI vegetation index. The decision trees tested were built with algorithm C4.5 (QUINLAN, 1993) in MatLab® environment. Imput data of classifier were the time series itself and the training samples of land use and cover classes, extracted from polygons selected in Landsat images, which, for presenting 30 m spatial resolution made possible the visual identification and delimitation of classes.

For Water, Beaches and Dunes, Forest, Silviculture and Grassland classes, the classifier used was Decision Tree (DA), while for agricultural classes (Rice, Soybean, and Mosaic of Cultures) a cultivation mask was generated and decision tree classifier was used within this mask and, finally, for Urban Area class, a combination of night images (*Defence Meteorological Satellite Program - Operational Linescan System-DMSP-OLS*) and EVI were used, according to methodology proposed by LIN et al. (2014).

Having finished LUCC maps for years 2000 and 2014, the next stage was quantification and analysis of LUCC transformations in the last 15 years. For such, cross tabulation of LUCC maps of 2000 and 2014, quantification and mapping of areas of LUCC classes that presented gains or losses and identification, for example, of advance in soybean culture and silviculture on grassland areas were made. Through diagrams and tables generated by the *Land Change Modeler* - IDRISI Taiga (LCM) module, spatial transformations occurred in Pampa biome in the last 15 years were analyzed and quantified.

The process of validation of accuracy of LUCC maps of years 2000 and 2014 was made based on reference samples selected in Landsat 5/TM (2000) and Landsat 8/OLI (2014) images for all classes of MODIS classification. As statistical analysis the global accuracy (EG) and Kappa (k) index were used.

The procedure for cross tabulation of maps of years 2000 and 2014, allowed the identification of 29 transitions of LUCC of interest in this study. Later, the 29 transitions were grouped in 7 processes (Fig. 02) using similar grouping methods according (Batistella & Valladares, 2009; Freitas et al., 2013). These methods for clustering the processes

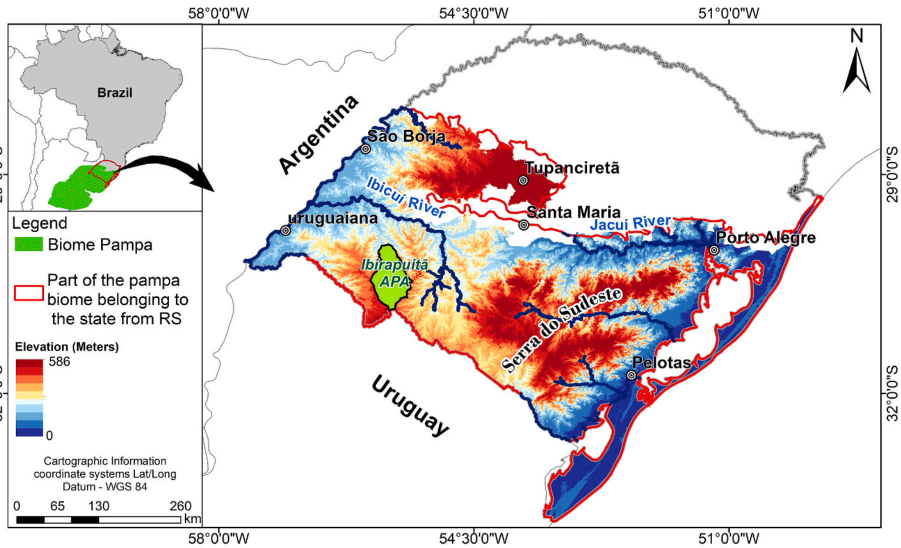

Fig. 01. Localization map of the area of study.

LULCC 2014 (columns) / LULCC 2000 (rows)

	ARR	SOJ	MOS	SIL	CAM	FLO	PRA	URB	AGU
ARR		2		1					
SOJ				1					
MOS		2		1					
SIL									
CAM	3	2/3	3	1/3					
FLO		2		1					
PRA				1					
URB									
AGU									

Fig. 02. Matrix of transition used to identify processes occurred in Land-Use and Land-Cover (LULC) maps from 2000 to 2014. Abbreviations: (1) Urbanization (2) Regeneration (3) silviculture expansion (4) Soybean expansion (5) Grassland degradation (6) Forest degradation (7) Intensification. ARR (rice) SOJ (soybean) MOS (mosaic of cultures) CAM (Grassland) FLO (forest) PRA (beaches and dunes) URB (urban area) AGU (water).

were adapted to meet specific demands of the area studied: (1) Urbanization, defined as any LUCC for Urban Area class; (2) Regeneration, defined as the transition of agriculture class to Forest class; (3) Expansion of silviculture, characterized by transitions occurred from any LUCC classes to silviculture class; (4) Expansion of soybean, defined as transitions occurred from any class (except for silviculture) to Soybean class; (5) Grassland degradation, defined as changes in Grassland class to LUCC classes for agriculture and silviculture purposes; (6) Forest degradation, defined as changes in Forest class to LUCC classes for agriculture purposes; and (7) Intensification, characterized as changes in silviculture class to agriculture areas, defined as change in technology in agriculture production process, including high levels of mechanization and use of fertilizers and other inputs in order to improve productivity per area unit of monocultures.

The processes presented were used as dependent variables, while predictive independent variables were socioeconomic, climatic, landscape metrics and geomorphometric factors.

2.3. Processing of geomorphometric, socioeconomic and environmental variables

The unit analysis used was IBGE census sectors' limits of the year 2010. The study area presents 1766 census sectors, which 37 were removed for lack of census information, with 1729 sectors remaining.

The present work used variables from different sources, including social, educational, economic, geomorphometric, climatic, road network and hydrographic data (Table 01). Geomorphometric data, as HAND model (Rennó et al., 2008), slope an elevation were obtained from SRTM (*Shuttle Radar Topographic Mission*) Digital Elevation Model (DEM), with spatial resolution of approximately 30 m. Socioeconomic data used were those from the last census made in Brazil, in 2010. Climatic data were obtained from *WorldClim - Global Climate Data* (http://www.worldclim.org/), with spatial resolution of 1 km. For the generation of maps of road and hydrographic network distances, the continuous vector cartographic base of Rio Grande do Sul was used, in scale 1:50.000 (Hasenack & Weber, 2010). Landscape metrics, as the number of patches (polygons) of processes analyzed, were processed in GIS environment.

The next stage was the creation of a spatial database to aggregate all information and to perform geoprocessing operations in independent variables. The contiguous census sectors classified as urban by IBGE were re-classified and aggregated in one single sector, in order to reduce the number of sectors in urban areas, since the number of census sectors classified as urban is very high, with reduced dimension (<1 ha), and are not compatible with MODIS sensor spatial resolution.

2.4. Global OLS (Ordinary least squares) and local GWR (Geographically weighted regression) regression models

The preparation of models begins with the procedure of selection of independent variables. In the set of independent variables there may be variables that have little influence in the set of dependent variables (processes). *IBM SPSS Statistics 20* software was used for selection of variables and proposition of regression model to be used. For such, the *best subset* (Neter et al., 1996) procedure was used with R^2 and adjusted R^2 criteria, through *backward stepwise* method with significance level equal to 0.05.

After the selected of the best set of variables, the global regression model (OLS) was executed, generating 7 regression models. Equation (1) used in OLS model is defined as follows:

$$y_k = \beta_{k0} + \sum \beta_{kj} x_{ij} + \varepsilon_k \tag{1}$$

where Y_i is the variable of localization response i, $\beta_0$is the intercept, β_k is the parameter estimated by independent variable k, X_{ik} is the value of independent variable k in localization i and $\varepsilon_i$is error. To assess the

Table 01
Independent variables used in analyses of global (OLS) and local (GWR) regression models.

Type	Variable	Initials	Description
Geomorphometric	HAND	HAND	Height Above the Nearest Drainage (m)
	Slope	SLOPE	Slope (degrees)
	Elevation	ELEV	SRTM data (spatial resolution 30m)
Climate	Annual Precipitation	P_YRS	Annual Precipitation (mm) - Worldclim data (spatial resolution 1 km)
	Seasonality of Precipitation	C_YRS	Seasonality of Precipitation (coefficient of variation) (mm) - Worldclim data (spatial resolution 1 km)
Density/Area	Soybean expansion patches	P_1	Number of patches (polygons) for the soybean expansion process
	Grassland degradation patches	P_2	Number of patches (polygons) for the grassland degradation process
	Silviculture expansion patches	P_3	Number of patches (polygons) for the silviculture expansion process
	Intensification patches	P_4	Number of patches (polygons) for the intensification process
	Forest degradation patches	P_5	Number of patches (polygons) for the forest degradation process
	Regeneration patches	P_6	Number of patches (polygons) for the regeneration process
Economic	Average monthly income	V009	Nominal average monthly income of people 10 years old or older ($)
	Average monthly income variance	V010	Nominal monthly income variance of persons 10 years old or older ($)
Demographic	Percentage of young people	<14A	(Population 0–14 years old/ Total population with known age) * 100
	Percentage of adults	15_59	(Population 15–59 years old/Total population with known age) * 100
	Percentage of elderly people	>60A	(Population >60 years old/ Total population with known age) * 100
	Resident population in households	V002	Residents in permanent private households or population residing in permanent private households
	Average number of dwellers in households	V003	Average number of residents in permanent private households
	Population density	P_DE	Resident population/Area (km^2)
	Total population	P_TO	Total resident population
Education	Illiteracy rate	ILL_R	(Population 10 years old or over who can not read and write a simple ticket in the language they know/Total population of this age group) * 100
Euclidian Distance	Distance from roads	D_ROA	Distance from roads (m)
	Distance from hydrography	D_RIV	Distance from hydrography (m)
	Distance from soybean expansion	D_1	Distance from soybean expansion (m)
	Distance from grassland degradation	D_2	Distance from grassland degradation (m)
	Distance from silviculture expansion	D_3	Distance from silviculture expansion (m)

spatial dependence of OLS models, the spatial autocorrelation of residuals was analyzed using Moran's I test, based on the null hypothesis of no presence of spatial autocorrelation in residuals. Tests were used to assess the need of using spatial regression techniques for the 7 different processes of LUCC based on these tests indicating the presence of spatial autocorrelation in models.

The Geographically Weighted Regression – GWR (Brunsdon et al., 1996) technique was used to model spatially heterogeneous processes (not stationary), that is, processes that vary (in mean, median, variance, etc.) in the regions. A regression model was adjusted for each region of the set of data (census sectors) using the geographic localization of the other observations to weight estimates of parameters, in order to localize local variations of variable existing in the study area. According to Fotheringham et al. (2002), given a global regression model (OLS), the equivalent expression for GWR (local) is given by:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_k \quad (2)$$

The above expression shows that the model parameters, represented by function β_k (u_i, v_i) vary according to values of (u_i, v_i), which represent the geographic coordinates latitude and longitude of each census sector (i), resulting in a distinct model for each region of the study. Thus, the GWR model makes regressions locally using the centroid of polygons of the nearest census sectors, based on Euclidian distance between points. It is worth mentioning that the assumptions of the classical linear regression model (OLS) remain for GWR.

In the present study the GWR4 version developed by the National Center for Geocomputation, from the National University of Ireland Maynooth was used, the weighting function used was Gaussian based on the minimization of Akaike Information Criterion (AIC), with variable size Kernel. For each of the 7 LUCC processes, GWR and OLS models were compared using the best subsets procedure, based on AIC, which is the most appropriate measure to compare models (Fotheringham et al., 2002). To estimate the spatial dependence of residuals in GWR regression models Moran's I test was applied.

2.5. Spatial clustering of land use and vegetation cover processes

For generation of spatial clustering of LUCC processes SKATER algorithm was used (Assunção et al., 2006), from software *Terra View* 4.2.2. The 1729 polygons of IBGE census sectors were used to generate spatial clustering. SKATER spatial clustering algorithm uses the concept of minimum generating tree.

The variables used for generation of LUCC processes clustering were the coefficients estimated by independent variables (β) in local regression models (GWR). The generation of clusterings was used for better visualization of results for the different variables of LUCC processes, with plotting in maps of diagrams as bars for each coefficient estimated by the GWR model. The number of 5 spatial regions for each process was adopted, according to methodology by Freitas et al. (2013). For the Urbanization ULLC process spatial clustering was not made in this stage of the work because it does not present spatial dependence in OLS model residuals.

3. Results and discussion

3.1. Changes in land use

Global Accuracy (EG) was 89.71% and Kappa (k) 0.8778 for year 2000 and Global Accuracy (EG) of 90.09% and (k) 0.8857 for year 2014. In both maps, the major accuracy were for Urban Area class and the least accuracy were for silviculture class. The major spectral similarities in LUCC maps were limited to silviculture, grassland and Forest. The mistaken allocation of points (pixel) made by the classifier, chiefly in classes with vegetation cover, proves the spectral and temporal similarity and the difficulty to classify them.

LUCC maps for years 2000 and 2014 (Fig. 03) are the basis to identify the main areas where processes of transformation of land use and cover change. The north region of the area studied, located in the middle plateau, near Tupanciretã municipality, presented large changes, mainly conversion of grassland class to soybean class. This region is characterized for presenting altitudes above 350 m, relief with low declivity and more fertile soils when compared to other areas of Pampa Biome. According to Moreira & Medeiros (2014) as of 1985, soybean was consolidated supported by the modernization of the agriculture sector in Rio Grande do Sul north-center and northwest, occupying traditional livestock areas. Therefore, in the north region of Pampa Biome, near Tupanciretã municipality, the process of soybean expansion occurred later, when compared to Rio Grande do Sul northwest region.

It is also possible to identify soybean expansion in other areas, as along Jacuí river and at Southeast of Pelotas city, traditional places for cultivation of irrigated rice in meadow areas. Serra do Sudeste, region with sharper slopes, shallow soils, and less fertility, when compared to other regions, is suffering great changes in its landscape in the last 15 years, particularly the conversion of grassland vegetation (grassland class) to silviculture areas.

Table 2 compares the values obtained in the 2000 and 2014 classification, and the reduction of grassland class and increase in agriculture classes (soybean, rice and mosaic of cultures) and silviculture class can be observed. The reduction in grassland class is very expressive, with reduction of approximately 25% of its total area in only 15 years, from 10,252,740 ha to 7,676,208 ha. Soybean class, on the other hand, in the same time interval, obtained increase of 145.56% of its total area, from 855,087 ha in 2000, to 2,099,837 ha in 2014. Silviculture class also increased more than 167% of its total area, mainly distributed in Serra do Sudeste and coastal strip. Beaches and Dunes classes presented differences between the years studied, however practically stable due to the area magnitude and MODIS sensor resolution.

The analysis of gains and losses per class showed (Fig. 04-A) that in grassland class, 98.02% of the total reduction of its area in 15 years is associated to anthropic activities as agriculture and silviculture. Soybean was responsible for more than 30.1% of the total conversion of grassland vegetation, with more than 777,645 ha, advancing on the grassland class, the Mosaic of Cultures class with 31.33% (807,337 ha), reminding that this class represents areas destined to agriculture, but in the specific years of classification (2000/2001 and 2013/2014 harvests) they were not being used for this purpose. They are areas of agriculture use that alternate irrigated rice and fallow with grassland or rotation of cultures with dry farming. Therefore, this class may contain areas with soybean cultivation, which reinforces the idea that the expansion of soybean areas is advancing on grassland vegetation. According to the classification data, soybean expansion advances chiefly on grassland class, 62.47% of the new areas cultivated occur on grassland class (Fig. 4-B).

Other anthropic activity responsible for the reduction in grassland class is silviculture, with approximately 520 thousand hectares converted from grassland class to silviculture. By analyzing Fig. 04-C, we can observe that practically the whole advance of silviculture class was on grassland vegetation areas, more specifically, 93.56% of the total advance was on areas from grassland class. It is worth highlighting that in 2004 the government of Rio Grande do Sul state, in order to provide development to the half South of the state and expand silviculture production, issued public policies to attract investments from silviculture sector companies. The socioeconomic goal would be to transform the conservative economic matrix, income concentrated, historically and culturally pastoral, into a region of wood and cellulose production (Binkowski, 2009).

Table 2
Comparison of values between the classified map for 2000 and the 2014 map, for Pampa Biome, values in hectares.

Class	2000	2014	Difference (ha)	Difference (%)
Water	411,746	405,649	−6096	−1.48
Urban Area	103,980	127,232	23,252	22.36
Rice	879,256	1,075,861	196,604	22.36
Grassland	10,252,740	7,676,208	−2,576,532	−25.13
Soybean	855,087	2,099,837	1,244,749	145.56
Silviculture	331,694	887,428	555,734	167.54
Forest	2,226,523	1,731,016	−495,507	−22.25
Beaches and dunes	97,802	111,231	13,429	13.73
Mosaic of cultures	13,34,161	2,378,527	1044365	78.27
Total	16,492,994	16,492,994		

The expansion of new areas from silviculture class can drastically change the landscape of Serra do Sudeste region, since the advance of this activity has occurred in predominantly grassland areas. According to information available by IBGE (2017), with regard to wood, firewood and charcoal production, data indicate that there was significant increase in the last 15 years in Pampa Biome, with gradual increase at each year.

Fig. 05 illustrates how much LUCC classes were changed in the 15-year interval (2000–2014) in each census sector. Generally, processes of grassland degradation, soybean expansion and silviculture expansion are the most important processes of transition analyzed, with regard to the size of the area converted. It is important to highlight that Ibirapuitã APA (environmental protection area), located at southwest of the area studied was important for the conservation of grassland vegetation, because it hindered the advance of soybean and silviculture expansion. Soybean expansion was larger in the north portion and along Jacuí river, and forest degradation, on the other hand, was larger in the west portion and along Jacuí river.

3.2. Models of global and local regression

In this stage results of global and local regression models (GWR) are presented for each LUCC process. First, the regressive coefficients of each variable for each process are shown (Tables 3 and 4). Only the three

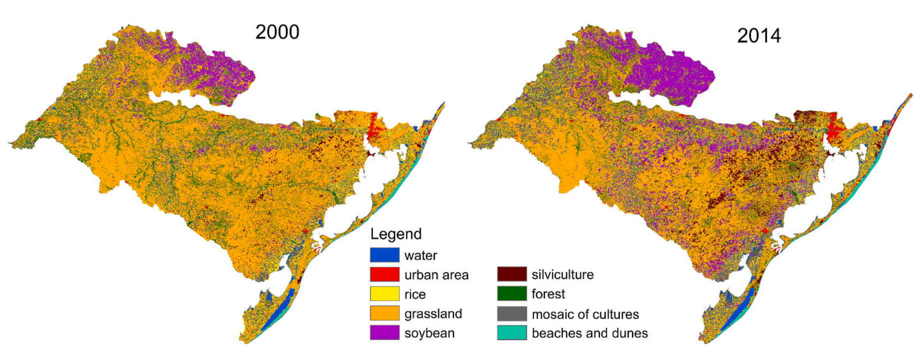

Fig. 03. Pampa Biome's LUCC map for years 2000 and 2014.

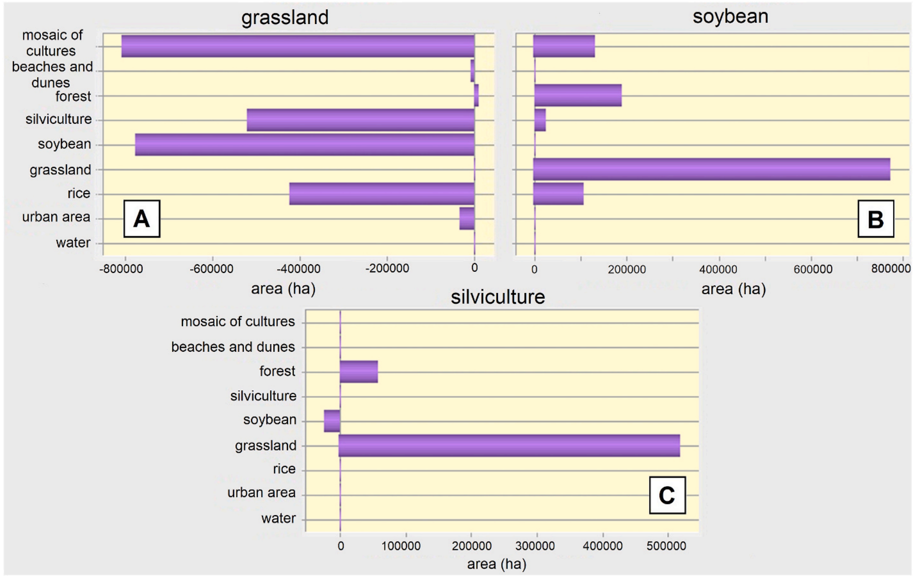

Fig. 04. Cross tabulation for Grassland (A), Soybean (B) and Silviculture (C) classes from 2000 to 2015, values in hectares.

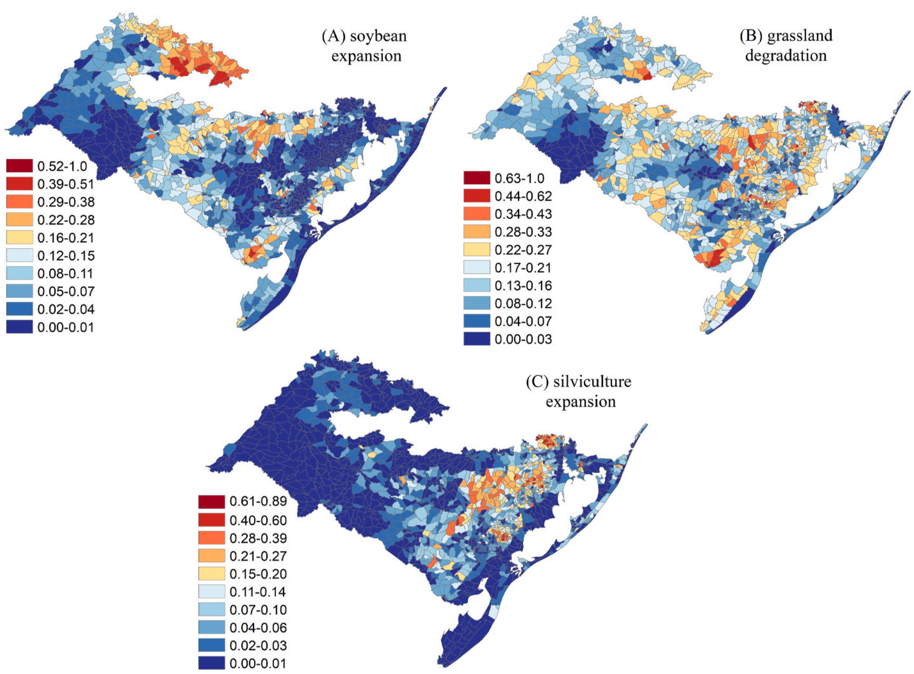

Fig. 05. Change for all LUCC processes occurred from 2000 to 2014 for each census sector.

main processes (grassland degradation, soybean and silviculture expansion) will be discussed in this stage, since they are the main transformers in terms of area converted in Pampa Biome. For better understanding, the estimator (β) of each variable was divided by the standardized error, and the importance of each variable in LUCC processes' global regression model is calculated.

The global regression model for soybean expansion process indicated that the topographic factor presents strong association with this process. Elevation data presented a positive correlation in the model (11.66), which makes sense, if we consider that soybean expansion presents the highest values of converted area in the north portion, with higher altitudes. Another factor was slope, with negative association (−1.93), since census factors with flatter terrains favors mechanized agriculture. According to Rudel & Ropper (1996), places with flatter topography favors deforestation, and countries or regions with small extensions of forests or with forest remains in general have large proportion of their forests in mountainous areas, with less economic attractive to be deforested, particularly for agriculture, due to high slopes and soil poor quality.

Another topographic factor with negative correlation (−3.52) for the model was the HAND model, which represents the vertical altitude against the nearest drainage. Studies indicate that soybean expansion in Rio Grande do Sul half south is also advancing to meadow areas, traditional in irrigated rice cultivation in the state (Mengue et al., 2016; Santos et al., 2014), with flood flat lands of Jacuí and Ibicuí rivers and the areas surrounding Lagoa dos Patos, which corroborates the results obtained.

Demographic factors also present direct relation with soybean expansion, with census sectors with young population (<14Y) showed negative correlation (−2.09). One hypothesis for this case is that in rural census sectors, the adult population is greater and the young population would be more concentrated in urban centers, like Porto Alegre Metropolitan Region (RMPA). Educational factors like illiteracy (ILL_R) presents positive relation with soybean expansion (1.68), indicating that soybean expansion advances to sectors or regions where schooling is lower, which reflects a character of less economic development with lands less valued.

Another important factor for the global regression model of soybean expansion was the climate factor, with annual precipitation presenting positive relation (6.76), showing that the areas where soybean is advancing are located in areas with higher precipitation. It makes sense, since the expansion is more concentrated in the north region with highest rainfall volumes, around 1800 mm/year. Seasonality of precipitation, on the other hand, presents negative relation (−7.45). One of the reasons is that new soybean areas are located where precipitation variation is low, more stable, in Pampa Biome's central and north regions, while the west border and south region, next to the city of Pelotas, precipitation variation is very high, not favoring soybean cultivation.

Proximity to degraded areas' factors, like distance from soybean areas (D_1) presented strong negative relation with soybean areas (−9.08), showing that nearer areas or areas in the frontiers of agricultural areas already consolidated are more favorable to soybean expansion.

For the process of grassland degradation, demographic factors presented negative relation, chiefly the population density variable (−4.33). Maybe the most mentioned and controversial variable, as vector of degradation of forest areas, is population or population growth, or, also, the notion of 'demographic pressure' (Alves, 2004). It happens due to a strong association of demographic factors and degradation of forest areas, found in global and regional models, usually diminishes or even disappears when other independent variables are added. In several regional models, it happens because demographic density is highly correlated to the road network, proximity to urban markets, soils' quality and spatial distribution of economic activities. Thus, the high correlation between demographic density and degradation of forest areas may be only reflecting the effect of other factors on forest degradation (Kaimowitz & Angelsen, 1998). In Pampa biome, low values of population density are associated to rural census sectors, particularly those located in west and south frontiers.

It is important to highlight, regarding topographic factors, that HAND model data presented negative correlation in the regression model (−2.73), indicating that grassland degradation in the period studied is strongly associated to low elevation areas, like meadow areas and areas close to the main water systems.

Proximity to grassland degradation patches' factor presented higher negative relation to the model (−25.86). Factors of landscape structure, like the number of patches of soybean expansion processes, silviculture expansion and intensification presented positive values in the model. Census sectors with high number of patches presented higher amount of grassland degradation. According to Vélez-Martin et al. (2015), ecological problems associated to the suppression of grassland can be more severe when the reduction in area is followed by fragmentation of remaining patches in the landscape. When there is a high number of smaller grassland patches, the contact surface between grassland species and surrounding environments is larger. It is the so called edge effect. Fig. 06 compares the classification of grassland class of year 2000–2014. Pixels' frequency of grassland class nearer soybean areas with distances of up to 1250 m is twice superior, and the hypothesis for this phenomenon is that forest patches are much more fragmented, thus increasing the proximity to soybean areas.

Factors presenting positive relation in the global model for grassland degradation process are: population residing in domiciles (1.89), average of number of residents in domiciles (1.76), number of soybean expansion patches (3.75) and distance from soybean expansion process (4.64).

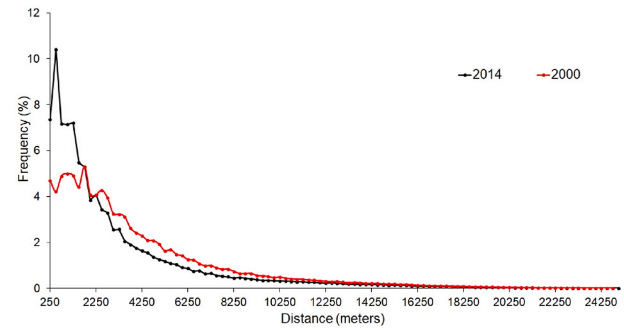

Fig. 06. Distance in meters of grassland areas mapped with MODIS sensor against soybean areas for years 2000 and 2014.

The global regression model of silviculture expansion process indicated that the topographic factor presented positive association with slope, with higher positive correlation in the model (10.92). Silviculture expansion is concentrated in Serra do Sudeste, in undulating topography with moderate slopes. The expansion of new silviculture areas occurs in areas with sharper slopes, like Serra do Sudeste; maybe that is why the slope factor presented positive influence in the global regression model.

Economic data, like monthly average yield, indicated positive relation (2.52) showing the census sectors with higher income levels presented direct relation with silviculture expansion. One justification that may sustain this parameter is that the highest levels of income in the region reflects a higher demand for agricultural and forest products and higher availability of resources to invest in activities turned to silviculture. The educational variable (illiteracy rate) presented negative relation with silviculture expansion (−2.45), indicating that census sectors with higher schooling have positive with the process, corroborating the silviculture relation with more developed regions.

The annual precipitation climate factor presented negative relation (−1.23) in the model because Serra do Sudeste region, where silviculture expansion is larger, presents lower average (1426 mm/year) when compared to the north region. Proximity factors like distances from roads presented positive relation (3.86) with global regression model, census sectors with high rates of silviculture expansion in the period studied are more distant from the main highways or when the road network is less dense. The relation with proximity to grassland degraded areas presented strong negative relation (−16.35) in the model, indicating that new silviculture areas are occupying remaining areas of grassland vegetation.

Table 4 shows that the best performance of the local model (GWR) for all processes compared to the global model is demonstrated by R^2 values significantly higher and lower AICc values. Through the use of GWR it was possible to identify the existence of spatial variations in predictive variables, allowing for the analysis on non-stationary relations among processes and independent variables. The important advantage of GWR process was the capacity to explore the spatial variability in relations of LUCC processes and explanatory variables through the mapping of local coefficients' parameters variation.

GWR, though offering many advantages when compared to the global model, requires that some parameters, like kernel bandwidth, used for spatial definition of neighbors (census sectors) have to be carefully analyzed due to their significant impact on the analysis results. In general, very small kernel bandwidth result in highly localized parameters' estimates and present high level of variation in the study area. On the other hand, when the kernel bandwidth is very high (for example, larger than the size of the study area), local regression results may be identical to those of a global regression (Wheeler & Tiefelsdorf, 2005). In the present work, the adaptive Gaussian method was used to choose the best kernel bandwidth for the GWR in LUCC processes ranged from 112 to 129 km.

In Fig. 07 GWR results are shown, where R^2 presents the degree of

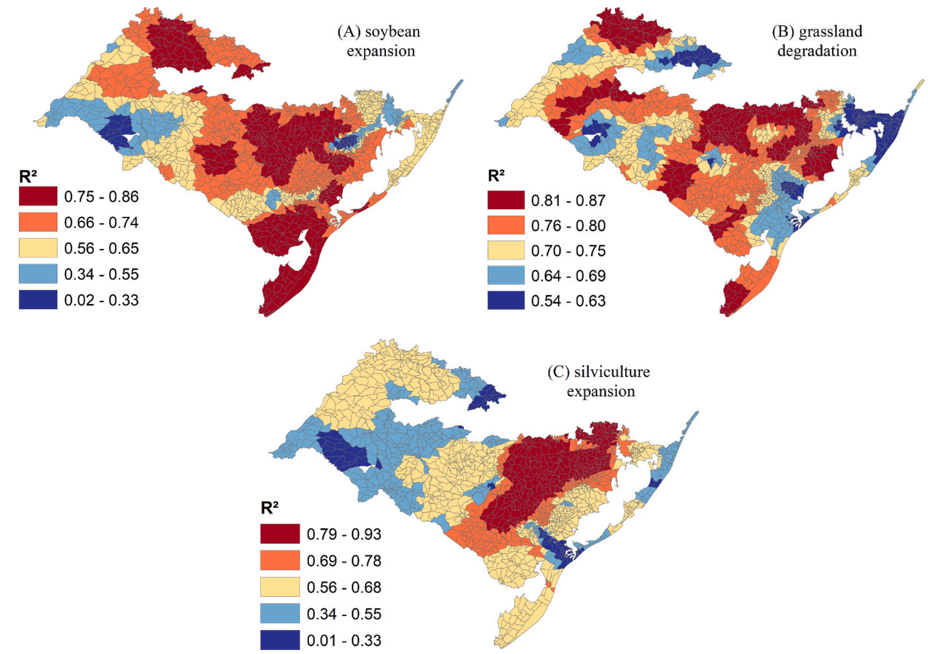

Fig. 07. Distribution of results of local adjustments of R^2 GWR among LUCC processes and independent variables.

adjustment of the model for LUCC processes. One can observe that census sectors in red and orange are the regions where the model presents the best adjustments. For soybean expansion process (A), the best adjustments of the model occur in south, central and north portions, where R^2 ranges from 0.02 to 0.86. In the local model of grassland degradation process, on the other hand, the best adjustments are locate in the far north portion, bordering Argentina, at the south and along Jacuí river, where R^2 ranged from 0.54 to 0.87. For the silviculture expansion process, the best adjustments of the model were concentrated in Serra do Sudeste, in the southwest-northeast portion, while in east and west portions the model did not explain well based on independent variables, and the variation was from 0.01 to 0.93.

When coefficients (β) of global and local parameters are compared (Table 03) it is possible to notice that they are very similar, but when local regression data are analyzed, the differences are very significant among the different regions in Pampa Biome area, revealing the important advantage of using local models to explain phenomena that are peculiar to each region. due to the large amount of independent variables in the GWR model for each LUCC process, in the next section the results of local parameters are synthesized by clustering the regions, using the SKATER method, in order to analyze the existing variability in the area of study.

3.3. *Spatial clustering (SKATER) of local parameters*

The analysis of spatial clustering generated by the SKATER method (Fig. 08) for all LUCC processes shows that some clusters are similar, mainly between soybean expansion process and grassland degradation at the north portion of the area of study. In the region bordering Uruguay and at west Argentina, spatial clusters formed large groups with large areas, explained by the fact that this region presents some similar characteristics like average size of agricultural areas and relief (mildly undulating).

The soybean expansion process exhibited different parameters in the GWR model for the different spatial clusters, which shows that there is large variability of independent variables in the area of study for this process. In the north portion (clusters 4 and 5), the factors that contribute most positively are annual precipitation, distance from silviculture expansion, HAND model and the mean of the number of residents in domiciles. Factors that contribute negatively, on the other hand, are slope, precipitation variation coefficient, and distance from soybean expansion and distance from grassland degradation. Spatial cluster 2, located in the lower portion of the relief, when compared to clusters 4 and 5, presented other factors. Positively, the main factor is the number of grassland degradation patches, negatively, we have annual precipitation, precipitation variation coefficient, distance from soybean expansion and distance from grassland degradation. Spatial cluster 1 is the largest in area size in east-west direction and does not present significant variable for the regression model. Spatial cluster 3, on the other hand, located in the far end of the state, presents some highly important factors for the soybean expansion model, and the main positive factors are slope and annual precipitation, while negative factors are the HAND model and the distance from soybean expansion process.

The grassland degradation process presented patterns of spatial clustering similar to those of soybean expansion process. Clusters 1 and 2 presented as positive factors the resident population and distance from soybean expansion process, and as negative factors precipitation variation coefficient and distance from grassland degradation. The variable with greater change between the two clusters was resident population, while in cluster 1 this variable presented strong negative relation, in cluster 2 it presented positive relation because census sectors located in clustering 2 are more populated. Spatial cluster 3 has the largest area among clusters and its main positive factor is the resident population and the number of grassland degradation patches. Cluster 4 comprises large portion of RS coastal area and also RMPA, a region where grassland vegetation degradation process started much earlier, marked by the strong presence of irrigated rice cultivation in flood flat lands of the main existing drainage systems.

Silviculture expansion process presented very distinct patterns of spatial clustering: two large clusters (1 and 2) dividing the area of study in two east-west portions, and other three smaller clusters near Serra do Sudeste, with higher concentration of silviculture expansion. In cluster 1 and 2 there is practically no variable with significant weight for the regression model. Spatial cluster 3, located near Encruzilhada do Sul municipality, presents as positive factor the silviculture expansion, the annual precipitation and as negative factor the distance from grassland degradation process and distance from silviculture expansion. Cluster 4,

Table 03
Parameters (β) estimated by regression models (mean of values) for global (OLS) and local (GWR) models.

Parameter	Soybean Exp.		Degr. grassland		Silviculture Exp.		Intensification		Degr. Forestry		Regeneration		Urbanization	
	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR
Intercept	0.058	0.034	0.146	0.126	0.052	$9,4e^{-3}$	$1,4e^{-3}$	$9,1^{-4}$[a]	0.017	0.021	$8,3e^{-3}$	$9,6e^{-3}$	$7,7e^{-3}$	0.014
HAND	−0.013	$-3,7e^{-3}$	$-7,3e^{-3}$	$-4,5e^{-3}$							$-3,1e^{-3}$	$-3,3e^{-3}$	$-3,6e^{-3}$	$-7,3e^{-3}$
SLOPE	$-7.5e^{-3}$	$-2,6e^{-3}$			0.032	0.011[a]								
ELEV	0.028	$7,4e^{-3}$			$-5.7e^{-3}$	0.014								
P_YRS	0.012	$-2,4e^{-3}$			$-2,4e^{-3}$	$-4,9e^{-3}$	$-1,0e^{-3}$	$-1,0e^{-3}$					$1,7e^{-3}$	$8,3e^{-3}$
C_YRS	−0.013	−0.014	$-6,5e^{-3}$	−0.013			$5,5^{-4}$	$3,8^{-4}$	$2,6e^{-3}$	$1,7e^{-3}$[a]				
P_1			0.013	0.025[a]	$-3,5e^{-3}$	$-1,0e^{-3}$[a]	$1,9e^{-3}$	$2,6e^{-3}$						
P_2	0.016	0.014					$-6,8^{-4}$	$-1,1e^{-3}$			$3,1e^{-3}$	$4,2e^{-3}$		
P_3	−0.010	$-4,6e^{-3}$[a]	$4,0e^{-3}$	$1,2e^{-3}$[a]					$-3,6e^{-3}$	$-2,8e^{-3}$[a]	$-1,0e^{-3}$	$-1,0e^{-3}$[a]		
P_4			0.01	$5,6e^{-3}$[a]							$-1,3e^{-3}$	$-9,5e^{-4}$		
P_5					$-6,8e^{-3}$	−0.015[a]								
P_6			$-8,4e^{-3}$	$-3,4e^{-3}$[a]			$-9,3^{-4}$	$-1,1e^{-3}$	$8,1e^{-3}$	$4,5e^{-3}$				
V009					$4,8e^{-3}$	$-1,0e^{-3}$[a]	$4,5^{-4}$	$2,5^{-4}$[a]	$-3,8e^{-4}$	$2,1e^{-4}$[a]			$6,2e^{-3}$	$-6,6e^{-4}$[a]
V010													$-2,3e^{-3}$	$-5,4e^{-3}$[a]
<14A	$-4,1e^{-3}$	$-5,1^{-4}$[a]											$1,4e^{-3}$	$-5,7e^{-4}$[a]
15_59			$-9,1e^{-3}$	$-5,8e^{-3}$					$-1,2e^{-3}$	$-9,1e^{-4}$				
>60A											$-1,1e^{-3}$	$-7,3e^{-4}$[a]	$-1,9e^{-3}$	$-7,0e^{-4}$[a]
V002			$5,1e^{-3}$	0.015										
V003	$3,3e^{-3}$	$4,1e^{-3}$	$4,2e^{-3}$	$1,7e^{-3}$	$3,4e^{-3}$	$4,0e^{-3}$	$-2,3e^{-4}$	$-2,0e^{-4}$						
P_DE			−0.012	$-8,1e^{-3}$			$-3,5e^{-4}$	$-3,5e^{-4}$					0.021	0.020
P_TO													$-5,1e^{-3}$	0.066
ILL_R	$3,3e^{-3}$	$3,2e^{-3}$			$-4,7e^{-3}$	$-2,1e^{-3}$[a]					$9,7e^{-4}$	$7,4e^{-5}$		
D_ROA					$8,2e^{-3}$	$1,6e^{-3}$[a]			$1,4e^{-3}$	$5,0e^{-4}$			$-3,9e^{-3}$	$-7,1e^{-4}$[a]
D_RIV		‘							$-2,2e^{-3}$	$1,3e^{-3}$	$9,2e^{-4}$	$5,7e^{-3}$		
D_1	−0.019	−0.037	0.012	0.01	0.029	0.029	$-6,6^{-4}$	$-4,5^{-4}$						
D_2	−0.02	−0.038	−0.067	−0.140	−0.038	−0.056			$-7,7e^{-3}$	−0.014	$-1,6e^{-3}$	$-4,6e^{-4}$	$4,8e^{-3}$	$4,9e^{-3}$
D_3	$5,6e^{-3}$	0.021			−0.010	−0.059	$-3,8e^{-4}$	$-4,3e^{-4}$[a]	$4,9e^{-3}$	0.012				

[a] Parameters not significant according to statistics t for hypothesis $\beta = 0$ ($\alpha = 0.05$).

Table 4
Results of global (OLS) and local (GWR) regression models.

Processes	Model Regression	R^2	AICc	DF	N° Variables
1 - Soybean Exp.	Global OLS	0,4216	−4325.86	1729	13
	GWR	0.8323	−5511.18	1239.66	
2 - Degr. grassland	Global OLS	0,3766	−3315.73	1729	12
	GWR	0.7677	−4177.80	1288.87	
3 - Silviculture Exp.	Global OLS	0,3984	−3977.57	1729	12
	GWR	0,8029	−4866.42	1209.91	
4 - Intensification	Global OLS	0,1056	−12,987.88	1729	10
	GWR	0,2325	−13,159.91	1657.90	
5 - Degr. Forestry	Global OLS	0,2828	−8171.63	1729	9
	GWR	0,7233	−8831.07	1234.47	
6 - Regeneration	Global OLS	0,2194	−10,427.52	1729	8
	GWR	0,4654	−10,693.62	1490.47	
7 - Urbanization	Global OLS	0,2719	−6528.85	1729	10
	GWR	0,7048	−7272.50	1303.71	

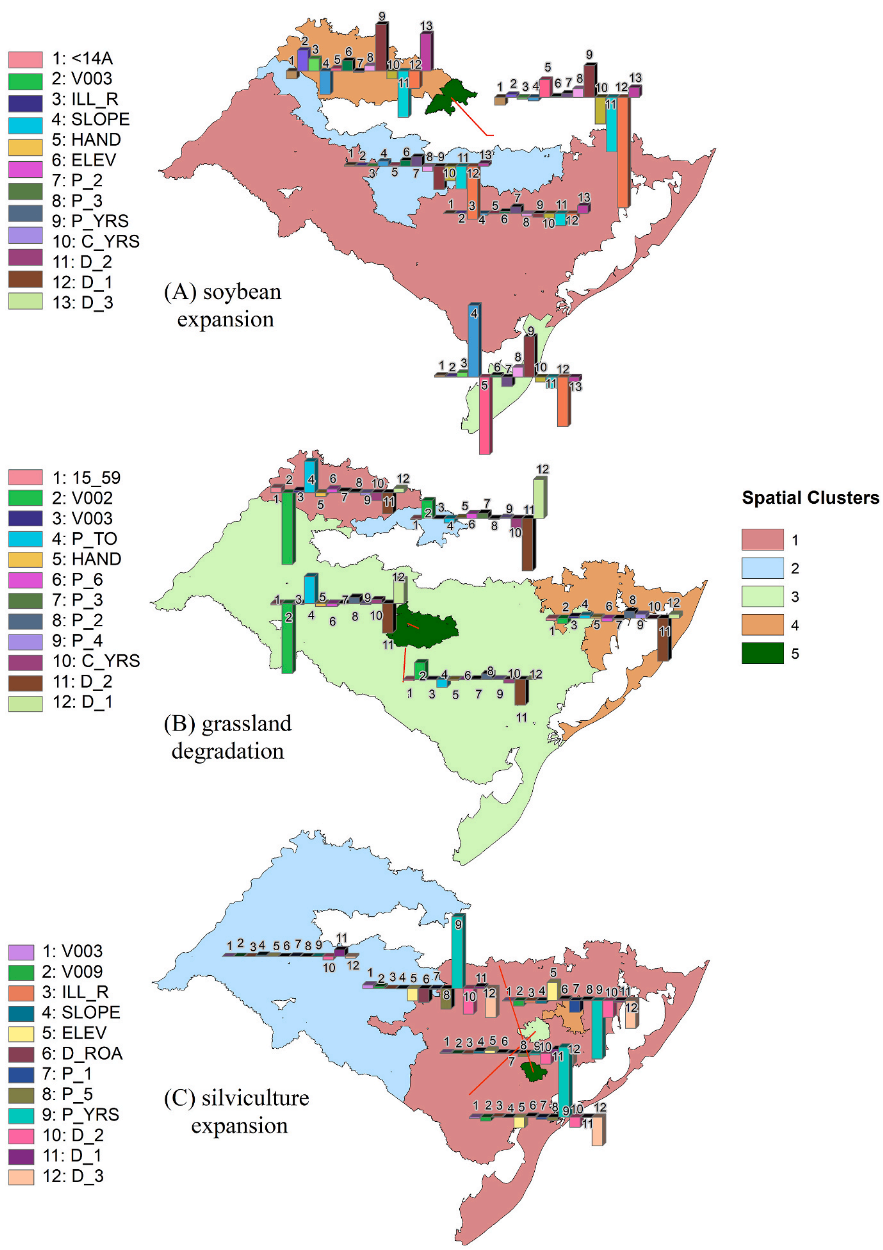

Fig. 08. Map of spatial clusterings using local parameters obtained with GWR for LUCC processes.

located near Camaquã municipality, presents as positive factor the elevation and as negative factors the annual precipitation, the distance from grassland degradation process and distance from silviculture expansion. Cluster 5, located near Canguçu municipality, presents as main positive variable the annual precipitation and as negative factors the number of forest degradation process patches, the distance from grassland degradation process and distance from silviculture expansion. Common variables for the three clusters (3,4 and 5) were the distance from grassland degradation process and distance from silviculture expansion.

4. Conclusions

The main processes that contributed to grassland vegetation degradation in the last 15 years were soybean and silviculture areas expansion. Using remote sensing and geoprocessing techniques it was possible to identify that the pattern of grassland vegetation degradation is a complex process involving a series of factors, tending to occur very close to areas already degraded previously. The main grassland vegetation degradation process in anthropic activities, particularly mechanized agriculture, like soybean cultivation and silviculture areas.

The combination of MODIS/EVI images and night illumination images (DMSP-OLS) made possible the identification and quantification of the approximately 1,244,750 ha increase of areas cultivated with soybean in Pampa Biome, which corresponds to around 145.56% increase. Silviculture areas also presented significant increase in area, with 555,734 ha, over 167% increase in their total area. On the other hand, there was reduction in grassland vegetation of around 25% of their total area in 15 years, losing a total of 2,576,536 ha.

The local (GWR) and local regression models' results showed that LUCC processes in Pampa Biome are associated to geomorphometric, climatic, distance from already degraded areas and socioeconomic variables. For the LUCC process of soybean expansion, the main factors identified were: topographic (elevation, declivity and HAND models), young population, educational factors (like illiteracy rate), and climatic factors (annual precipitation and seasonality of precipitation), and factors involving proximity to degraded areas.

In f silviculture expansion LUCC process, the main factors identified are: declivity, monthly average yield, illiteracy rate, annual precipitation and proximity to grassland degraded areas. In grassland degradation LUCC process, the main factors identified are: population density, population residing in domiciles, HAND model, grassland degradation patches, average of number of residents in domiciles, soybean expansion patches and distance from soybean expansion process.

The local regression model (GWR) is important to understand the high level of complexity of Pampa Biome landscape, characterized by a considerable level of heterogeneity, spatial fragmentation and aggregation, particularly in its north portion and in Serra do Sudeste. Regionalization by SKATER method makes possible to analyze the existing variability of independent variables in the different regions of the area of study for LUCC processes, grouping in 5 spatial clusters, and so improving the understanding of the processes' dynamics in Pampa Biome territory.

CRediT authorship contribution statement

Vagner Paz Mengue: Conceptualization, Methodology, Investigation, Resources, Writing - review & editing. **Marcos Wellausen Dias de Freitas:** Conceptualization, Methodology, Supervision. **Tatiana Silva da Silva:** Conceptualization, Methodology, Supervision. **Denise Cybis Fontana:** Conceptualization, Methodology, Supervision. **Fernando Comerlato Scottá:** Validation, Methodology, Supervision.

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