Local Deforestation Patterns in Mexico
An Approach using Geographiccally Weighted Regression

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Abstract: This study identifies drivers of deforestation in Mexico by applying Geographically Weighted Regression (GWR) models to cartographic and statistical data. A wall-to-wall multitemporal GIS database was constructed incorporating digital data from Global Forest Change (2000-2012); along with ancillary data (road network, settlements, topography, socio-economical parameters and government policies). The database analysis allowed assessing the spatial distribution of deforestation at the municipal level. The statistical analysis of deforestation drivers presented here was focused on the rate of deforestation during the period 2007-2011 as dependent variable. In comparison with the global model, the use of GWR increased the goodness-of-fit (adjusted R^2) from 0.46 (global model) to 0.58 (average R^2 of GWR local models), with individual GWR models ranging from 0.52 to 0.64. The GWR model highlighted the spatial variation of the relationship between the rate of deforestation and its drivers. Factors identified as having a major impact on deforestation were related to topography (slope), accessibility (road and settlement density) and marginalization. Results indicate that some of the drivers explaining deforestation vary over space, and that the same driver can exhibit opposite effects depending on the region.

1 INTRODUCTION

Mexico, with a total area of about two million square kilometres, is a megadiverse country, but it presents high rates of deforestation (FAO, 2001). Various studies have attempted to assess land use / cover change (LUCC) over the last decades (Mas et al., 2004) but there have been few attempts to assess the main causes of deforestation at national level (Figueroa et al., 2009); (Pineda Jaimes et al., 2010); (Bonilla-Moheno et al., 2013). Given the complexity of Mexico territory, the processes of change and its factors are expected to be different depending on the region. Geographically Weighted Regression (GWR) has been applied in exploring spatial data in the social, health and environmental sciences. The goal of this study is to evaluate the spatial patterns of deforestation with respect to drivers reported to influence LUCC using Geographically Weighted Regression (GWR).

2 MATERIAL AND METHODS

2.1 Material

In order to elaborate the GIS database, the following data were used:

- Map of forest loss from the Global Forest Change 2000–2012 data base at 30 m resolution (Hansen et al., 2013).
- Maps of ancillary data (digital elevation model, slope, roads maps, human settlements, climate, soils, municipal boundaries). (Figure 1)
- Socio-economic data from the National Institute of Geography, Statistics and Informatics (INEGI for its Spanish acronym) organized by municipality (Population census for 2005 and 2010). (Figure 2)
- Government policies (rural and cattle-rearing subsidies, and protected areas). (Figure 3)

GIS operations were carried out with the following programs: ArcGIS (ESRI, 2011) and Q-GIS (www.qgis.org/). Statistical analysis and graphs

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were created using R (R Development Core Team, 2009). Geographically weighted regressions (GWR) were carried out using the packages: gwrr (Wheeler, 2007 and 2012) and spgwr (Bivand and Yu, 2012) in R.

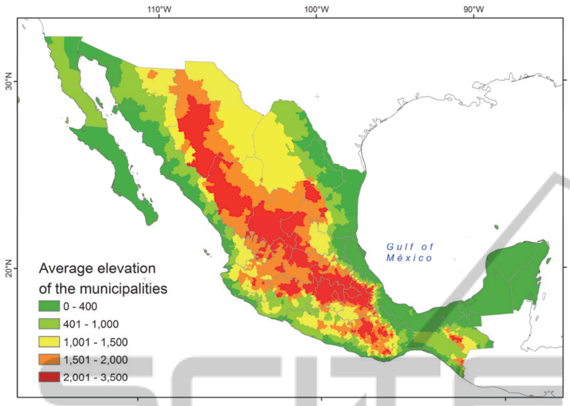

Figure 1: Average elevation of the municipalities.

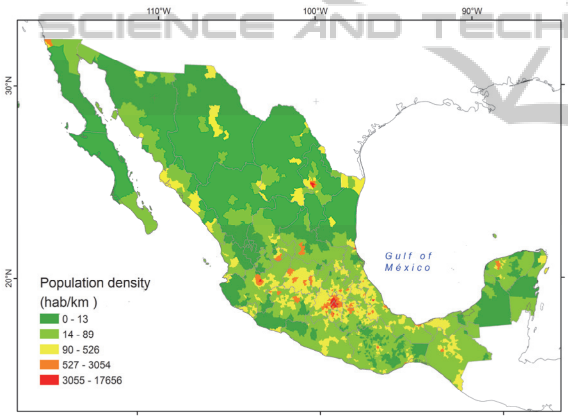

Figure 2: Municipal population density in 2010.

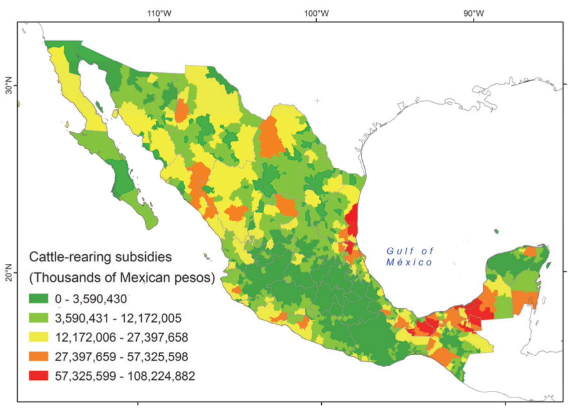

Figure 3: Cattle-rearing subsidies (2007-2011).

2.2 Deforestation Rates and GIS Database Elaboration

Deforestation rates were calculated at municipality level (2456 municipalities) based in the Global Forest Change 2000-2012 database (Hansen et al., 2013). In this study, the rate of deforestation was computed as the total area of forest loss during 2007-2011 normalized by the municipality area.

In order to determine which ancillary variables are most likely to be indirect drivers of deforestation, we calculated, for each municipality various indices describing: population, economic activities and the resources accessibility. These indices were: a) Population density in 2010 (people per km^2); b) Density settlements (number of settlements per km^2); c) Index of marginalization, which takes into account incomes, level of schooling and housing conditions (CONAPO, 2010), d) Cattle density, e) Goat density, f) Mean slope (degrees), g) Mean elevation, h) Road density (km of road per km^2), i)Amount of governmental subsidies for agriculture and cattle ranching (thousand of Mexican pesos per km^2), j) Proportion of municipality with protected areas.

2.3 Statistical Analysis

Geographically Weighted Regression is a local spatial statistical technique for exploring spatial nonstationarity (Fotheringham et al., 2002). It supports locally modelling of spatial relationships by fitting regression models. Regression parameters are estimated using a weighting function based on distance in order to assign larger weights to closer locations. Different from the usual global regression, which produces a single regression equation by summarizing the overall relationships among the explanatory and dependent variables (for the whole Mexican territory in that case), GWR produces spatial data that express the spatial variation in the relationships among variables. Maps that present the spatial distribution of the regression coefficient estimates along with the level of significance (e.g. t-values) have an essential role in exploring and interpreting spatial nonstationarity. Fotheringham et al., (2002) provide with a full description of GWR, and Mennis (2006) gives useful suggestions to map GWR results.

The first stage of the study was correlation analysis between explanatory variables using the Spearman coefficient in order to discard highly correlated variables. Due to the uneven distribution and size of the municipalities, the weighting function used an adaptive kernel which selects a proportion of the observations (k-nearest neighbours) assigned to each municipality and calculates the weights using a Gaussian model. The optimal size of the bandwidth (in this case the proportion of observations) was evaluated by minimizing the root mean square error. A map was elaborated for each explanatory variable showing the value of the regression's coefficients (color scaling of the symbol) and statistical significance (gray mask).

3 RESULTS

3.1 LUCC Monitoring

As shown in Figure 4: The rate of deforestation varies over space. The coastal floodplains of the Gulf of Mexico and the southern part of the country exhibits high rates of deforestation.

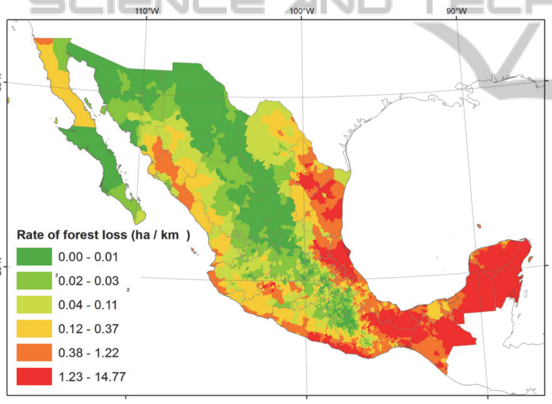

Figure 4: Per municipality deforestation (2007-2011).

3.2 Geographically Weighted Regression (GWR)

In this paper, we report the results of the GWR using as dependent variable the rate of deforestation in the period of 2007-2011. The weighting function was based on a 5% of the observations. A global model was fitted and obtained an adjusted-R^2 of 0.46. The use of GWR slightly increased the strength in the relationship in terms of the goodness-of-fit (adjusted R^2) to 0.58 (average R^2 of GWR local models), with local GWR models with adjusted R^2 ranging from 0.52 to 0.64. Figure 5 presents the spatial distribution of the goodness of fit.

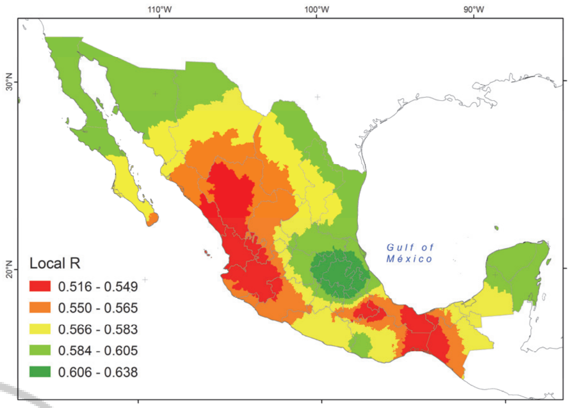

Figure 5: Distribution of local R^2.

Some variables such as population and road density and slope exhibit a significant relationship with the rate of deforestation for the whole territory. As expected, the first two variables have a positive effect on this proportion while slope presents a negative relationship (steeper slope less deforestation) also there is a "stronger" relationship in flat regions, or with more recent deforestation (Figure 6). Other explanatory variables have a more contrasted pattern. In example, the marginalization index presents a significant relationship with the rate of deforestation. It presents a positive relationship in the Baja California states, the border with the USA and the north strip along the Gulf of Mexico and a negative relationship in the center of Mexico (Figure 7).

Many studies have associated poverty and deforestation (Rudel and Horowitz, 2013). The region in the center south, where the relationship between marginalization and deforestation is negative is related to indigenous regions where municipalities with higher marginalization indices present lower deforestation rates. Previous researches have reported that the most conserved natural areas in Mexico are often located in poor rural areas and/or community lands (Klooster 2000); (Alix-Garcia de Janvry and Sadoulet, 2005); (Figueroa et al., 2009); (García-Barrios et al., 2009).

With respect to the government policy variables, protected areas (PAs) have no relationship to deforestation in most of the territory, but where the relation exists, it indicates that there is less deforestation in municipalities with more protected areas (Figure 8). Various studies reported contrasting effects of PAs on changes (Pineda et al., 2010); (Bray et al., 2008).

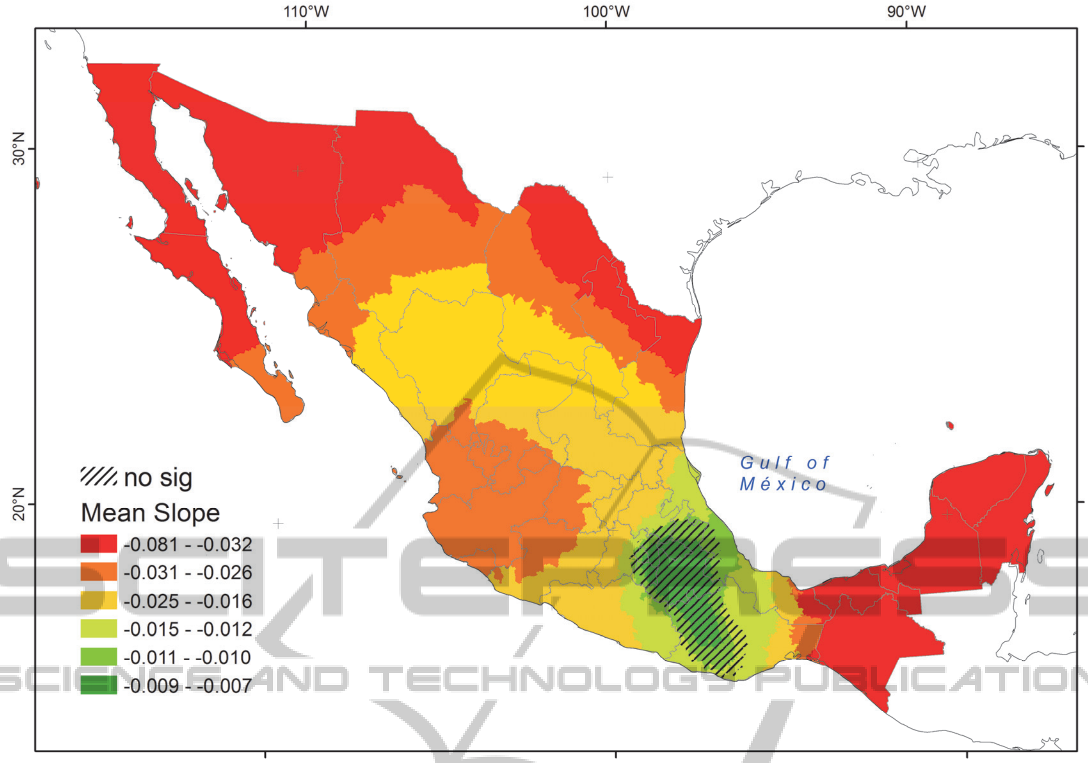

Figure 6: GWR coefficient and significance values for mean slope.

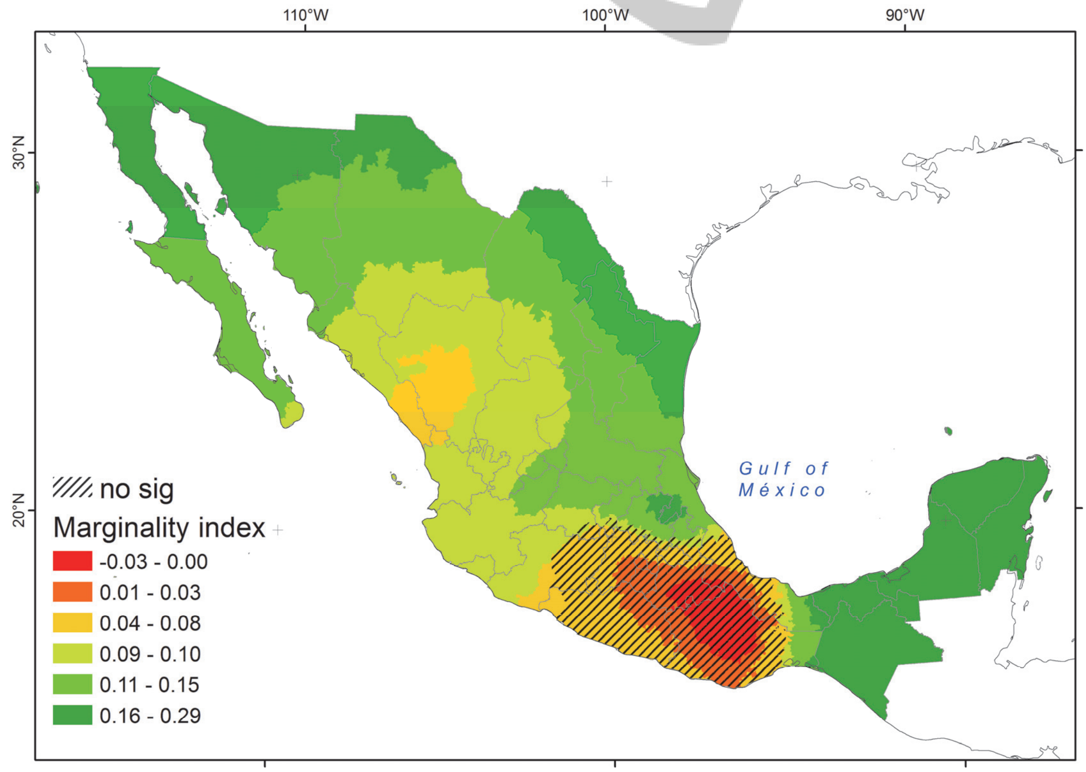

Figure 7: GWR coefficient and significance values for marginalization.

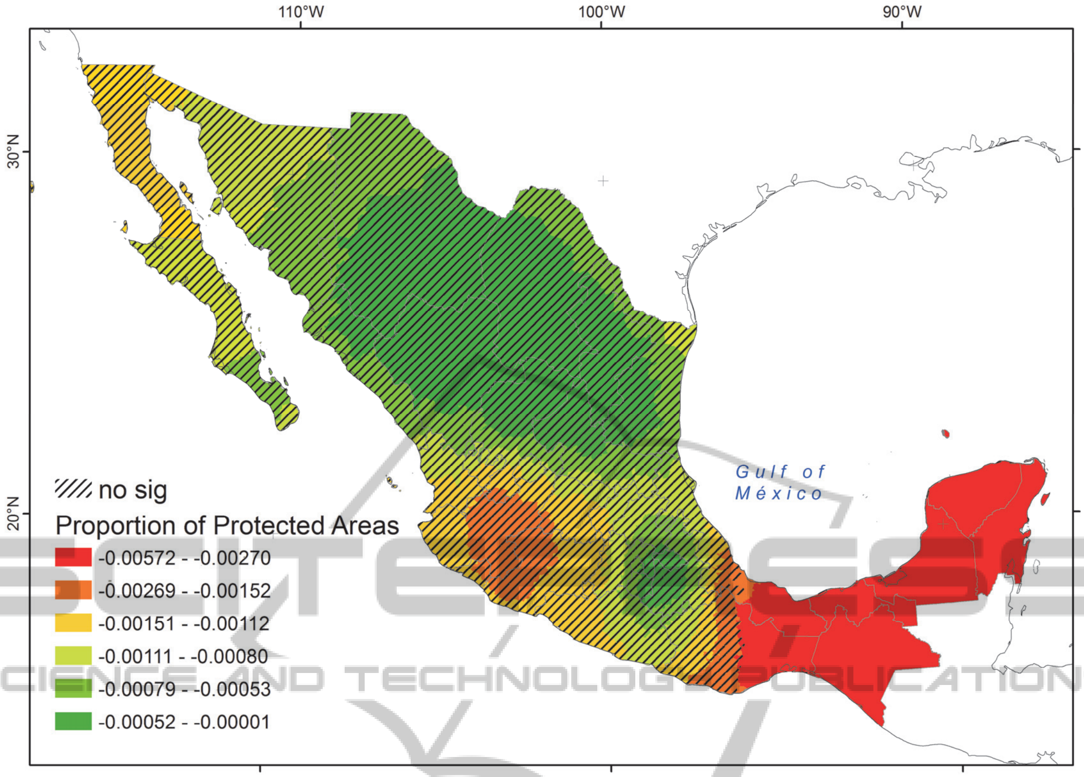

Figure 8: GWR coefficient and significance values for protected areas.

4 DISCUSSION

Some limitations of this study have been identified. Some of them are related with input data and with the way information is summarized at municipality level: i) Change data is based only on a drastic change of land cover (forest loss), it does not consider cover degradation. This factor has to be considered during the results interpretation. For example in some regions goat density is associated with lower levels of deforestation, however it is likely related with vegetation cover degradation rather than deforestation. ii) The rate of deforestation shows change from 2007 to 2011, but the drivers variables (population, marginalization, government subsidies) are from a particular date at different times of the period depending on data availability. The temporal issue cannot be totally addressed due to the lack of information. Additionally, in some cases, it could be interesting to calculate rates of change of these indices. For instance deforestation may be more related to the increase of population density than to population itself, iii) Another limitation is the averaging of indices at municipality level which may end up with a figure that does not reflect the actual situation over much of the area. For instance, a municipality with flat and steep slopes will present the average value corresponding to moderate slope. Moreover, deforestation can occur in small regions which present very different features from the average figure. A way to minimize those effect could be to calculate the indices taking into account only the forested area. For instance, average slope of municipality forest area is used to explain deforestation instead of the slope average over the entire municipality, iv) Finally, as depicted in figure 4, the set of explanatory variables we used did not allow to explain the dependent variable in a satisfactory manner for the entire territory. More drivers have to be taken into account for future analysis.

Other limitations are related with the method used and the deforestation process itself: Deforestation is a complex process that depends on interacting environmental, social, economic and, cultural drivers. Some of them cannot be used into the model because they are unable to be mapped. Moreover, the GWR uses municipality information to explain deforestation but is unable to take into account shifting effects (deforestation in a given municipality is due to the actions from inhabitants from other municipalities) and effects at different scale (as the GWR use the same bandwidth for all the explanatory variables). It worth noting that some drivers cannot act with very fuzzy spatial pattern or no pattern at all (e.g. global economy effect such as import/export of agriculture goods).

It is likely that the effect of a driver on a given region is related to the time such driver has been shaping the landscape and that different drivers have affect at different temporal and spatial scales, which makes the interpretation of the results difficult. Considering the rate of deforestation during different past periods of time will enable us to analyze the dynamic of deforestation in its temporal and spatial dimensions.

5 CONCLUSIONS

Some limitations of this study have been identified and will be addressed in forthcoming researches. However, results clearly show the advantages of a local approach (GWR) over a global one, to assess different drivers' effect on LUCC over such a complex and diverse territory as Mexico.

In future researches, alternative deforestation rates will be computed, new explanatory variables such as land tenure will be integrated into the model, the effect of correlation between explanatory variables at local scale will be tested and a workshop will be organized to carry out deep interpretation of the results.

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