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Invasion by *Eragrostis plana* Nees in areas of the Brazilian Pampa biome modelled with remotely sensed data and GARP species distribution model

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--ABSTRACT--
In Brazil, the remnants of Pampa biome represent an area of high environmental fragility due to the expansion of the agricultural frontier and to overgrazing, which promotes conditions for the rapid spread and establishment of invasive species such as Eragrostis plana Nees. The areas most susceptible to invasion by this species are the areas degraded by overgrazing and intensive agriculture, abandoned crop fields, and roadsides. Considering the problems that arise from species invasion in natural areas, and particularly from Eragrostis plana in the Pampa biome, the objective of this study was to use the GARP (Genetic Algorithm Rule-set Production) species distribution model to map, at the local scale, the probability to invasion by this species using as input variables remotely sensed data, as well as, verify the influence of roads maps as input variable at model´s results. The environmental and topographic variables used as input variables were obtained from the spectral images of the MODIS-Terra and OLI-Landsat 8 sensors, from SRTM digital elevation model, and from road maps. The association between GARP species distribution models and remotely sensed data had positive effect in order to modeling plants patterns of invasion at local scale and a greater probability to invasion was found in areas nearest the roads, independent of the use it as the input variable in the model.
KEYWORDS - *Invasive species, South African lovegrass, NDVI, Grasslands, Rangelands, MODIS, Landsat.*

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I. INTRODUCTION

The use of remote sensing data with species distribution models is a great tool for monitoring invasive species, as well as for predicting areas most vulnerable to further invasion [1-3]. The objective of species distribution models is to relate the presence of a given species to information on environmental conditions, to identify the distribution potential that the studied species has in a certain locale [4]. They also serve as a baseline in assessing the impacts of human intervention and other environmental changes on organisms' distribution patterns [5]. Orbital remote sensing data allows a better understanding of the spatial and temporal distribution dynamics of invasive species, contributing to the study of invasive processes and ecosystem degradation [6] by generating information such as land use and cover, net primary production, humidity level, vegetation phenology, and topography, among other variables [1]. Moreover, the use of remote sensing information to model species distribution helps to reduce the high spatial correlation found in other sources of information such as average temperature or precipitation [1,7], which are good predictors when working at the region scale, but they vary little at the local scale [8].

Invasive exotic species are considered a serious threat to the loss of global biodiversity, second only to deforestation [9]. Ecosystems and land use changes, such as the establishment of urban areas and farming activities, increase vulnerability to invasion by exotic species [10]. Natural resource degradation resulting from invasion reduces food production, negatively impacting the economy [11]. Invasive species also affect water quality, damage streets and access roads, and spoil landscapes of touristic value. Thus, the impacts can lead to high economic costs related not only to direct damage, but also to the control and eradication of these species [12].

In Brazil, the remnants of Pampa biome represent an area of high environmental fragility due to the expansion of the agricultural frontier and to overgrazing, which promotes conditions for the rapid spread and establishment of invasive species such as *Eragrostis plana* Nees. The Pampa biome is broadly classified as Rio da Prata grasslands, formed by large areas dominated by grasslands and shrubs and covers an area of approximately 700,000 km^2 in Argentina, Uruguay and in the southern part of Brazil. This biome exhibits extensive biodiversity, with approximately 2,200 vegetal species, where coexists C_3 and C_4 species that are adapted to subtropical to temperate climates [13-14]. The primary economic activity in this biome is livestock production. In this biome, *E. plana* is considered the main invasive species and the most difficult to control, occupying an area estimated at 10% of the Brazilian part of the Pampa biome. *E. plana* originated in South Africa and was introduced to Brazil in the 1950s as a forage species that is resistant to cold. In the 1970s, due to uncontrolled dispersal of this species, it became regarded as an environmental and socioeconomic problem. The areas most susceptible to invasion by this species are the areas degraded by overgrazing and intensive agriculture, abandoned crop fields, and roadsides [15]. This species also has other characteristics that favor its high competitiveness, including rapid growth, a long reproductive phase, the allelopathic effect that inhibits the growth of other species, a high production of small seeds with high germination capacity, and the formation of large seed banks in the soil [16].

Considering the problems that arise from species invasion in natural areas, and particularly from *Eragrostis plana* in the Pampa biome, the objective of this study was to use the GARP (Genetic Algorithm Rule-set Production) species distribution model to map, at the local scale, the probability to invasion by this species using as input variables remotely sensed data, as well as, verify the influence of roads maps as input variable at model´s results.

II. MODELING PROCESS

Study area and samples.

Aceguá municipality is located in the south of the Rio Grande do Sul state, Brazil, on the border with Uruguay (Figure 1). It has an area of 1,502 km^2, contained entirely within the Pampa biome. According to the Köppen classification, the municipality’s climate is mesothermic, subtropical type, Cfa class, with an annual precipitation of 1,300 mm and an annual average temperature of 18 ºC; frosts occur between April and November. The municipality’s elevation ranges from 50 to 300 m above sea level, with a relief that varies between flat and moderately undulated, with soils composed mainly of expansive clays [17]. The vegetation is dominated by herbaceous and shrubby species, mainly of the families Poaceae and Fabaceae [14,18]. The municipal economy is based largely on the primary sector such as livestock, where the main herds being cattle, horses and sheep, and annual crops of rice, corn and sorghum.

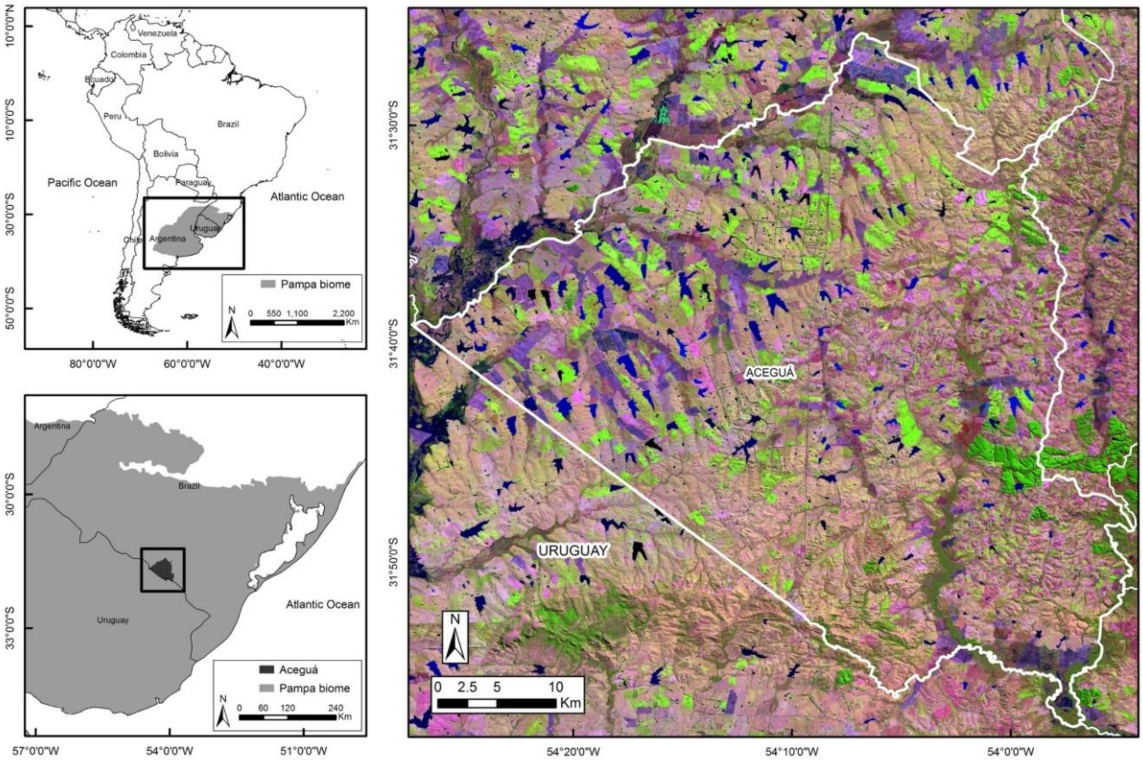

Fig.1 - Study area location

The fieldwork was conducted during the first week of June 2016, when was collected information about 226 sampling points. In the end of autumn and beginning of the winter season (in the south hemisphere) the *E. plana* has morphological differences between the native grasses, allowing its rapid identification Considering that roads are the main source of *E. plana* dispersal [19], sampling points were situated in relation to the public roads (Figure 2). At each point, the land use and the presence or absence of *E. plana* were identified and the geographic coordinates were obtained using a GPS receiver.

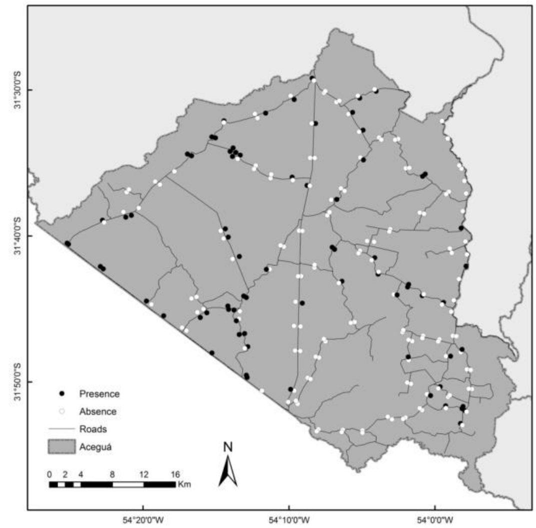

Fig. 2 - Road map and sample points with presence and absence of *E. plana*

GARP (Genetic Algorithm for Rule Production).

The GARP species distribution model was used to identify, at the local scale, the susceptibility to invasion by *Eragrostis plana* in the Pampa biome. It is implemented at openModeller v1.5.0 plataform. GARP has the capacity to apply different types of rules simultaneously to explain nonlinear relationships between the occurrence of a species and the predictor variables. The algorithm learns with each interaction of the rules and applies those that best describe the relationship between the variables and the species' presence [20]. GARP is a genetic algorithm constructed by an interactive process of selection, evaluation, and incorporation or rejection of rules that represent a possible solution of the model. To generate the rules, the algorithm first selects an initial random population of rules, which interact using a genetic algorithm, eliminating the rules that present a low performance and maintaining the interaction of those with high performance, until the model either converges on a value or reaches the maximum number of interactions [21]. The sample data were divided into two sets: one for training the model, composed of 70% of the samples, and the other set for model validation, comprising the remaining 30% of the samples. These divisions being done randomly at each model´s run. The model´s output is an image with continuous values between 0 and 100, where values close to 0 represent a very low probability that the invasive species will establish itself at that point, when the value is closer to 100 it means that this point has a high potential for invasion of the species being modeled. The performance of the models was assessed by analyzing the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve [2,24-26]. The AUC of the ROC curve provides a single value independent from any threshold chosen to define the potential presence or absence of the species. The AUC values vary between 0.5 and 1, being 1 when all cases are classified correctly, and 0.5 when the model is not different from random classification [24]. This process was conducted to observe the behavior of the results with data not included in the training of the models, and to calculate the respective ROC curves and AUC values [27].

Input variables.

The environmental and topographic variables used to model the study area's probability to invasion by *E. plana* were obtained from the spectral images of the MODIS-Terra and OLI-Landsat 8 sensors, from data of the SRTM digital elevation model, and from road maps. The geographic information system GRASS v7.0.6svn was used to process the images. The information was originally in two spatial resolutions (30 m and 250 m) because the two different orbital sensors used to calculate the spectral variables had different resolutions. Therefore, all variables were resampled to 250 m generating models at this resolution, since when implementing models with the finest spatial resolution, model performance did not necessarily improve, and there was no greater effect on the predictions [28].

An OLI-Landsat 8 sensor—Surface Reflectance product, acquired May 2015, path/row 223/082, with 30-m spatial resolution, was used to calculate the Normalized Difference Vegetation Index (NDVI), the Linear

Spectral Mixture Model and the Tasseled Cap Transformation. In vegetation studies, the NDVI is commonly used to highlight the signal of photosynthetically active vegetation, based on the relationship of the near infrared (NIR) and red (R) wavelengths [6]. The Linear Spectral Mixture Model (LSMM) is a procedure that separates the spectral information at the subpixel level, based on the spectral response of the endmembers that compose the pixel's final spectral response [29]. During the period of analysis, *E. plana* is taller (Figure 3A) than the native vegetation (Figure 3B), and pixels with presence of this species have more shade inside. This shade occurs as a result of animals' selectivity during grazing, as they preferentially consume the native species [15], which allows unrestricted growth of *E. Plana*. To include the shade fraction as an input variable in the species distribution models, the LSMM was calculated using three endmembers representing the vegetation, the soil and the shade. The Tasseled Cap Transformation reduced the number of reflectance bands to three uncorrelated orthogonal components: Brightness, Greenness and Wetness [30-31]. Brightness is the weighted sum of all reflectance bands, representing the principal variation in soil reflectance. The second component, Greenness, is the contrast between the near infrared and visible bands, thus highlighting the vegetation. Wetness is associated with humidity of the soil and vegetation [32]. The Wetness component has been used successfully as a variable to model invasive species distribution [8].

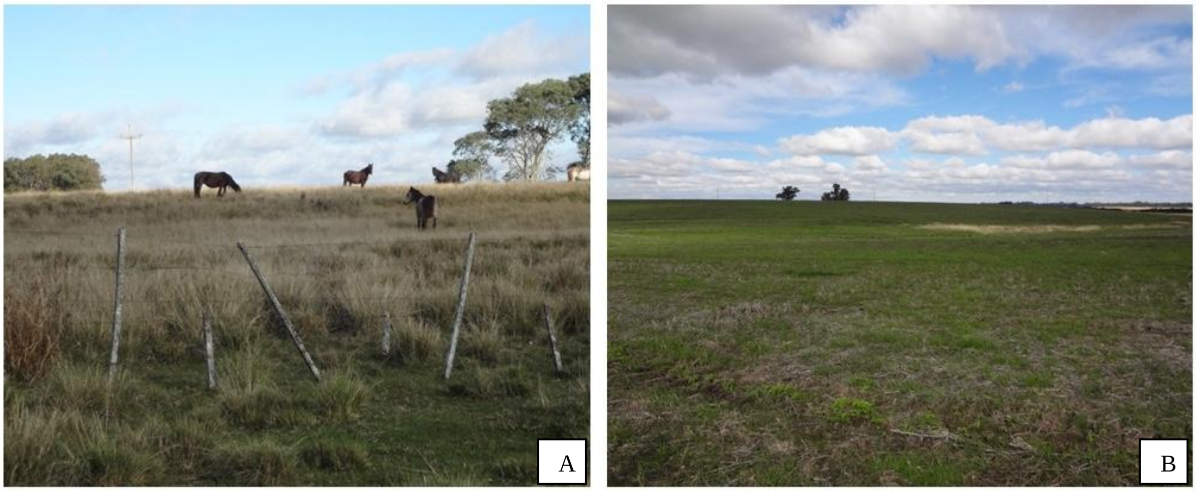

Fig. 3 - Area with invasion by *E. plana* (A) and without *E. plana* (B)

Based on the MODIS MOD13Q1 product, a NDVI time series ($NDVI_{ts}$) was created for the period 2011–2015. The MODIS MOD13Q1 product provides composite images of maximum NDVI, with a 16-day temporal resolution and 250-m spatial resolution, enabling the generation of complete time series of these indices [33]. To summarize the time series data, the Harmonic Analysis of Time Series (HANTS) transformation was applied to extract only the information relevant to land cover variation [34]. The HANTS algorithm (implemented in GRASS v7.0.6svn, module r.hants) is based on the Fourier transform. Given that the vegetation has a seasonal behavior, the NDVI time series can be represented by low-frequency sine functions of different wave amplitudes and phases [35]. The amplitude represents land use and land cover variations, and the phase represents the vegetation's phenological cycles. These variables are important for modeling invasive species distribution, since increasing disturbance of the natural vegetation heightens the potential for invasive species to establish [8,15]. From the HANTS transformation, the following variables were obtained: first harmonic phase, first harmonic amplitude, second harmonic phase, second harmonic amplitude, combination of the maximum values and combination of the minimum values of $NDVI_{ts}$.

The layers depicting the relief conditions were calculated based on the Shuttle Radar Topography Mission (SRTM) elevation model with 30-m resolution. These types of variables are also related to conditions influencing the species distribution, such as surface water drainage, soil loss, soil humidity, wind exposure, nutrient availability, among others [36-37]. The variables calculated from the elevation model were altitud, declivity, slope orientation, water flow accumulation, and relief shape; these calculations were made in the software GRASS v7.0.6svn.

Once the roads are an important variable in the species' dispersal [15], a raster image, with 30-m spatial resolution, was generated to represent the Euclidean distance of each pixel to the nearest road. This image was created in GRASS v7.0.6svn using the map of municipal roads and the centroid of each pixel in the image.

III. RESULTS AND DISCUSSION

The Jackknife test were performed, discarding the layers whose contribution was not significant (α = 5%), to avoided a model overfit [22-23], using the R statistical package. The Jackknife test determining that the HANTS transformation was able to represent a good part of the spatial variability of *E. plana* from the variables (1) first harmonic amplitude and (2) first harmonic phase. The rest of the selected variables were (3) NDVI, (4) Wetness, (5) minimum $NDVI_{ts}$, (6) altitud, (7) slope aspect, (8) slope declivity, and (9) Euclidean distance of the road network, defining these variables as the set of input variables were used in the modeling process. The Figure 4 presents the maps for probability to invasion by *E. plana*, ranges from 0 to 100%, with these respective frequency histograms. The model A was generate with distance of the road as input variables and model B without this variable. The AUC obtained values of 0.84 (Model A) and 0.81 (Model B). The AUC values between 0.5 and 0.7 indicate a low fit; values between 0.7 and 0.9 are good models that can be used; and values above 0.9 represent a high fit [25]. Thus, we can observed that the GARP model was able to represent the potential spatial distribution of *E. plana* in the Pampa biome, corroborating with other studies, which also obtained good fit when GARP was used to model the distribution of *E. plane* in the South Americas [38].

The distribution and spatial variation of the probability of invasion values for the two models shows that orbital remote sensing data allows a better understanding of the spatial and temporal distribution dynamics of invasive species, contributing to the study of invasive processes and ecosystem degradation and those can be used to represent the local variations of the environment. Even when the variable distance from roads (Model B) is excluded, a greater concentration of areas with a high probability of invasion can be observed along the roads in the municipality, which were identified by the GARP due to the different spectral pattern between the areas invaded and not invaded by *E. plana* grass. The *E. plana* invasion also depends a lot on management and control practices, as it is a very aggressive species and has adaptive characteristics that favor its establishment [19], this being a complex characteristic to modeling, but the variables obtained by remote sensing proved to be efficient to represent these modeling processes at the local scale, as can be seen in the model outputs.

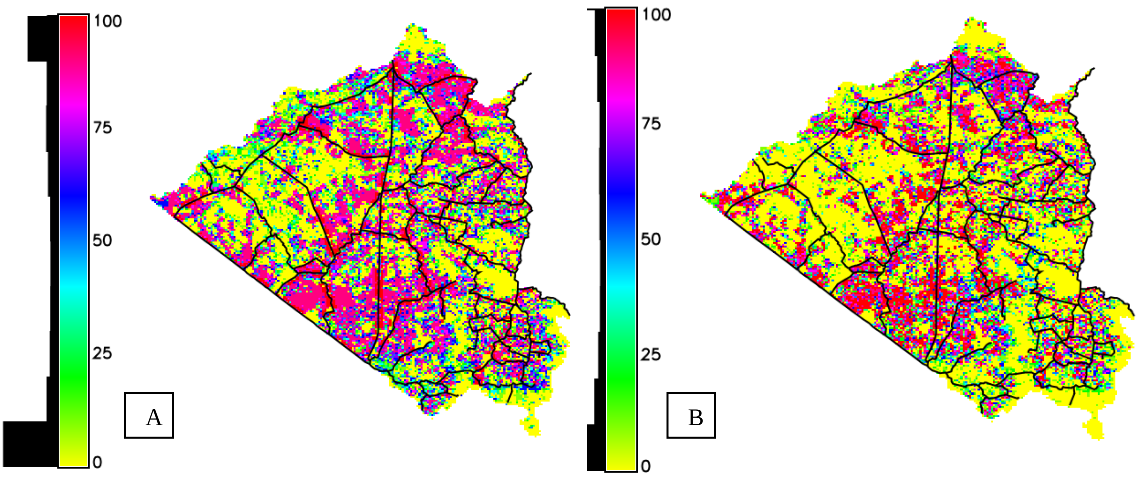

Fig. 4 - Maps generated by the modeling process (A) with distance of the roads and (B) without this input variable

In relation to the distance of the roads, the observed pattern was expected, showing that the areas with high potential to invasion are closest to the roads. From the frequency histograms and by the analysis of percentage of the municipality's area by cutting threshold (Table 1), can be observed that model A, which includes the variable distance from roads, presents a percentage of larger area with moderate to high probability of invasion. The road network serves as an important point of dispersion of *E. plana* grass seeds [19], which GARP is able to adequately represent when it identifies areas close to roads as the most likely to be invaded.

Cutting threshold	Municipality's area (%)	
	Model A	Model B
90	24.04	20.48
80	30.52	25.96
70	37.33	29.64
60	42.94	33.57
50	47.24	37.28

Table 1 - Percentage of Aceguá municipality’s area with probability of invasion by cutting threshold.

IV. CONCLUSION

The association between GARP species distribution models and remotely sensed data had positive effect in order to modeling invasive plants spatial patterns. Assessing the probability to invasion by *E. plana* in areas of the Pampa biome was possible due to the spectral separability of the invaded and non-invaded areas, which permitted the use of remote sensing variables to identify the spatial variability of the presence of this species in the study area.

The probability map identifying a large area with high potential to invasion by *E. plana* in areas of the Pampa biome, at local scale. A greater probability to invasion was found in areas nearest the roads, independent of the use of roads as the input variable in the model.

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