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Improved spatial model for Amazonian deforestation: An empirical assessment and spatial bias analysis

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A R T I C L E I N F O

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A B S T R A C T

Rainforest deforestation is a process controlled by both environmental and socioeconomic factors unevenly distributed in space. We tested the efficacy of a Machine Learning approach, based on MaxEnt models, to predict deforestation in the Brazilian Amazon, with special attention to the effects of the distance to the areas with higher present deforestation rates on model predictions. We use a set of variables that describe most of the mechanisms involved in the deforestation process such as infrastructure, social-economy and deforestation previous to 2008 to fit the model and evaluate model accuracy using real deforestation within 2009–2011. MaxEnt models were very effective for predicting new deforestation areas in spite of the high heterogeneity among Amazon municipalities. Both model sensitivity and positive predictive rate increased from areas with higher current deforestation to not deforested areas. There is higher model sensitivity near areas where deforestation process is more active. Our results support this approach as an effective tool for spatial prediction of deforestation and guide command & control operations against Amazonian deforestation.

1. Introduction

Deforestationis the most persistent environmental problem in the Brazilian Amazon, with serious consequences for global biodiversity (Peres et al., 2010) and ecosystem services on a global scale (Fearnside, 2012). Consequently, there is an increased effort to stop deforestation or, at least, slow it (Arima et al., 2014; Nepstad et al., 2009). Most of these efforts are related to a consortium of public policies known as PPCDAM (Prevention and Control of Deforestation Action Plan in Brazilian Amazon). This plan has focus in increase command-and-control actions and preventive surveillance to deter illegal deforestation, and has as results a deforestation rate decrease of almost 52%, between 2004 and 2012 (Assunção et al., 2012). Those actions must rely on good spatial prediction of current and future deforestation in order to produce persistent and effective effects. Nevertheless, current strategies are mostly based on reactive responses to past deforestation actions, and became only palliative since the damage to the forest has already been done (IPEA, 2010; Laurance et al., 2001). A pro-active response is advised and broadly expected, but it is extremely dependent on effective prediction of the spatial distribution of near-future deforestation in the region.

The Amazon forest is a mosaic of heterogeneous ecological and socioeconomic systems, varying largely in relation to occupation history and the role played by different social actors and environmental factors (De Souza et al., 2013). Usually, initial deforestation results from the implantation of cattle raising activities in areas with low land values (Rodrigues et al., 2009). Otherwise, in flat relief landscapes that help mechanization, the current land use changes favored the cultivation of soybean (Fearnside, 2001; Morton et al., 2006), favoring rapid land conversion. This shift in land use was accompanied by an increase in the land's value, and may be partially responsible for the differences in deforestation rates across other Amazonian areas (e.g. south of Amazonas state). As a consequence of this process, it is possible to devise a general conceptual model for Amazonian deforestation that uses the distance to the deforestation frontier as a surrogate for the ecological and socioeconomic factors that affect deforestation (Laurance et al., 2002; Rodrigues et al., 2009). A pre-frontier distance class have low levels of deforestation activity, large forest remnants and small deforestation (< 5%). A frontier class (recent or current deforestation activity) has a high level of deforestation activity with a deforestation rate between 40–60% of the area. The post-frontier classes (old deforestation) have low level of current deforestation activity

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simply because the forest is almost gone. These differences resulted from the socioeconomic processes current acting in each region, and may affect the efficiency of models designed to predict the spatial distribution of deforestation. For instance, it is possible to hypothesize that models that use previous deforestation information and the activity of socioeconomic processes will be more effective in frontier and post-frontier areas, where those processes are current active or was active during the near past.

Knowledge of the factors that affect deforestation is accepted as a fundamental tool for the continuous fight against deforestation. Some models simulate changes in the environmental attributes of the geographic territories and represent an effort to understand how the system developed under predetermined conditions (Soares-filho and Coutinho, 2002; Soares et al., 2006). Obviously, spatial models for deforestation must rely on a good understanding of how socioeconomic, political, and environmental conditions affect deforestation. Such enterprises may also help to provide a proper evaluation of the extent that surveillance efforts against deforestation are efficient (Linkie et al., 2010). Consequently, the past 20 years witnessed extensive research on the causes and factors affecting deforestation (Fearnside, 2008; Nepstad et al., 2009; De Souza et al., 2013). An analysis of these studies suggests that there are two sets of factors associated with the local occurrence of deforestation. The first set is explicitly related to deforestation as a spatial process. Thus, the presence of a deforested area can be a strong predictor of the likelihood of future deforestation nearby (de Souza and De Marco, 2014; Laurance et al., 2002).Otherwise, there are socioeconomic processes that may turn deforestation more easy or more profitable in a given location. This second set of factors is linked to market availability and the difficulty of surveillance, which may represent additional costs (Borner et al., 2010). The most common variables that operationally describe these relationships are the distance from roads and rivers (Barber et al., 2014; Laurance et al., 2002), the presence of livestock (Laurance et al., 2002), the expansion of agriculture (mainly soybeans) (Martinelli et al., 2010), and the absence of conservation units (Barber et al., 2014; Ricketts et al., 2010).

A large number of different approaches are current in use to model the deforestation process, which could be included in a broad view of land use change models (López-Carr et al., 2012; Marín et al., 2011; Parker et al., 2003). A spatial model approach allows an improved ability to identify locations at higher risk for future deforestation by combining a set of environmental/socioeconomic conditions with the occurrence of local deforestation. This may resemble the modern approach of predicting species distributions by formulating correlative rules between the presence of species and a set of climate variables or other environmental conditions (Elith et al., 2006; Peterson, 2006). More broadly, these methods use numerical tools to combine observations of the occurrence of a target class (e.g. species) with environmental variables, predicting the distribution of species across regions, and sometimes requiring extrapolation in space (Elith and Leathwick, 2009). A large number of different algorithms are currently used to these general problems (Elith et al., 2006; Phillips and Dudík, 2008; Wisz et al., 2008). One common and successful approach is the use of the maximum entropy concept, as implemented in the MaxEnt program (Phillips and Dudík, 2008), to generate predictions. The flexibility and efficiency of this tool has been well stablished in a broader number of problems such as the identification of a landscape class in a remote sensing problem (Li and Guo, 2010) or spatial prediction of fire in landscapes (Chen et al., 2015; Parisien and Moritz, 2009). For instance, MaxEnt was used to assess regions that were more prone to wildfires in the United States of America, and specifically, to the state of California (Parisien and Moritz, 2009). Furthermore, a study, using this algorithm estimated deforestation and was successful in modelling its future distribution for a limited region in the western Brazilian Amazon (de Souza and De Marco, 2014). Despite the promising results of this first attempt to the predict Amazonian deforestation, a more complete evaluation of its efficiency considering the heterogeneity of the process across different areas are essential to support it application both in academic and police strategy studies.

Here, we present the predictions of the spatial distribution for the entire Brazilian Amazon deforestation using the Species Distribution Modelling approach (SDM) and discuss how the spatial heterogeneity of the possible deforestation controlling factors may affect these results. At the biome scale, we assume that the spatial prediction of deforestation is affected by the form of the human occupation process (Laurance et al., 2002; Rodrigues et al., 2009), expressed by variations in deforestation rates and accompanying socioeconomic processes in relation to the deforestation frontier. Since the driving factors of deforestation may vary along the gradient from post to pre-frontier areas, we expect that our predictive ability will be lower in pre-frontier areas where the existence of previous deforestation in low. Nevertheless, this is the key-issue of deforestation prediction: an efficient prediction of future deforestation in pre-frontier areas is the key for controlling deforestation. A better predictive model under this scenario might be able to deal with these differences and maintain its predictive power. This is also important since there has been no attempt to evaluate the variation of the predictive power of the previous deforestation models in relation to the changes in deforestation rates, as well as the socioeconomic issues derived from the deforestation frontier framework (Rodrigues et al., 2009). We expect that this novel approach will serve to foster more efficient planning of surveillance actions for deforestation control.

2. Methods

2.1. Study area

The study area comprises all municipalities in the Brazilian Legal Amazon, distributed across nine states. This region accounts for more than 61% of the Brazilian territory (5,217,423 km^2) (Fig. 1). Approximately 22 million people live in the region, but the area maintains an overall low population density and includes some of the poorest regions in Brazil. This area is a important frontier for agriculture expansion in Brazil that includes a notably high conversion of natural vegetation to livestock pasture and soy monocultures. Over the past ten years, the Brazilian Amazon has undergone large infrastructure projects, such as the construction of dams and the creation and/or paving of major highways. These changes directly affect the risk of deforestation (Laurance et al., 2002; Soares-Filho et al., 2004) and affect the process of agricultural frontier expansion (Nepstad et al., 2002).

2.2. Occurrence of deforestation

The Deforestation Monitoring Program (PRODES – Available at: http://www.obt.inpe.br/prodes/) of the National Institute for Space Research (INPE), which provides information regarding deforestation from 1997 to 2013, provided the deforestation data used in this study. The PRODES is restricted to forested areas and excludes some savannah enclaves into the Amazonian forests, such as a large area of the Maranhão State. Those areas are also excluded from this analysis. Considering the law enforcement efforts against deforestation that took place in 2008 (Brasil, 2008), we choose to use deforestation until 2008 as our baseline data for training the models used to predict the deforestation rates. We used the observed spatial distribution of deforestation during the period of 2009–2011 to validate the generated models. We choose the deforestation until 2008 as baseline, because in this year, a law was implemented that created a public black list, limiting the ability to obtain loans and generate business for persons and companies that have committed environmental crimes. This law was a new paradigm in the fight against deforestation in Brazil, since it creates an effective economic mechanism reaching the main avenues of support for those engaged in deforestation – agricultural loans.

For all analysis, the area unit was a 1 km × 1 km cell. Original deforestation data are polygons with very detailed spatial information.