IS THE INTEROCEANIC HIGHWAY EXPORTING DEFORESTATION?

A comparison of the intensity of regional Amazonian deforestation drivers within Brazil, Bolivia and Peru

by

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Abstract

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The Inter-Oceanic highway is a 1.9 billion dollar project that bisects southern Amazonia between the triple border region of Peru, Brazil and Bolivia. Many believe that a project of this magnitude will not only spur the trade of goods and services between these countries, but fear that Brazil's appalling deforestation rates will exacerbate the existing deforestation trends within Peru and Bolivia. By applying remote sensing techniques and a statistical logistic regression model I was able to depict deforestation prior to 1989, the increase between 1989 and 2000 and the cumulative effect by the year 2000, in the area of the Inter-Oceanic highway and other related human infrastructure. I found that the Peruvian deforestation rates will be exacerbated and, despite common belief, the Inter-Oceanic highway is not going to be the main culprit, but the secondary road network and population centers, that the highway will encourage. Furthermore, I project that the urban explosion of certain population centers will put under severe pressure the protected areas of Tambopata in Peru and the extractive reserve of Chico Mendes in Brazil. Finally we acknowledge that countries unique socioeconomic dynamics can clearly contradict the results of classic Pan-Amazonian deforestation models.

Date: ____________________

Approved:

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Introduction

The Inter-Oceanic highway is the final chapter of the infrastructure integration efforts between Peru and Brazil, joining the two coasts of the South American continent through a continuous paved road that bisects southern Amazonia, under the promotion of the *Initiative for the Integration of Regional Infrastructure in South America* (IIRSA)[1]. It is estimated that this road will benefit more than 13.3 million dwellers of the triple border region between Brazil, Bolivia and Peru (IIRSA 2007). However, the international scientific community has growing concerns about the possible impacts to the relatively pristine Peruvian and Bolivian tropical rainforests due to probable land-use changes triggered by the socioeconomic integration of these two countries with Brazil. These fears are based on the idea that the highway will not only spur the trade of goods and services between these countries, but that Brazil's appalling deforestation rates[2] will exacerbate the deforestation trends within Peru and Bolivia. On the other hand, supporters of the road strongly believe that road construction is an essential step to reduce poverty in these remote Amazon regions. Although the debate carries on, the road is scheduled to be fully operational by the year 2009, therefore the changes are already in motion and the uncertainties of its influence will start to be revealed in the near future. It is essential to characterize a deforestation baseline prior to the full completion of this road project. This baseline will be essential to quantify, if any, the deviation from the recent deforestation trends and reveal if the Inter-Oceanic highway is not only exporting goods and services, but deforestation too.

[1] The Initiative was adopted at a meeting of South American presidents held in the city of Brasilia, Brazil, in August 2000, at which the region's leaders agreed to take joint actions to promote South American political, social and economic integration that includes the streamlining of regional infrastructure and specific measures to foster the integration and development of isolated sub-regions. http://www.iirsa.org/

[2] According to 2000-2005 UN-FAO statistics Brazil has the highest average annual deforestation rate of primary forests with 3.4 million hectares per year.

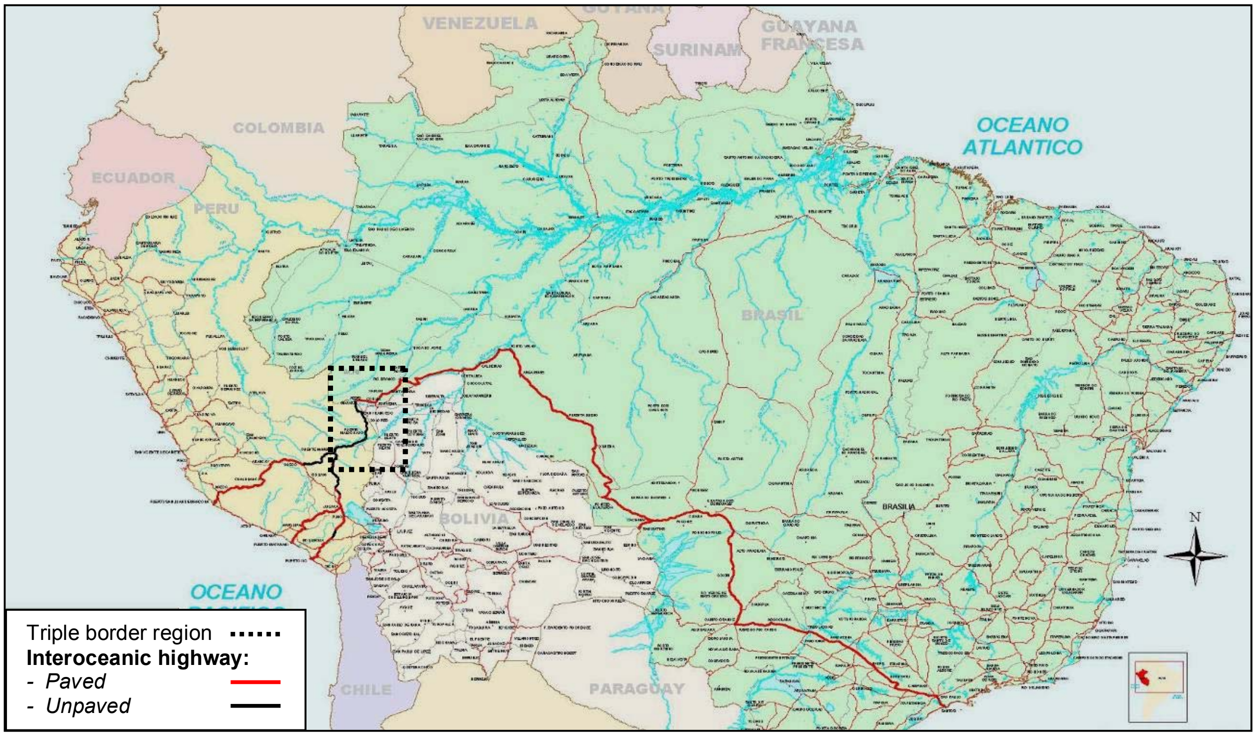


Figure 1*: The Inter-Oceanic highway route and the location of the triple border between Brazil, Bolivia and Peru. (Original source: MTC-Peru)*

According to some scientists, deforestation models on South America present certain bias towards treating the Amazon basin as a political and socioeconomic continuum, failing to acknowledge that the Amazon basin is roughly the size of the United States of America consisting of more than six countries. They argue that deforestation predictions must take into account national differences, including socioeconomic organization, population characteristics and dynamics, government systems, public policies, environmental laws and degree of enforcement, (Soares-Filho et al. 2006, Perz et al. 2005). Geist and Lambin (2001) separate tropical deforestation drivers in three proximate causes (agricultural expansion, wood extraction, expansion of infrastructure) and five broad categories of underlying driving forces (demographic, economic, technological, policy/institutional, and cultural or socio-political factors). Therefore, we cannot predict in a reliable manner the deforestation of a multinational road project such as the Inter-Oceanic highway by relying in current Pan-Amazonian deforestation models that do not account for the national differences in the underlying factors.

Several empirical techniques are typically used to analyze the driving factors, the relationships between driving factors, and related decision making processes of land use change (Lesschen et al. 2005). The actual use of empirical techniques differs: often the prime interest of social scientists is explanation of observed land use changes, while ecologists focus on prediction (Lesschen et al. 2005). In this particular case I not only approach a land-use change model as a social scientist by including the secondary road network, the population centers (markets), and national deforestation dynamics due to cultural or socio-political factors, but also as an environmental scientist by predicting the impacts of deforestation. Finally, it is important to acknowledge in the scope of this project that the term deforestation exclusively refers to clear-cutting of the forest. Therefore, selective logging and forest degradation by non-timber extractive activities are excluded. It is also important to understand that tropical rain forest is the predominant land-cover of the study area, and that any land-use change will consequently generate a lost in forest cover.

Objective

The primary objective of this project is to answer the question that entitles this research project: *Is Inter-Oceanic highway exporting deforestation?* In other words I will determine if Brazilian deforestation dynamics will exacerbate the ones in Bolivia and Peru, due to the pavement of the Inter-Oceanic highway and geospatially predict the possible deforestation scenarios on this region of the lowland Amazon rainforest. However, in order to reach this objective is essential to accomplish the secondary goals stated below.

- Quantify the deforestation rates regionally and within each country in the study area for the study time periods (1989-2000). This deforestation geospatial analysis will not only depict the land-use changes on the region, but identify the key geospatial deforestation drivers.
- Create a series of statistical models to detect the maximum likelihood estimator (MLE) of each geospatial deforestation driver within each country. Besides the fact that these models will allow the selection of significant geospatial deforestation drivers, they will create a temporal scale to better understand the relation between deforestation and human infrastructure.
- Rely on the MLE's to project the current deforestation trends into the near future. Two scenarios were created; a "*Pan-Amazonian*" under which there are no differences between the deforestation dynamics of the countries in the study area, and the "*Controlling by Country*" under which the projection will internalize the historic differences in the deforestation dynamics of the countries involved.

Study Area

The study area engulfs more than 13 million ha of the Low Tropical Wet Forest located between 110 and 520 m above sea level, on the triple border of the Amazon provinces of Madre de Dios (Peru), Acre (Brazil), and Pando (Bolivia). In ecological terms this is one of the most species-rich biomes in the world, harboring more than 1/3 of all species on the globe (Turner 2001). However, the importance of this region goes beyond its natural beauty and its genetic diversity, it is considered an important player in the carbon cycle. Scientists believe that Amazonian evergreen forests account for about 10% of the world's terrestrial primary productivity and 10% of the carbon stores in ecosystems (Melillo et al. 1993).

Table 1: Description of the Study Area

Country	Region (Province)	Main City (Capital)	Area (km^2)		Pop. Density	HDI (2000)
Peru	Madre de Dios	Puerto Maldonado	43,292	33 %	1.10 hab/km^2	0.621
Brazil	Acre	Rio Branco	56,455	43 %	4.50 hab/km^2	0.697
Bolivia	Pando/Beni	Cobija	31,081	24 %	0.96 hab/km^2	0.624

Source: United Nations Development Program (UNDP). http://hdr.undp.org/en/

The Human development Indexes (HDI)[3] for this region are considered medium/low depicting incipient infrastructure, basic services and economic development (Table 1) and although the state of Acre has a slightly advantage is still under the Brazilian HDI mean. The study area also includes the three main regional cities, for each country. These urban centers are Puerto Maldonado in Peru, Rio Branco in Brazil and Cobija in Bolivia (Table 1). It is important to highlight that although the Inter-Oceanic highway is not located on Bolivian territory, the

[3] The Human Development Index (HDI) is the normalized measure of life expectancy, literacy, education, standard of living, and GDP per capita for countries and regions worldwide. The index is used since 1990 by the United Nations Development Program in its annual Human Development Report.

urban continuum formed by the Bolivian city of Cobija and the Brazilian city of Brasiléia (connected to the Inter-Oceanic highway) allows this particular region of Bolivia to benefit from the road project without being a physical part of it (figure 2). In economic terms the region

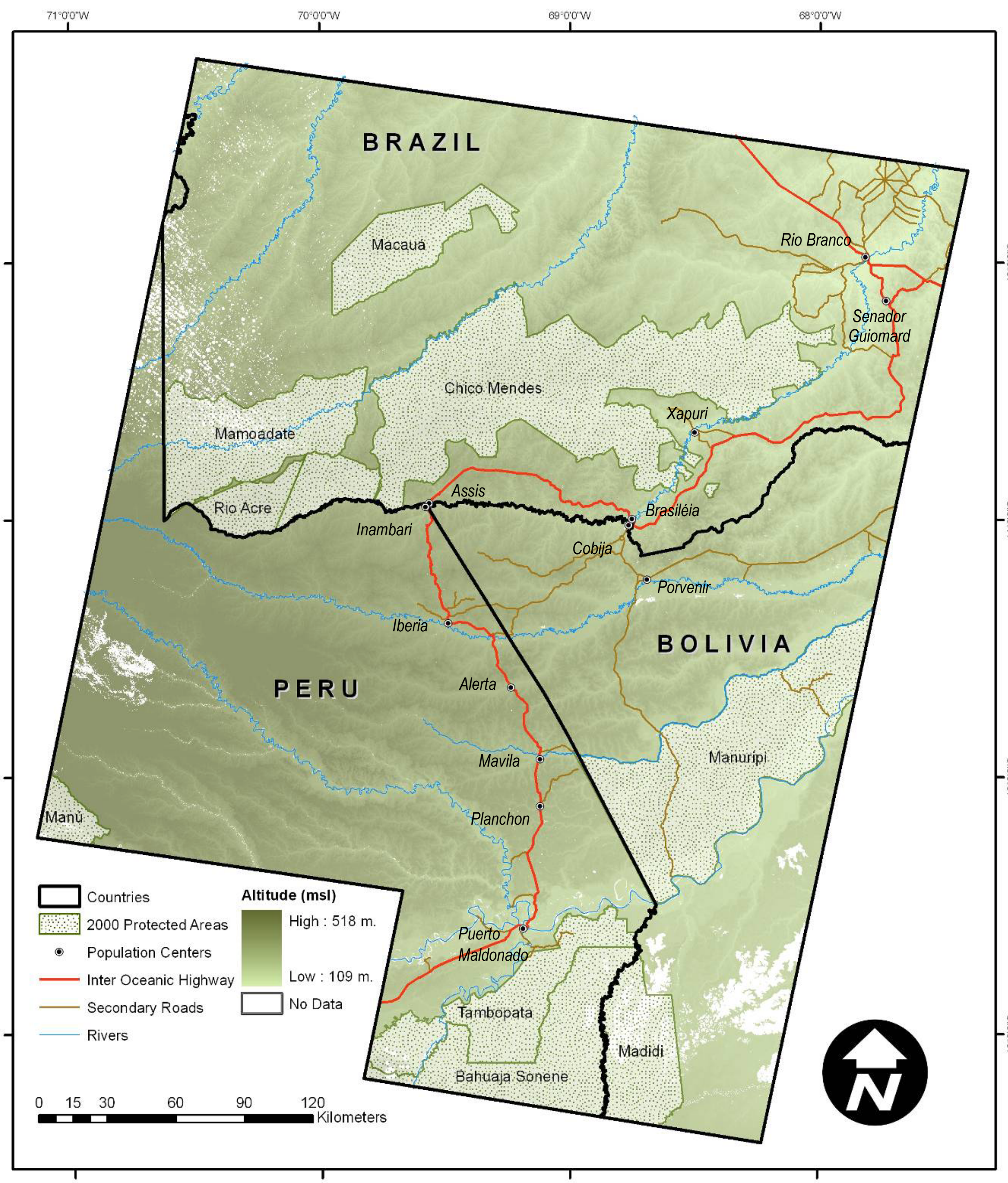


Figure 2: *Geographic, political and conservation template of the study by the year 2000.*

sustains the same basic extractive economic activities throughout the three countries; subsistence and industrial farming (palm oil, cacao, and sugar cane), cattle grazing, timber and non-timber forest products such as rubber and Brazilian nut. To depict the economic irrelevance and isolation of this region, Acre accounts for the 0.2% of the Brazilian economy while Madre de Dios sums 0.3% of the total Peruvian GDP. It is also relevant to mention that soybeans are not farmed in this particular region due to climatic and soil conditions.

At different scales of analysis, different driving forces dominate the land use system: at the national level this can be the local policy or the presence of ecologically valuable areas; at the regional level distance to the market, ports or airports may be the main determinant of land use change (Verburg et al. 2003). In that context the shape and extent of the study area was determined by the necessity to capture the national deforestation dynamics as proxies for institutional and cultural, or socio-political, differences within each country.

Methods and Materials

I used remote sensing techniques to quantify deforestation trends and patterns regionally and with in each country. Then applied a binomial logistic regression model to quantify the maximum likelihood estimator (MLE) of the human infrastructure driving land use changes. Finally, I relied on the regional and country MLE's to create two future deforestation scenarios.

Data

Five Landsat images representing the year 1989 (± 3 years) and five images representing 2000 (± 1 years) were acquired from the Global Land Cover Facility (Table 2) made available by the Earth Satellite Corporation of Rockville, Maryland, under NASA contracts NAS13-98046 and NAS13-02032 (Tucker et al. 2004). Complementary, vector GIS data of protected areas and political boundaries was downloaded from the World Database of Protected Areas[4], Atrium[5] and SisCom[6]. Each image was geometrically rectified to less than one pixel (30 m) RMS error, radiometrically corrected to at-satellite reflectance using parameters specified by Chander et al. (2007) and atmospherically corrected to surface reflectance using Dark-Object Subtraction (Chavez 1988, Conghe et al. 2001). Location of ground control points was complicated by changing river meanders and the lack of permanent features such as paved roads or urban development. Surface reflectance images for each date were then composited into 5-scene image mosaics by using the *ERDAS Imagen* mosaic tool as specified in Toivonen et al. (2002). The mosaics were clipped to a study area boundary, designed to capture the three countries unique

[4] WDPA: Global dataset on marine and terrestrial protected areas available. It is a joint venture of UNEP and IUCN, produced by UNEP-WCMC and the IUCN World Commission on Protected Areas (IUCN-WCPA) working with governments and collaborating NGOs; http://www.unep-wcmc.org/wdpa/
[5] Atrium: Biodiversity Information System for the Andes to Amazon Biodiversity Program. 2007. n. pg. Botanical Research Institute of Texas; http://atrium.andesamazon.org
[6] SisCom: Brazilian Government (IBAMA) Environmental Information Sharing System; http://siscom.ibama.gov.br/

deforestation dynamics as proxies for policy/institutional, and cultural or socio-political particularities.

Table 2: Landsat Images

1989 TM LandSAT Composite				2000 ETM+ LandSAT Composite			
Sensor	Path	Row	Date	Sensor	Path	Row	Date
5 TM	002	067	06/06/1993	7 ETM+	002	067	08/02/1999
4 TM	002	068	07/13/1992	7 ETM+	002	068	11/24/2000
5 TM	002	069	10/25/1986	7 ETM+	002	069	08/23/2001
5 TM	003	067	07/28/1986	7 ETM+	003	067	05/23/2000
5 TM	003	068	10/16/1986	7 ETM+	003	068	07/26/2000

Landcover

Landcover was mapped using all bands, except thermal, by Maximum-Likelihood (supervised) classification of the surface reflectance image mosaics. More than 150 spectral signatures representing forest, anthropogenic clearings (agricultural fields), water bodies, and shoals were captured manually per image for the two different time periods (due land-cover changes as well as radiometric differences between TM and ETM+). Speckle was reduced by applying a 3x3-pixel majority filter; filtered land-cover grids were re-sampled to 1-ha resolution to avoid erroneous landcover changes resulting from spatial misregistration. The outputs were three landcover grids depicting deforestation for the pre-existing conditions in 1989, the deforestation increase between 1989 and 2000 and the accumulative effect up to the year 2000. The 1-ha landcover grids were then reclassified to grids of forest and clearings (y=1 if deforested, y=0 if not deforested), converting all other pixels to background values.

Predictors

The landcover grids created above were used as the dependent variable of three logistic regressions. To avoid statistical correlations between the deforestation caused by road itself and the one generated by the land-use change triggered along its margins, the dependant variables (landcover grids) were resample from a 900 m^2 (30x30 pixels) resolution to a 10,000 m^2 (1 ha pixels) to dilute the deforestation caused directly by the roads. The independent variables were generated from political GIS vector layers and the identification of certain key features of the LandSat composite images. By measuring Euclidian distances from particular features, several geospatial independent variables were generated (Table 3). Population centers were defined as urban centers with more than 1000 habitants that serve as markets for the surrounding areas.

Table 3: Prediction Variables in relation with their Response Variable					
1989 Deforestation (pre-existing)		**1989-2000 Deforestation (11 years)**		**2000 Deforestation (accumulative)**	
Variable Name	**Type/Unit**	**Variable Name**	**Type/Unit**	**Variable Name**	**Type/Unit**
Bolivia	dummy	Bolivia	dummy	Bolivia	dummy
Brazil	dummy	Brazil	dummy	Brazil	dummy
Peru	dummy	Peru	dummy	Peru	dummy
Inter-Oceanic Highway	dist. (m)	Inter-Oceanic Highway	dist. (m)	Inter-Oceanic Highway	dist. (m)
Population Centers	dist. (m)	Population Centers	dist. (m)	Population Centers	dist. (m)
1989 Sec. Roads (pre)	dist. (m)	1989-2000 Sec. Roads	dist. (m)	2000 Sec. Roads (all)	dist. (m)
Rivers	dist. (m)	Rivers	dist. (m)	Rivers	dist. (m)
Topographic Elev.	alt. (m)	Topographic Elev.	alt. (m)	Topographic Elev.	alt. (m)

For the regression model to accommodate the national differences in the deforestation dynamics, three dichotomous "dummy" variables representing each country were created. Using the Hawth's tools in ArcGIS 9.2, 16,674 randomly generated points were use to sample the dependant and independent variables.

Statistical Model

In statistics, a binomial logistic regression is use to predict the probability of occurrence of a binary output (Lesschen et al. 2005). However, it does not assume linearity between the dependent and independent variables, does not require a normal distribution, nor doesn't assume homoscedasticity[7]. In general logistic regression has less stringent requirements, which will allow us to work with the limited and not normalized datasets. Furthermore, a binomial logistic regression applies maximum likelihood estimation (MLE) after transforming the dependent into a logit variable. In this way, logistic regression maximizes the log likelihood, which reflects how likely it is that the observed values of the dependent variable may be predicted from the observed values of the independents variables (Lesschen et al. 2005). Some relevant examples of this approach can be found in the Schneider and Pontius (2001) deforestation model in the Ipswich watershed of Massachusetts, the Geoghegan et al. (2001) tropical deforestation and land use intensification model in the southern Yucatán peninsular region, and the Amor Conde et al. (2007) Maya jungle deforestation predictions due to road building. The final logit function model is presented below:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \mathbf{x}_i\boldsymbol{\beta} + \boldsymbol{\varepsilon}_i \qquad (1)$$

Where:

- ***pi*** is the probability of deforestation,
- $\mathbf{x}_i$ is the vector of covariates (eg:, altitude, country, distance to roads, etc.) for point *i*
- is the vector of parameters linking $\mathbf{x}_i$ and $\boldsymbol{p}_i$.

[7] In statistics, a sequence or a vector of random variables is homoscedastic if all random variables in the sequence or vector have the same finite variance.

Analysis

Prior to running the logistic regressions it is important to understand the mechanics of the deforestation process and compare it to the structure of our datasets. It is clear that the human access to a deforested patch will be from the nearest road, regardless of its importance (Inter-Oceanic highway of secondary roads). However, our data considered all the distances from deforested patches to all roads, without discriminating which road is nearest to the deforested patch. This does not necessarily reflect the deforestation dynamics on the ground. Therefore, in order to run a logistic regression reflecting these processes only the distance to the nearest road during that time period was included. Using the generalized linear model function (GLM) of the R statistical software, the three logistic regressions were run. The first model depicted the existing 1989 deforestation as the response variables and the infrastructure and social network in place for that date. The second regression model did the same for the deforestation detected only for the period 1989-2000. The third regression took into account the accumulative deforestation by the year 2000 as the response variable, and the entire infrastructure network present in that period. Finally the resulting MLE's for the 2000 accumulative deforestation model were introduced into a "single map output equation" in Spatial Analyst of ArcGIS 9.2 and the spatial deforestation predictions (20 years into the future in current deforestation rates) were projected.

Results

Landcover Changes

The main results of the deforestation geospatial analysis depict a shocking regional deforestation accumulation of 737,306 ha by the year 2000 (almost 6% of the study area) and an annual deforestation rate of 22,002 ha/year for the 11 year period between 1989 and 2000. It is important to take note that at least 81% of this deforestation is located in Brazil, while Peru and Bolivia are responsible for 7% and 11% respectively. The national deforestation rates were calculated in 17,584 ha/year for Brazil, 1,883 ha/year for Peru and 2,535 ha/year for Bolivia.

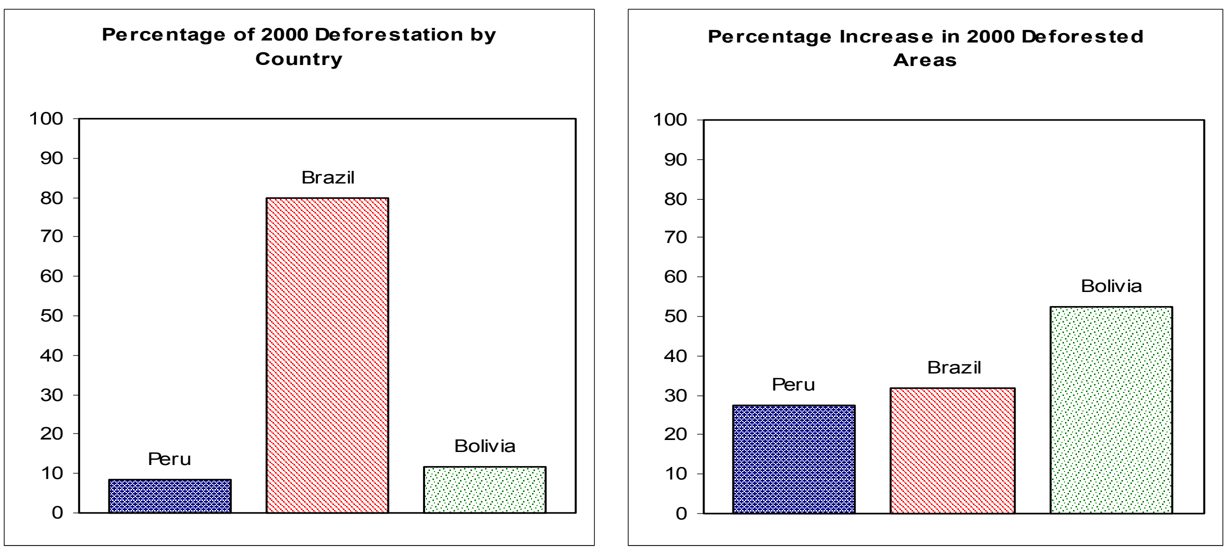
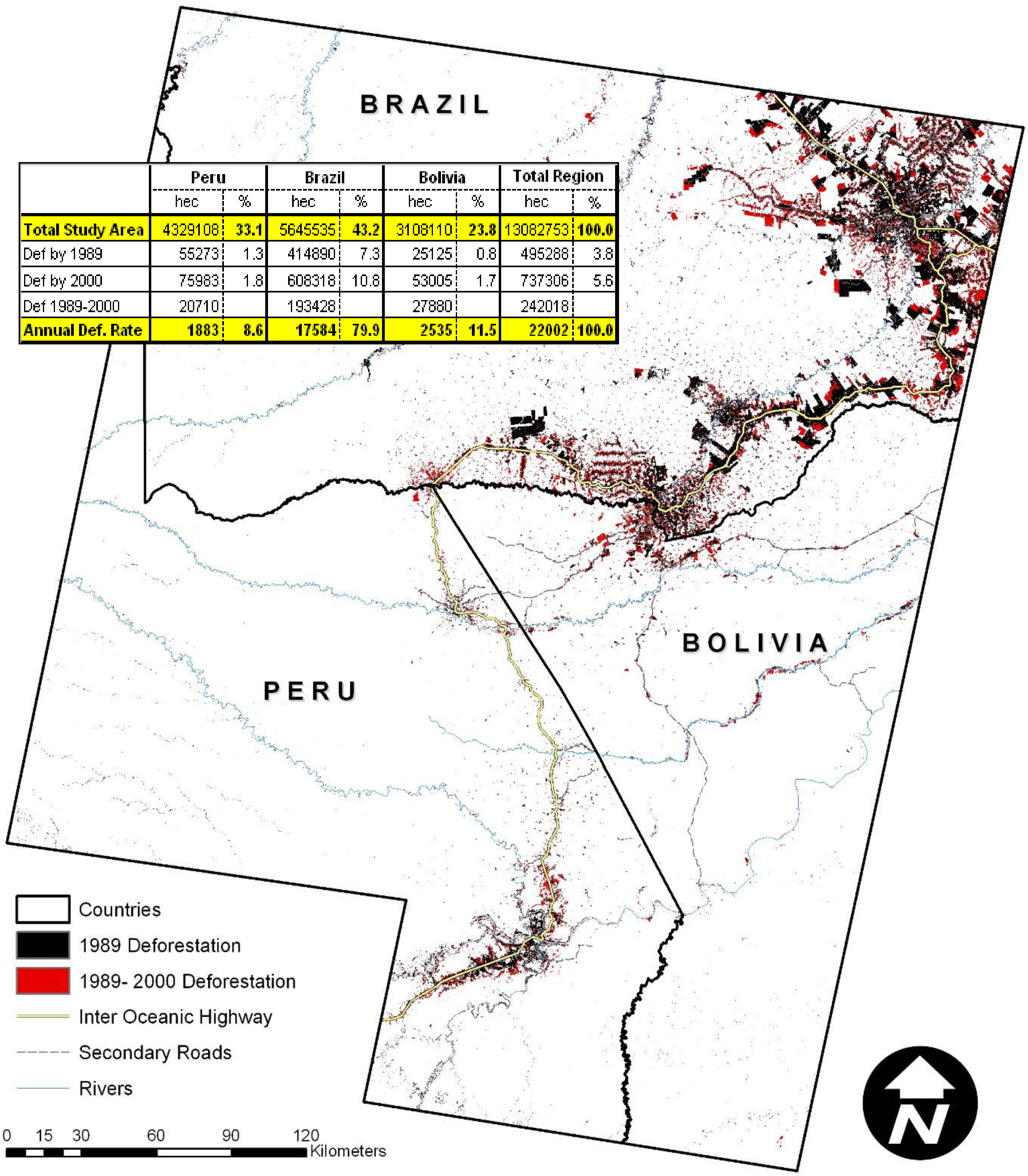


Figure 4: *On the left is the country percentage of total regional deforestation by 2000, on the right is the 2000 deforestation percentage increase in relation to 1989 deforested areas.*

However, if we measure the deforestation percent increase by the year 2000 in relation with the 1989 deforested areas, Bolivia jumps to first place. Nevertheless, this measurement can be misleading because the Bolivian deforested area is still insignificant in relation to Brazil. In absolute values, Brazil continues to be the greatest deforester of the region.



	Peru		Brazil		Bolivia		Total Region	
	hec	%	hec	%	hec	%	hec	%
Total Study Area	4329108	**33.1**	5645535	**43.2**	3108110	**23.8**	13082753	**100.0**
Def by 1989	55273	1.3	414890	7.3	25125	0.8	495288	3.8
Def by 2000	75983	1.8	608318	10.8	53005	1.7	737306	5.6
Def 1989-2000	20710		193428		27880		242018	
Annual Def. Rate	**1883**	**8.6**	**17584**	**79.9**	**2535**	**11.5**	**22002**	**100.0**

Figure 5: *Regional and national deforestation rates and spatial patterns in context with the study area. By the year 2000 more than 6 % of the forest cover in the study area was lost.*

Geospatial Analysis

From the analysis of the deforestation spatial patterns (Figure 5), relevant relationships between human development infrastructure and national deforestation rates were quantified. Figure 6 depicts the probability of encountering a deforested patch (1 ha) in relation to the distance from the Inter-Oceanic highway and secondary roads. These plots not only measure the intensity of the clear-cutting on the y-axis, buts its extension into the rain forest on the x-axis. Notice that in Brazil the Inter-Oceanic highway presents 55% of deforestation probability at the side of the road, in comparison with 15% in the Peruvian side. Nevertheless, for both countries, the deforestation disappears approximately 40 and 60 km from the edge of the highway respectively. On the other hand, the deforestation caused by Brazilian and Peruvian secondary roads can be felt more than 100 km and 50 km away from their edges respectively. Therefore, it is important to acknowledge that although the probability of the deforestation near the Inter-Oceanic highway is higher, the extent of deforestation into pristine rain forest is

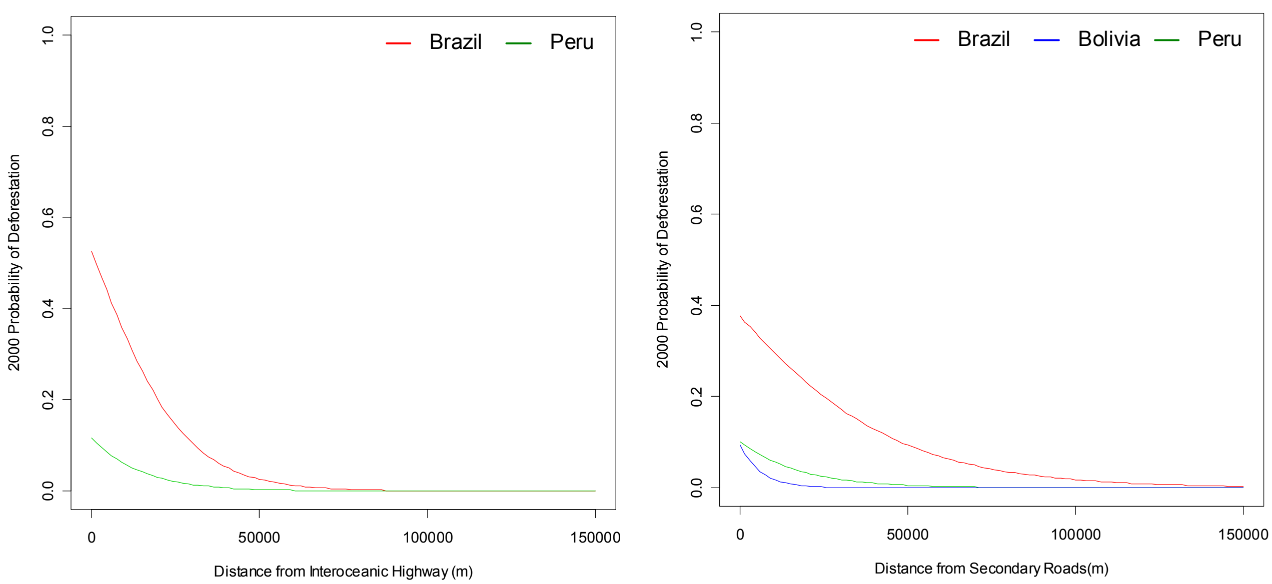


Figure 6: *On the left is the 2000 probability of deforestation against the distance from the Inter-Oceanic highway, on the right is the same probability against distance from all secondary roads by 2000*

potentially deeper along secondary roads. The same types of plots were measured to calculate the probability of deforestation due to population centers and rivers (Figure 7). It can be noticed that Brazilian population centers (urban centers/markets above 1000 hab) present the highest deforestation probability of 60%, followed by Bolivia with 30%, and Peru 10%. Regarding riverine areas, the three countries exhibit low probabilities of deforestation along such river margins, although Brazil again showed the highest deforestation probabilities.

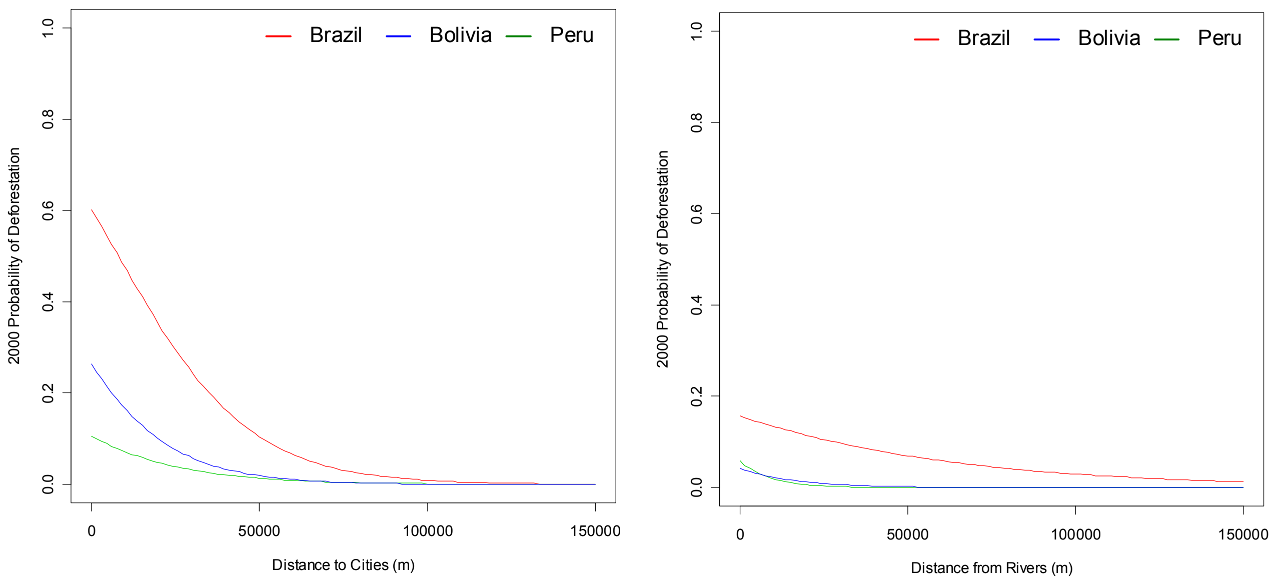


Figure 7: *On the left is the 2000 probability of deforestation in relation to distance from population centers, on the right is the same probabilities against distance from rivers*

Approximately 20,000 ha of deforestation were found within protected areas by 2000. This was considered insignificant in the context of the study area because it accounts for less than 1% of protected forests. It is relevant to mention that in 1989 protected areas seem to be effective because the probability of deforestation was approximately zero until 50 km outside their boundaries (Figure 8). However by 2000 this spatial relationship had dramatically changed as all three countries show evidence of deforestation inside protected areas. A large part of these patterns can be explained by the fact that between 1989 and 2000 six new protected areas were placed near the deforestation frontier presumably to control its advances, therefore we

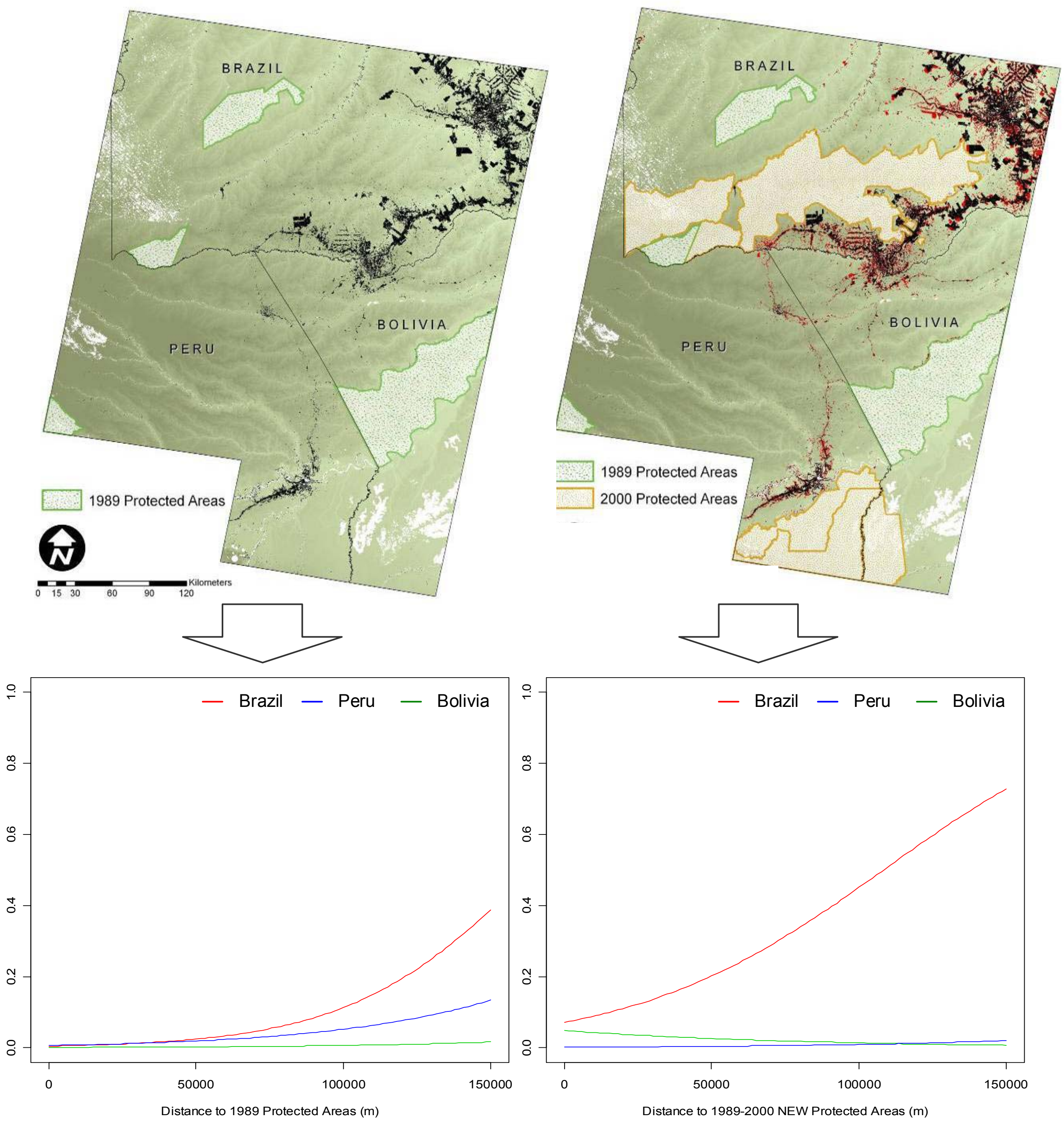


Figure 8: *On the left the 1989 probability of deforestation from the boundary of the 1989 (pre-existing) protected areas. On the right the 2000 probability of deforestation from the boundaries of the new protected areas created between 1989-2000*

cannot conclude which one was first: the protected areas or the clear-cutting. Nonetheless the intrusion into protected areas is relatively insignificant. Currently, almost 35% of the study area is under some kind of legal protection, (23% in the year 2000) which indicate some level of territorial management from the countries involved in the Inter-Oceanic highway project (Peru and Brazil).

Statistical Analysis

The three logistic regressions models generated the maximum likelihood estimators (MLEs), not only allowing the quantification of each independent variable but their comparison between periods, creating a temporal dimension in the data analysis (Table 4). The analysis of the 1989 (pre-existing conditions) model detected that historically all the variables in the model are highly significant except "Peru" and "Rivers" in explaining deforestation patterns. Meaning that on the one hand, the main contributors to the regional 1989 deforestation were the unpaved Inter-Oceanic highway, the secondary road network, the population centers, the topographic elevation and the Bolivian - Brazilian deforestation dynamics. On the other hand, human movement through rivers and the Peruvian historic deforestation dynamics were irrelevant in the large scale of the study. However, analyzing only the areas of change (1989-2000), we see that deforestation is not related with the Inter-Oceanic highway but with the existing secondary road network (1989) and the new secondary roads (1989-2000) build in that time period. Furthermore, from the three dummy variables depicting the countries deforestation dynamics, only Peru presents significance. The last time series, depicting the accumulative effect by the year 2000 presents high significance in all the variables, including "Rivers" and the three dummy variables for "Bolivia", "Brazil" and "Peru".

Table 4: REGIONAL LOGISTIC REGRESSION CONTROLING BY COUNTRIES

	1989 Regression pre-existing conditions			1989–2000 Regression 11 years change			2000 Regression Accumulative		
Covariate	**Coefficient**	**S. Error**	**Sig**	**Coefficient**	**S. Error**	**Sig**	**Coefficient**	**S. Error**	**Sig**
(Intercept)	2.204000	0.315500	***	-0.103100	0.870100		0.971300	0.354300	**
Inter-Oceanic Highway	-0.000068	0.000006	***	0.000010	0.000008		-0.000044	0.000006	***
Bolivia	2.204000	0.315500	***	-0.103100	0.870100		0.971300	0.354300	**
Brazil	1.603000	0.146600	***	-0.152900	0.425700		1.742000	0.184000	***
Peru	0.220800	0.170400		0.788900	0.412700	.	0.619000	0.202200	**
Populated Places	-0.000019	0.000003	***	-0.000017	0.000008	*	-0.000022	0.000003	***
1989 Secondary Roads	-0.000143	0.000010	***	-0.000059	0.000022	**			
1989 – 2000 New Secondary Roads				0.000024	0.000010	*			
2000 Secondary Roads (All)							-0.000090	0.000009	***
Rivers	-0.000002	0.000004		-0.000001	0.000010		-0.013820	0.000004	.
Topographic Elevation	-0.015890	0.001126	***	-0.018360	0.003125	***	-0.013820	0.001228	***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
n = 16674

Finally a detailed multi-temporal analysis of the regional coefficients or MLE's (Table 4) indicates a decrease in the influence of the Inter-Oceanic highway and an increase of population centers and secondary roads as deforestation drivers from 1989 to 2000. To evaluate each country separately, logistic regression by country was performed, using the same time series (see appendix). The multi-temporal analyses of the logistic regressions MLE's show that Brazil's infrastructure/deforestation interactions, although highly significant, are actually decreasing. On the Peruvian side the Inter-Oceanic highway and population centers were irrelevant regarding deforestation, but the secondary road network presented high levels of significance, possibly suggesting a subsistence extractive economy. Bolivia presented a unique situation under which its population centers are growing consistently but its road network is insignificant as a deforestation predictor.

Deforestation Scenarios

Two deforestation scenarios were projected into the near future using the regression model MLE's. The first scenario was called "Controlling by Country" because it included dummy variables that internalized the unique deforestation dynamics of each country in the study area (Figure 9). The second deforestation scenario was named "Pan-Amazonian" because it excluded these dummy variables, allowing the remaining prediction variables to act on the landscape as a continuous template (Figure 10). Both scenarios present very similar outcomes for Peru and Brazil, especially along the Inter-Oceanic highway, patterns in Bolivia vary among scenarios. While in the "controlling by country" scenario, the Bolivian deforestation clusters

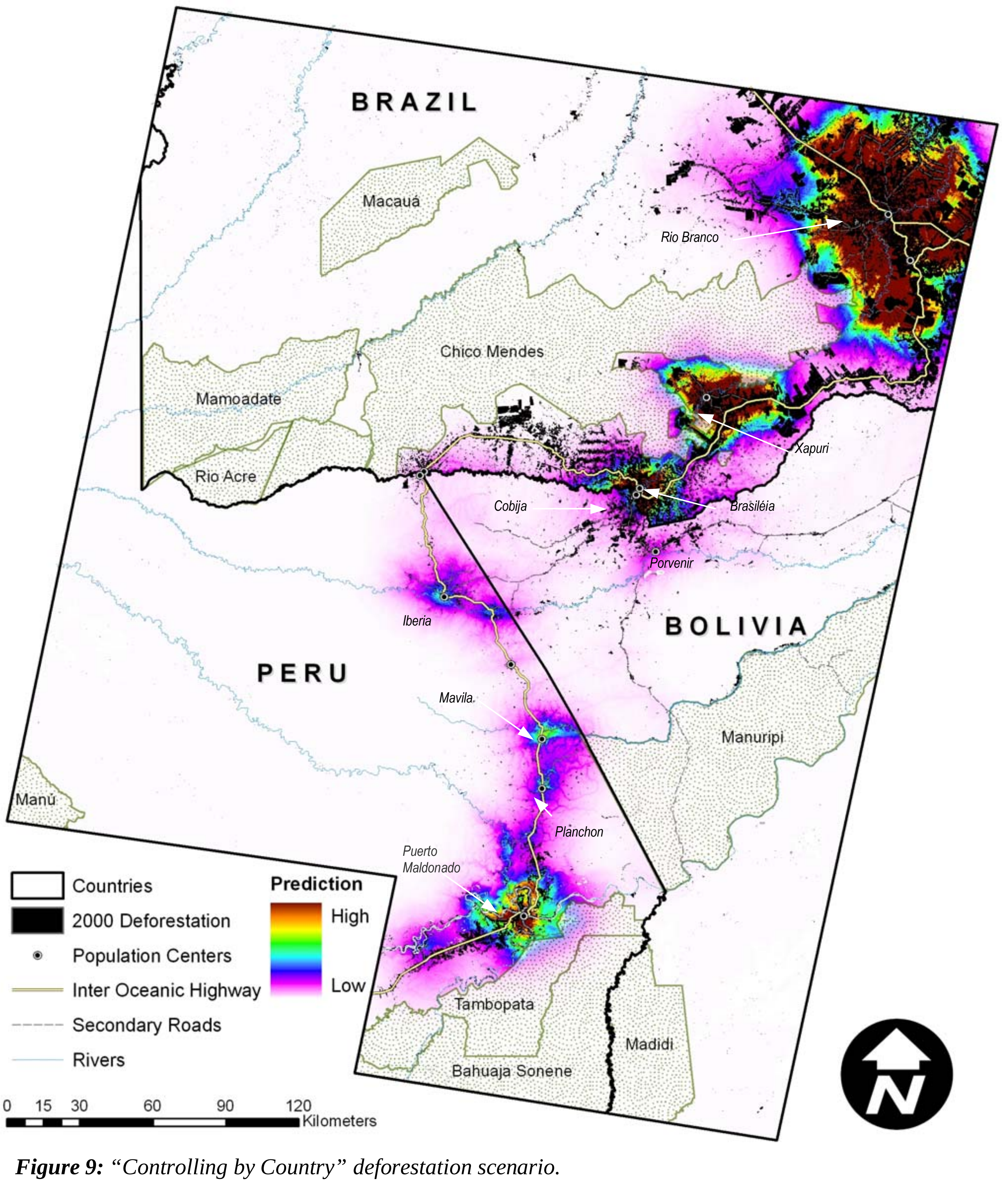


Figure 9: *"Controlling by Country" deforestation scenario.*

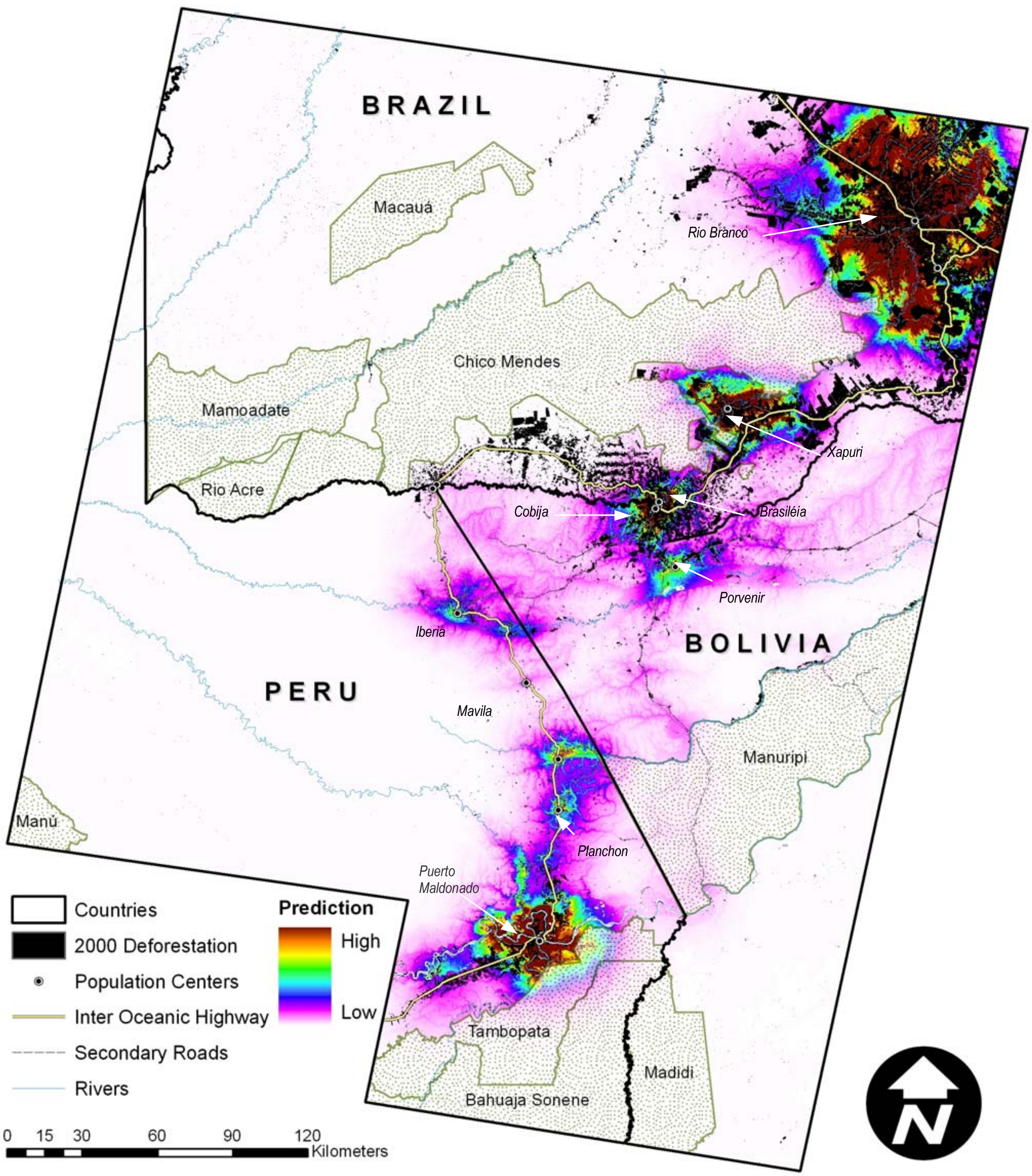


Figure 10: *"Pan-Amazonian" deforestation scenario under which Bolivia step up its deforestation rates, because its unpaved road network is acting as a shortcut between the Peruvian and Brazilian population centers.*

around the population centers adjacent to the Brazilian border with an impact level classified as low, the "Pan-Amazonian" scenario elevates this impact to medium/high and includes the Bolivian unpaved road network as a relevant deforestation contributor. It is clear that in the "Pan-Amazonian" scenario the unpaved Bolivian road network is acting as an alternative route to the Inter-Oceanic highway, joining the population centers (markets) of Peru and Brazil. This fact depicts a possible spatial trend to deforest the areas along the Peru – Bolivia border. Finally, both scenarios clearly project that in the near future the urban explosion Puerto Maldonado (Peru) will put severe pressure on the protected area of Tambopata, and the ongoing expansion of the Brazilian settlements of Rio Branco, Xiparu and Brasiléia will do the same on the extractive reserve of Chico Mendes.

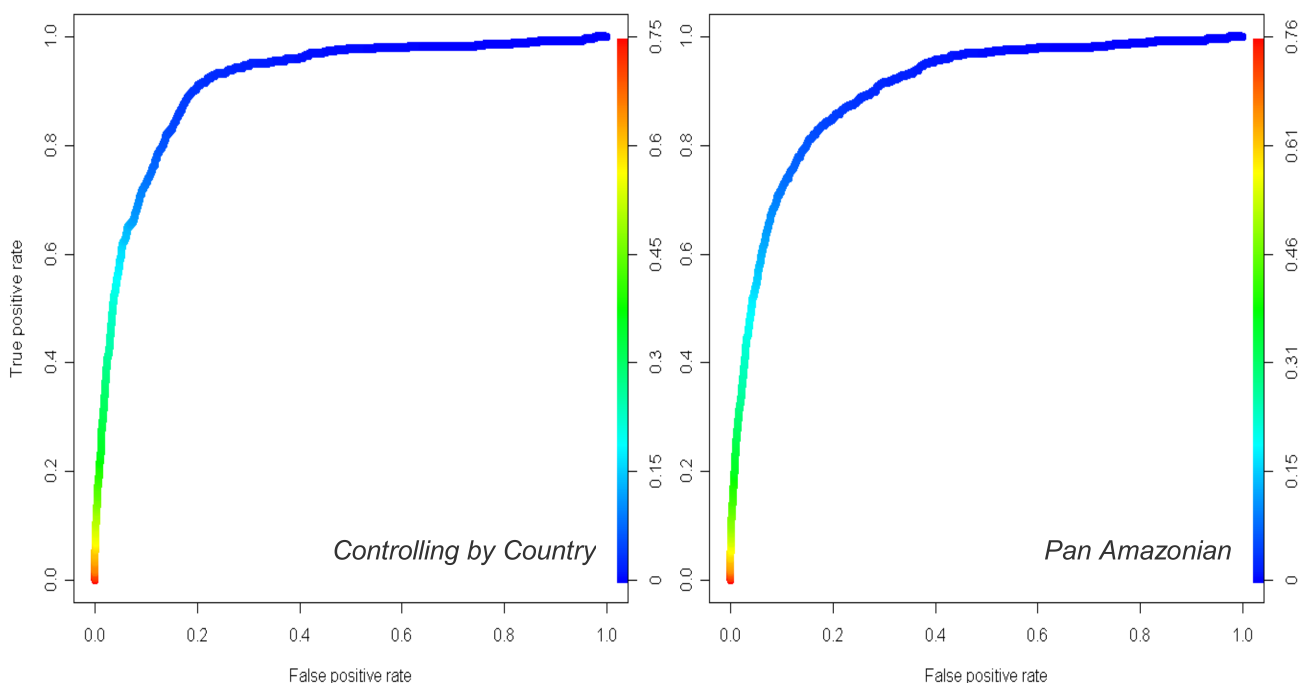


Figure 11: *ROC curves of the deforestation scenarios. Accuracy is measured by the area under the curve (AUC). An area of 1 represents a perfect model; an area of .5 represents randomness. In this case both scenarios present and AUC > 0.9*

Receiver operating characteristic (ROC) curves were use to evaluate the accuracy of both scenarios (Figure 11). The accuracy of the models depends on how well the regression separates the variables into those with forest and without forest, measured by the area below the ROC curve. An area of 1.0 represents a perfect model; an area of 0.5 represents pure randomness. In this case, both scenarios presented an area under the curve of more than 0.90, which is considered and excellent model fit. According to the ROC curve, the "Controlling by Country" presented a slightly better fit than the "Pan-Amazonian" scenario, meaning that the country variables managed to capture some of the institutional, cultural and socio-economic dynamics behind the deforestation dynamics within each country.

Discussion

The results section present a robust affirmative answer to the question that entitles this study: *Is the Inter-Oceanic highway exporting deforestation?* However, it also depicts a complex relationship between human infrastructure and land-cover changes, due to changes in land-use, the role play by national borders in deforestation modeling and the importance of the temporal dimension in geospatial analysis.

The overall data analysis confirms that there is a significant correlation between infrastructure development and land-cover changes in this Amazon region, due to land-use changes. Nevertheless, the finer analysis of the geospatial and temporal dimensions depict the complexity and non-linearity of this process. The fact that the Inter-Oceanic highway and its related human infrastructure were significant only in certain time periods, suggests that non-geospatial factors are acting at the national level like on/off switches of this process. Although these switches may be identified by economic, political or demographic analyses, particular to each country, a conscious effort to separate them in the models was done by the dummy country variables. On the other hand, it was also found that currently the Inter-Oceanic highway is not the main contributor to deforestation but the secondary road networks that radiate from the Inter-Oceanic itself and the population centers. This suggests that the new deforestation frontier is only reachable through the secondary road network and that the land-use changes triggered by the Inter-Oceanic highway were already consolidated by 1990, at least on Brazil. However the relationship between primary highways and secondary roads in the Amazon reveal a vicious circle and a dilemma for environmental governance (Perz et al. 2008). A primary paved road such as the Inter-Oceanic raises land values, which provides the incentive to exploit natural resources farther out from official road corridors. This in turn is made possible via construction or extension of secondary roads, which then generate income that facilitates additional road building (Brandão et al. 2006, Pfaff et al. 2007). Finally the inclusion of multiple time periods reveals an effort to control landcover changes by the creation of protected areas (Figure 8) depicting a possible selection bias on the shape and location of recent protected areas. Therefore, recent studies like Oliveira et al. (2007), suggesting that land-use allocation (protected areas and indigenous reserves) in Peru can provide effective protection against forest damage may have not considered the circumstances nor date when certain Peruvian protected areas were created, falling into a selection bias trap.

Both prediction scenarios are highly conservative because they rely on the existing infrastructure to spatially predict future deforestation; needless to say that the creation of new roads in other areas could dramatically change these predictions. The scenarios failed to generate the famous fishbone pattern so often associated with Amazon deforestation. Yet these fishbone patterns do not result from spontaneous deforestation generated by roads linking population centers (markets), but unique results of the well-planned resettlement schemes carried out by the Brazilian government under the National Integration Program (PIN) since 1970. Under the PIN, small-farmer settlements were to be concentrated along the newly constructed section of the current Inter-Oceanic highway (BR-230), an east-west penetration road that would link the Brazilian Atlantic ports with the Peruvian border (Moran 1981, Smith 1982, Millikan 1992). Furthermore, a recent pan-tropical meta-analysis on deforestation patterns founded that among 152 cases only 10 (7%) presented the fishbone patterns and all of them were located in the Amazon lowland of Brazil: Pará, Rondônia, and Acre States (Geist & Lambin, 2001).

Nevertheless, both deforestation projection scenarios in this study are a valuable tool that provides an easily communicable idea of were current deforestation trends maybe leading.

On the regional context, Bolivia is in an interesting situation, because although the Inter-Oceanic highway is not located on its territory, the urban continuum formed by Cobija (Bolivia) and Brasiléia (Brazil), which is connected to the Inter-Oceanic by the Brazilian side, allows this Bolivian population center to reap the benefits of this road project. Bolivian urban centers are projected to grow more than its Peruvian counterpart (Figure 7), without feeling the deforestation impact generated by its own road network (Figure 6). The “Controlling by Country” scenario internalize this situation in its outcome, while the “Pan-Amazonian” scenario simply treated the Bolivian entire road network as secondary to the Inter-Oceanic, under which Bolivian land-use changes are projected to sprawl towards Brazil and Peru borders (Figure 10).

The present study did not include a Landsat image mosaic depicting the current state of the study area. It is essential to acknowledge that remote sensing methods used to quantify Amazon deforestation fall short in capturing the complexities and evolution of the deforestation dynamics themselves; they are simply snap shots of the conditions at a certain moment in time. Therefore, this study includes a temporal quantification of deforestation dynamics by employing a statistical model and weighing the impact of critical variables over time. Moreover, the study provides a methodological framework for projecting the impact of human infrastructure in sensitive tropical regions for future studies.

References

- Amor D., Burgues I., Fleck L., Manterola C., Reid J. 2007. "Análisis Ambiental y Económico de Proyectos Carreteros en la Selva Maya, un Estudio a Escala Regional" *Conservación Estratégica.* Serie Técnica N°9
- Brandão Jr, A. O. and Souza Jr, C. M. 2006 "Mapping unofficial roads with Landsat images: a new tool to improve the monitoring of the Brazilian Amazon rainforest". *International Journey of Remote Sensing* 27, 177–189.
- Chander G., Markham B., and Barsi J. 2007 "Revised Landsat-5 Thematic Mapper Radiometric Calibration" *IEEE Geoscience And Remote Sensing Letters,* Vol. 4, No. 3.
- Chavez, P. S., Jr. 1988. "An improved dark-object subtraction technique for atmospheric scattering correction of multi-spectral data." *Remote Sensing of the Environment* 24:459–479.
- Geist H.J. and Lambin E.F. 2001. "What Drives Tropical Deforestation? A meta-analysis of proximate and underlying causes of deforestation based on sub-national case study evidence." *Land Use Cover Changes,* Report Series No. 4, 1-110.
- IIRSA 2007 "Planificación Territorial Indicativa – GTE 2007 – Resultados y Cartera de Proyectos 2007 (Anexo)" *Iniciativa para la Integración de la Infraestructura Regional Suramericana*, *http://www.iirsa.org/acercadeiirsa_ENG.asp?CodIdioma=ENG*
- Laurence W.F., Albernaz A.K.M., Schroth G., Fearniside P.M., Bergen S., Venticinque E.M., Da Costa C. 2002. "Predictors of Deforestation in the Brazilian Amazon" *Journal of Biogeography*, 29, 737–748.
- Lesschen P, Verburg P, Staal S. 2005 "Statistical methods for analyzing the spatial dimension of changes in land use and farming systems" *Land Use Cover Changes,* Report Series No. 7, 1-81

- Millikan B.H. 1992. "Tropical Deforestation, Land Degradation and society: Lessons from Rondônia, Brazil" *Latin American Perspectives*, Vol. 19, No.1, 45-72.
- Olivera P.C., Asner G.P., Knapp D.E., Almeyda A., Galvan-Gildemeister R., Keene S., Raybin R.F., Smith R.C. 2007. "Land-Use Allocation Protects the Peruvian Amazon" *Science,* Vol 317, 1233-1236.
- Perz S., Brilhante S., Brown F., Caldas M., Ikeda S., Mendoza E., Overdevest C., Reis V., Reyes J. F., Rojas D., Schmink M., Souza C.and Walker R. 2008. "Road building, land use and climate change: prospects for environmental governance in the Amazon" *Philosophical. Transactions of the Royal Society B,* 363, 1889–1895
- Perz S.G., Aramburu C. and Bremner J. 2005. "Population, land use and deforestation in the pan-Amazon basin: a comparison of Brazil, Bolivia, Colombia, Ecuador, Peru and Venezuela" *Environmental Development and Sustainability*, 7, pp 23-49
- Pfaff, A. et al. 2007 "Road investments, spatial spillovers, and deforestation in the Brazilian Amazon". *J. Reg. Sci.* 47,109–123.
- Smith, N. 1982. "Rainforest Corridors: The Transamazon Colonization Scheme" Berkeley, Los Angeles, London: University of California Press.
- Soares-Filho B.S., Nepstad D.C., Curran L.M., Cerqueira G.C., Garcia R.A, Acevedo C., Voll E., McDonald A., Lefebvre P. Schlesinger P. 2006. "Modeling conservation in the Amazon basin" *Nature*, Vol: 440, 23
- Song C., Woodcock C.E., Seto K.C., Lenney M.P. & Macomber A.. 2001. "Classification and change detection using Landsat TM data: When and how to correct atmospheric effects?" *Remote Sensing of Environment*, 75, 230-244.

- Spellerberg I. F. 1998 "Ecological Effects of Roads and Traffic: A Literature Review" *Global Ecology and Biogeography Letters*, Vol. 7, No. 5. 317-333.
- Toivonen T, Kalliola R, Driesprong A. 2002 "Western Amazonian GIS Creation process of Landsat TM image mosaic" *University of Turku – Finland – Laboratory of Computer Cartography (UTU-LCC publications).* Vol N° 4.
- Turner I. M. 1996 "Species Loss in Fragments of Tropical Rain Forest: A Review of the Evidence" *The Journal of Applied Ecology*, Vol. 33, No. 2, 200-209.
- Tucker C, Grant D, Dykstr J. 2004 "NASA's Global Orthorectified Landsat Data Set" *Photogrammetric Engineering & Remote Sensing.* Vol. 70, No. 3, 313–322.
- Verburg P.H., de Groot W.T. and Veldkamp A. 2003. "Methodology for multi-scale land-use change modeling: Concepts and challenges." *Global environmental change and land use*. Kluwer Academic Publishers, Dordrecht, the Netherlands.

Appendix

Appendix 3) Brazil deforestation regression

BRAZIL REGRESSION									
	1989 Regression			1989 – 2000 Regression			2000 Regression		
Covariate	**Coefficient**	**S. Error**	**Sig**	**Coefficient**	**S. Error**	**Sig**	**Coefficient**	**S. Error**	**Sig**
(Intercept)	2.482000	0.299700	***	0.682500	0.366800	.	3.243000	0.272100	***
Inter-Oceanic Highway	-0.000094	0.000010	***	-0.000040	0.000007	***	-0.000084	0.000008	***
Populated Places	-0.000019	0.000004	***	-0.000002	0.000004		-0.000014	0.000003	***
Secondary Roads	-0.000206	0.000019	***	-0.000073	0.000010	***	-0.000147	0.000011	***
Rivers	-0.000005	0.000005		0.000003	0.000005		-0.000002	0.000004	
Topographic Elevation	-0.011260	0.001429	***	-0.012090	0.001814	***	-0.013630	0.001286	***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
n = 7210

Appendix 4) Peru deforestation regression

PERU REGRESSION									
	1989 Regression			1989 – 2000 Regression			2000 Regression		
Covariate	Coefficient	S. Error	Sig	Coefficient	S. Error	Sig	Coefficient	S. Error	Sig
(Intercept)	5.046000	0.808300	***	2.350000	1.073000	*	3.865000	0.797000	***
Inter-Oceanic Highway	0.000009	0.000009		-0.000016	0.000015		-0.000025	0.000013	.
Populated Places	-0.000011	0.000008		-0.000003	0.000010		-0.000006	0.000008	
1989 Secondary Roads	-0.000222	0.000056	***	-0.000144	0.000044	**			
89 – 00 New Secondary Roads				-0.000027	0.000018				
2000 Secondary Roads (All)							-0.000115	0.000023	***
Rivers	0.000003	0.000013		-0.000017	0.000022		-0.000037	0.000018	*
Topographic Elevation	-0.031380	0.003381	***	-0.021590	0.004527	***	-0.023360	0.003406	***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
n = 5589

Appendix 5) Bolivia deforestation regression

BOLIVIA REGRESSION

	1989 Regression			1989 – 2000 Regression			2000 Regression		
Covariate	**Coefficient**	**S. Error**	**Sig**	**Coefficient**	**S. Error**	**Sig**	**Coefficient**	**S. Error**	**Sig**
(Intercept)	4.498000	1.799000	*	7.916000	1.889000	***	8.847000	1.554000	***
Populated Places	-0.000045	0.000007	***	-0.000049	0.000007	***	-0.000058	0.000006	***
1989 Secondary Roads	-0.000143	0.000036	***	-0.000101	0.000030	***			
89 – 00 New Secondary Roads				-0.078420	7.497000				
2000 Secondary Roads (All)							-0.000150	0.000028	***
Rivers	0.000030	0.000028		0.000034	0.000024		0.000058	0.000021	**
Topographic Elevation	-0.023590	0.007294	**	-0.038680	0.007639	***	-0.038220	0.006215	***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
n = 3873