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Spatial modeling of deforestation processes in the Central Peruvian Amazon

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ABSTRACT

This study examines the relation between primary forest loss and landscape characteristics in the Ucayali region, Peru. Seven variables (rivers, elevation, annual precipitation, soil suitability for agriculture, population density, paved roads, and unpaved roads), were identified as potential deforestation drivers. The variables were converted into spatially explicit layers of continuous data and divided into a 9 km^2 grid. A multiple regression analysis was conducted to determine variable significance. Distance to paved and unpaved roads were strongly associated with deforestation, followed by distance to rivers, annual precipitation and elevation. All significant variables were negatively correlated with deforestation. Variables excluded from the model were population density and soil suitability for agriculture, suggesting that the influence of population density on forest clearing across the study area was not significant, and that deforestation activities were undertaken regardless whether soils are suitable for agriculture or not. Based on the linear regression analysis, the significant variables were selected and added to the Land Change Modeler in order to project primary forest coverage by 2025. The modeling results predict extensive deforestation along the Aguaytia River and at the forest/non-forest interface along the paved highway. The rate of primary forest removal is expected to increase from 4783 ha y^{-1} (for the 2007–2014 period) to 5086 ha y^{-1} (for the 2015–2025 period). A preliminary survey questionnaire conducted to explore deforestation intentions by farmers in the region, partly confirmed the overall deforestation trends as projected by the model.

1. Introduction

Tropical deforestation is regarded as one of the greatest environmental crises in human history and poses major concern to society and the scientific world. Although global deforestation rates decreased between 1990 and 2010 (Achard et al., 2014; FAO, 2010; Hansen et al., 2013), most forest loss continues to occur in the tropics whereas gains are observed in boreal and temperate zones. At the global scale, tropical forests play a key role in the support of fundamental biophysical processes such as climate regulation and carbon sequestration (Foley et al., 2007). In addition, the decline of tropical ecosystems is the greatest contributor to species extinction since the tropics contain most of the world's biological diversity (Rolland, Condamine, Jiguet, & Morlon, 2014). Moreover, the decline of tropical ecosystems has direct and indirect impacts on the livelihoods of local human communities living in tropical regions. Many indigenous populations directly rely on the goods and services provided by tropical ecosystems. Yet, due to the continued conversion of tropical forests to other land uses, the most basic necessities of life such as food, medicine and shelter are at risk (Koziell, 2001). Poor forest management also affects the livelihoods of non-indigenous populations. Sediment retention, water quality, and pollination are indirect ecosystem services provided by tropical forests and required for the agricultural activities that tend to follow deforestation processes in tropical regions such as in the Central Peruvian Amazon (Porro, Lopez-Feldman, & Vela-Alvarado, 2015).

The Amazon region accounts for about half of the world's remaining tropical forests. Two thirds of the Amazonian forests are located in Brazil, where deforestation has dropped dramatically from 27,000 km^2 (0.68%) in 2004 to approximately 7000 km^2 (0.18%) in 2010, according to the Brazilian Institute for Space Research (Malingreau, Eva, & De Miranda, 2012). Similar Amazon

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deforestation rates have been observed in other South American countries. Colombia's annual deforestation rate was 0.62% between 1990 and 2005 (Armenteras, Cabrera, Rodríguez, & Retana, 2013), while Bolivia lost 0.48% of its forests per year between 2001 and 2004 (Killeen et al., 2007). The deforestation rate in Northern Ecuador was 1.21% in the period 1990–2000, yet sharply decreased to 0.47% per year in the period 2000–2008 (Holland et al., 2014). Peru contains approximately 16% of the total Amazonian forests, which represents the second-largest portion of the Amazon region. Deforestation rates in Peru are relatively low compared to its neighboring countries (0.07% for the period 1999–2003 and 0.17% in 2005 (Oliveira et al., 2007)). While deforestation rates in Peru are lower, they have remained steady. According to the most recent figures published by the Peruvian Ministry of the Environment, deforestation in Peru was 0.16% in the period between 2010 and 2011 (Piu & Menton, 2014). Projections of future deforestation in the Peruvian Amazon are scarce and vary considerably. These can range from 10% forest loss by 2030 (Velarde, Ugarte-Guerra, & Tito, 2010), up to 91% by 2041 (Dourojeanni, Barandiarán, & Dourojeanni, 2009). Improved deforestation forecasting is necessary for implementing land management strategies that target the development of local communities as well as environmental conservation objectives.

The Ucayali region in the Central Peruvian Amazon is one of the four lowland Amazon states of the country and represents approximately 8% of Peru's national territory. The population in Ucayali has grown from about 16,000 people in 1940 to more than 430,000 in 2007 (INEI, 2014). The vast majority of the population is located within the Aguaytia River basin and primarily concentrated in and around Pucallpa, the state's capital city. The construction of the Federico Basadre Highway connecting Pucallpa to Lima in the 1940s, has provided access to the area for companies engaged in logging and stock farming (Ichikawa, Ricse, Ugarte, & Kobayashi, 2014) and immigrants from other regions (Goy & Waltner-Toews, 2005). Particularly, migration from the Peruvian Andes is known to be an important cause for population growth and a driver of deforestation in the Ucayali region (Guerra, 2009; Oliveira et al., 2007; Perz, Aramburú, & Bremner, 2005). Settlement policies and development programs in the 1940s used to promote Andean migration to the Amazon region. Nowadays, people leave the highlands mainly due to the lack of economic opportunities there compared to the growth of extractive markets in forested areas (Piu & Menton, 2014). The most extensive deforestation and changes in land use have occurred in the Aguaytia River basin, especially along the Federico Basadre Highway. Though often recognized for its direct effects on the forest cover, the establishment of infrastructure is a crucial condition for the expansion of agriculture and for most of the other land use changes as well. According to the Ministry of Transport and Communication, the Peruvian Amazon includes a road network of 7900 km, of which 1940 km are paved roads. In addition to the official roads, secondary road networks, probably encompassing thousands of kilometers, have been constructed over the years by local authorities, farmers, miners, and communities working in the oil and timber industry (Dourojeanni et al., 2009). In the Ucayali region, the establishment of secondary roads in particular has enhanced the colonization of forest areas by migrants which has led to extensive forest removal (Guerra, 2009; Ichikawa et al., 2014).

Assessing the driving forces behind land cover change is key for understanding changes in our global environment and for reducing the uncertainty regarding the spatial and temporal occurrence of future deforestation. Knowledge on the drivers of change has taken a central stage in the development of adequate conservation policies (Hosonuma et al., 2012). Many authors (Ernst et al., 2013; Salvini et al., 2014; Weatherley-Singh & Gupta, 2015) distinguish between direct and indirect drivers because of their different influence on land cover change. Direct deforestation drivers are defined as human activities or actions at the local level which directly lead to the conversion of forested areas into another land use, such as the construction of a road, agricultural expansion, and mining. The underlying or indirect drivers are complex social processes at the local, national or global level, which underpin and sustain the direct deforestation drivers, such as increasing economic wealth, population growth and consumption power by society (Geist & Lambin, 2001). Most deforestation literature focusses on anthropogenic drivers although changes in ecosystems can also be induced by natural processes such as volcanic eruptions and natural forest fires. Over 115 natural and anthropogenic variables have been identified which potentially influence deforestation (Kaimowitz & Angelsen, 1998). Many of these variables are recognized to trigger rather than to drive deforestation (Geist & Lambin, 2001). For instance, biophysical features such as soil quality and precipitation could potentially influence the susceptibility of a forest to be converted to agriculture. Similarly, other landscape features such as slope and the location of water bodies can influence the accessibility to a forest and consequently the vulnerability to conversion into a different land use. While indirect deforestation drivers are mainly influenced by anthropogenic variables, the impact of direct drivers is influenced by both the natural landscape and local anthropogenic conditions. Hence, research on deforestation processes at the forest frontier involves taking into account both natural and anthropogenic landscape properties.

Spatial regression models attempt to relate the location of land cover change with maps of spatially explicit variables, which are integrated in a geographic information system (GIS) (Chowdhury, 2006; Lambin, 1994). The models have been used in a wide range of tropical study regions to identify the causes of forest cover change and to allocate the areas across the landscape with highest susceptibility to deforestation (Kaimowitz, Mendez, Puntodewo, & Vanclay, 2002; Ludeke, Maggio, & Reid, 1990; Mertens & Lambin, 1997). Population density, topographic landscape features, and distance measures are regularly included to explain the variation in deforestation, whereas non-spatial variables as sociocultural and political drivers are often beyond the scope of the models (Chowdhury, 2006; Lambin, 1994; Mas, Puig, Palacio, & Sosa-López, 2004). Some of the variables that can be included in models could be indicators of drivers; for instance, population density over time may reflect population growth; and the presence of roads reflects the effect of transportation infrastructure development, a direct driver of deforestation. Also, landscape variables like soil characteristics, precipitation, and elevation influence the suitability of land for agricultural production, which is a direct driver of deforestation in the Amazon. Etter, McAlpine, Wilson, Phinn, & Possingham (2006) for instance, found that fertile soils are related to higher deforestation rates in Colombia, whereas Laurance et al. (2002) demonstrated that in addition to soil-fertility also soil waterlogging is correlated with deforestation in the Brazilian Amazon. An alternative to spatial regression modeling is land cover change simulation modeling, which enables the projection of future land cover changes as a function of historic land cover transitions and a set of explanatory variables (Irwin & Geoghegan, 2001). Unlike spatial regression models, land cover change simulation models produce output maps of net future forest loss. Land cover change simulation is based on more sophisticated techniques such as Markov chain models and cellular automata, which describe the likelihood of the landscape to change from one land cover class to another (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Simulation models can support the exploration of future deforestation scenarios and the development of conservation policies.

The objectives of this study were to (1) identify and assess the effect of anthropogenic and biophysical landscape variables, which are associated with direct deforestation drivers, on deforestation in the Ucayali region, and to (2) predict the status of primary forests