International Institute for Applied Systems Analysis
IIASA
www.iiasa.ac.at

Simulating Future Global Deforestation Using Geographically Explicit Mode

Witmer, F.

IIASA Interim Report
March 2005

International Institute for
Applied Systems Analysis
Schlossplatz 1
A-2361 Laxenburg, Austria

Tel: +43 2236 807 342
Fax: +43 2236 71313
E-mail: publications@iiasa.ac.at
Web: www.iiasa.ac.at

Interim Report **IR-05-010**

Simulating Future Global Deforestation Using Geographically Explicit Models

Frank Witmer (witmer@colorado.edu)

Approved by

Sten Nilsson
Deputy Director and Leader, Forestry Program

9 March 2005

Contents

Abstract

What might the spatial distribution of forests look like in 2100? Global deforestation continues to be a significant component of human activity affecting both the terrestrial and atmospheric environments. This work models the relationship between people and forests using two approaches. Initially, a brief global scale analysis of recent historical trends is conducted. The remainder of the paper then focuses on current population densities as determinants of cumulative historical deforestation. Spatially explicit models are generated and used to generate two possible scenarios of future deforestation. The results suggest that future deforestation in tropical Africa may be considerably worse than deforestation in Amazonia.

Acknowledgments

Many thanks to Michael Obersteiner for his helpful comments and encouraging words throughout this project. Also, thanks to Ian McCallum for both his GIS and forestry expertise and to Elena Moltchanova for her statistical input and for converting me to R. Thanks also to my fellow YSSPers and the entire Forestry Group at IIASA. This research was completed during the 2004 YSSP program and funded through the National Academy of Sciences, which is the US National Member Organization of IIASA.

About the Author

Frank Witmer received his Master's degree in geography from the University of Colorado at Boulder in 2003. He is currently working on his Ph.D., also in geography at the University of Colorado. His primary field of interest is studying the effects of anthropogenic activity on the natural environment.

Simulating Future Global Deforestation Using Geographically Explicit Models

Frank Witmer

1 Introduction

The last decade has been filled with gloomy reports about deforestation (Williams, 2003:495). Though the future of the world's forests is surrounded by much uncertainty, it is clear that their fate is tied closely to the actions and policies of humanity. Global variation in the processes affecting deforestation, however, makes it challenging to predict just what the distribution and extent of forests might look like fifty or one hundred years from now. Such information can be useful in influencing how governing bodies think about the management of such a global resource.

Historically, the effects of human activity on land cover change have been easy to identify and understand at very local levels (Williams, 2003). With the advent of the world economy some 500 years ago and its associated trade and transportation networks, the close link between local resources and local populations has weakened (Wallerstein, 1974; Williams, 1990). Geography, in particular the relative distribution of forests and people, still matters as most populations seek natural resources from nearby locations first.

Though such increased interconnectedness may impede research and make projections more difficult, especially at the global scale, it does not obviate such work. Instead, it requires researchers to consider geographical variation more carefully, and explicitly address spatial variation as part of any approach.

Anthropogenic causes of deforestation can be categorized broadly as proximate and underlying causes (Geist and Lambin, 2001). Proximate causes are the human activities that directly affect changes in forest cover such as agricultural expansion, wood extraction, and infrastructure extension. Underlying or driving forces of deforestation are the fundamental forces that underpin the more immediate proximate causes. These are characterized by economic, political, technological, cultural and demographic factors.

The interplay and relative importance of these factors is not well known globally or regionally. Proximate forces can often be readily identified at local scales, but it can be difficult to scale up such case study information to larger spatial scales (Geist and Lambin, 2001). And though the details of such proximate forces may vary greatly between regions, agriculture expansion has historically been the major change in land use globally (Houghton, 2001; Ramankutty *et al.*, 2001; Williams, 2003).

Since agricultural expansion is driven by human food demands, this study focuses on population density as a driving force of deforestation. Though disagreement still exists in the literature over the nature of the relationship between population density and deforestation (Kaimowitz and Angelsen, 1998; Geist and Lambin, 2001; Lambin *et al.*, 2001), other research supports the expected positive relationship of population growth associated with deforestation (Pahari and Murai, 1999; Mather and Needle, 2000; Uusivuori *et al.*, 2002). The relationship between population density and deforestation is not simple and is often linked to social, political, and infrastructural changes (Lambin et al., 2001). Nevertheless, the driving force of population growth is often the underlying force behind some of these other changes (e.g., road building). Though there is still uncertainty in measures of population, especially for Africa, the number of people in a given area is one of the few driving forces of deforestation that is simple and readily measurable (Meyer and Turner, 1992).

This report presents the results of two different approaches aimed at characterizing the relation between human activity and deforestation. The first approach examines recent historical trends from 1820–1990. Then, using the lessons learned from this section, an alternative analysis that considers deforestation as a long-term process of change is conducted. This latter section first replicates the work of Pahari and Murai (1999) using updated datasets to measure cumulative historical deforestation. It then modifies the regional definitions used by Pahari and Murai, and extends their work by applying geographically weighted regression (GWR) (Fotheringham *et al.*, 2002). GWR provides a way of generating spatially explicit models without introducing what can often be awkward regional borders to the problem. Lastly, results from the GWR models are used, in conjunction with spatially explicit population projections, to speculate on levels of deforestation through to the year 2100.

2 Data Overview

Data limitations to such global scale models are severe, especially at spatial resolutions more detailed than country-scale and temporal coverage prior to 1950 (and often later). Table 1 summarizes some of the global databases for land cover and socioeconomic conditions, with an emphasis on historical gridded data. A more thorough review of land-cover data is available from Lepers (2002). Though not all of the listed datasets are used for this study, they were all considered as possible inputs to the global deforestation models.

The data analysis for this study first uses country-scale aggregations, and then increases the spatial resolution to several thousand sub-country areal units. Though government policy can make a real difference in land cover change, both at the country scale and smaller administrative units, this study is essentially apolitical, with no attempt made to quantify the effect of different government policies on deforestation. This reflects, in part, the difficulty of quantifying policy variations, especially for sub-country polities. This means, for instance, that government policies aimed at promoting economic growth through infrastructure improvements are not captured, even though road construction is known to exacerbate deforestation in places such as Brazilian Amazonia (Laurance *et al.*, 2004).

Table 1: Selected global datasets

Description	Resolution		Units
	Temporal	**Spatial**	
Land Cover			
Global Historical LCLU (Goldewijk, 2001)	1700–1950[a], 1970, 1990	0.5, 1 degree	19 classes
Global Historical Croplands (Ramankutty and Foley, 1999)	1700–1850[a], 1860–1980[b], 1986–1992[c]	0.5, 1 degree	fraction cultivated
Original Forests (UNEP-WCMC) (Kapos, 2000)	8,000 years ago	polygon varies by source	forest type
Global Land Cover (GLC2000 v2) (ECJRC, 2003)	2000	1x1 km	22 classes
Global Potential Veg (Ramankutty and Foley, 1999)	–	0.5 degree	15 classes
Suitability for Agriculture (Ramankutty *et al.*, 2002)	–	0.5 degree	fraction suitable for agriculture
Socioeconomic			
Global Pop of the World (CPW), v2 (CIESIN *et al.*, 2000)	1990, 1995	0.25, 0.5, 1 degree	people and per km^2
SRES/IIASA Pop and GDP/capita (Grübler, 2004)	1990–2100[b]	0.5 degree	people/km^2, GDP/ha
Global Gridded GDP (Yetman *et al.*, 2004)	1990	0.25, 0.5, 1 degree	1,000 US Dollars
Population and GDP/capita (Maddison, 2004)	1820, 1870, 1913, 1950–2003[c]	Country	1,000 people, Geary-Khamis Dollars

[a] 50-year interval; [b] 10-year interval; [c] 1-year interval.

Performing the analysis at a gridded scale was considered, but quickly abandoned for several reasons. First, datasets often use population density data, which can be measured relatively easily using day and night-time satellite imagery (Elvidge *et al.*, 1999; Sutton *et al.*, 2001) to create spatial estimates of other socioeconomic data such as GDP per capita (Yetman *et al.*, 2004). Additionally, in most parts of the world, processes of deforestation operate at much larger scales than 0.5 degree grid cell. Attempts to link human activity and changes in forest cover at these smaller resolutions therefore make little sense.

3 Trend Assessment: 1820–1990

The first approach for this research considers the global relation between annual changes in population and gross domestic product (GDP) versus annual rates of deforestation. Two data sources were used for the analysis and yield a temporal span from 1820–1990.

First, to measure deforestation, Goldewijk's (2001) History Database of the Global Environment (HYDE) was used. This is a gridded dataset that uses 19 categories to describe land cover over the period 1700 to 1990 (Table 1). The global 0.5 degree gridded data were reclassified into forest (boreal forest, cool conifer forest, temperate mixed forest, temperate deciduous forest, warm mixed forest, tropical woodland and tropical forest classes) and non-forest land.

The second data source is Maddison's (2004) world historical statistics (Table 1). Since no spatially explicit (e.g., 0.5 degree grid) historical data describing socioeconomic change exist, these data were used to provide the historical record of population and GDP by country. Data prior to 1820 are too sparse for analysis, making this year the starting point.

In order to detect temporal trends in the processes affecting deforestation, the time period was further divided. For the period after 1950, Maddison's data are quite complete, making Goldewijk's data the limiting factor. This yielded common years of 1950, 1970, and 1990. From 1820 to 1950, Maddison's dataset only has good coverage for the years 1870 and 1913. Since the length of the time periods vary, the percent average annual change for both population and GDP were calculated to allow comparison between time periods.

Before any comparisons could be made, the spatial and temporal mismatches in the data were resolved. The forest land cover data were aggregated to the country scale areal unit for each time interval from 1800 to 1990. Forest area for years prior to 1950 was linearly interpolated to yield comparable years of 1820, 1870, and 1913. Then, average annual deforestation, in percent, was calculated for each country over the five time periods.

The results of a simple bivariate correlation analysis are shown in Table 2. The first group of rows shows the correlation coefficients and their statistical significance for average annual deforestation and average annual population growth during each of the time periods. Note that even though all of the coefficients have the expected relation (of high population growth associated with high rates of deforestation), only the periods from 1870–1913 and 1970–1990 are statistically significant.

For percent annual GDP growth, the correlation results are also similarly weak, with again only two time periods (1870–1913 and 1950–1970) showing a statistically significant relation (Table 2). Though the statistical significance is weak, it is interesting to note the change in the relationship near the beginning of the 20th century. It is possible that this change in relationship reflects the increasing wealth of places such as Europe and North America, leading to higher demand for local environmental preservation while externalizing environmental costs to less developed countries. Limited data prior to 1950 (Table 2), however, renders any cross-century comparisons difficult.

One of the goals for this approach was to develop models for each time period to assess the extent and direction of change of processes affecting deforestation. Such an understanding could then have been used to project how the relation might continue to change in the future. These initial results, however, are too weak to have any confidence in such a trend, and are only likely to weaken further once the issue of spatial autocorrelation is addressed (Anselin, 1988).

Table 2: Correlation coefficients for annual deforestation (%).

Variable	Time Period	Coefficient	Significance	Number of Countries
Annual Population Growth (%)	1820–1870	0.22	0.05	81
	1870–1913	0.26	0.02[a]	82
	1913–1950	0.05	0.68	83
	1950–1970	0.04	0.66	146
	1970–1990	0.24	0.00[b]	145
Annual GDP Growth (%)	1820–1870	0.25	0.08	52
	1870–1913	0.39	0.00[b]	61
	1913–1950	-0.06	0.66	65
	1950–1970	-0.18	0.03[a]	139
	1970–1990	-0.16	0.06	138

[a] Correlation is significant at the 0.05 level; [b] Correlation is significant at the 0.01 level.

These findings re-enforce the conclusions reached by Kaimowitz and Angelsen (1998). They found that attempts to characterize global trends through correlation and regression methods suffer from poor data quality and an inability to capture regional variation. Instead, they recommend researchers focus on regional models (among other approaches) that emphasize the importance of spatial variation. The next section adopts just such an approach.

4 Cumulative Change: 8000 Years Ago

To address some of the shortcomings of the 170 year trend assessment, an alternative approach was used that views anthropogenic deforestation as a long-term process, closely tied to population distribution. By using current population density to predict deforestation over the last 8,000 some years, all trends, short- and long-term, are compressed into one measure of cumulative deforestation. This, of course, masks potentially significant recent shifts in human activity such as those of technological change (e.g., agricultural intensification), improved transportation networks, urbanization (Lambin *et al.*, 2003) and the influence of global markets (Lambin *et al.*, 2001). It does, however, capture well long-term land use change, which is driven especially by the proximate forces of cropland and pasture area expansion (Houghton, 2001; Ramankutty *et al.*, 2001; Williams, 2003). This linkage is expected to be strongest where processes such as subsistence agriculture dominate, and weaker where market forces of the global economy dominate (Meyer and Turner, 1992). More temporary forest clearing occurring in, for instance, managed forests are therefore less represented in this long-term perspective. Also the reduced biodiversity and biomass associated with managed forests are also not captured in this measure of deforestation.

This approach follows from Pahari and Murai's (1999) study which relies on population density data to model cumulative global deforestation, using a pre-anthropogenic vegetation base map. For their study, Pahari and Murai generate a land cover map of historical natural land cover prior to any human impacts. This map is based on a global grid of average temperature and precipitation data for the last 30 years. A regional, country-scale analysis was then conducted for six regions covering tropical forests and Europe. For each region, separate regression models were developed using current population density to predict cumulative global deforestation. These models were then used to predict deforestation to 2025 and 2050 according to UN median variant population projections.

The next section updates Pahari and Murai's (1999) study with more recent data land cover data and a different historical measure of forests. Then, their study is extended using sub-country areal units and geographically weighted regression.

4.1 Country-scale Comparison

To assess current land cover, the Global Land Cover (GLC) 2000 dataset from the European Commission Joint Research Center (ECJRC, 2003) was used (Table 1). This dataset was produced in collaboration with 30 research teams and has been chosen as a core dataset for the Millennium Ecosystems Assessment. The data represent land cover for the year 2000 at a global 1 km × 1 km spatial resolution. For this study, the 22 map categories of GLC 2000 were reclassified into forests (all non-mosaic categories containing tree cover) and non-forests.

A significant source of uncertainty for this approach is found in the historical representation of global land cover. This analysis was initially attempted with Ramankutty and Foley's (1999) global potential vegetation map (Table 1). These data are available at a 0.5 degree global resolution and consist of 15 categorical biome classes. Use of these data, however, proved difficult due to land classified as savanna (10–30% forest canopy), especially for Sahelian Africa. When excluded from the forest reclassification, considerable portions of land in the GLC 2000 classification appear forested, in opposition to the potential vegetation map which shows these land areas as never forested. And alternatively, when savanna lands are included as potential forests, those areas show extraordinarily large cumulative deforestation. This highlights one of the difficulties in classifying land cover as simply forest or non-forest.

To mitigate the forest classification problem, data from the United Nations Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) were used. These data estimate what the original forest cover would have been 8,000 years ago prior to any significant anthropogenic disturbance (Kapos, 2000). The data are provided in polygon format for four forest types: tropical montane, temperate broadleaved, tropical dry, and needleleaf. Since this research does not differentiate between forest type or value, these four forest categories were reclassified into simply forest and non-forest land (Figure 1). Though the difficulties of classifying savanna and sparse forests remain, these data match the GLC 2000 dataset better.

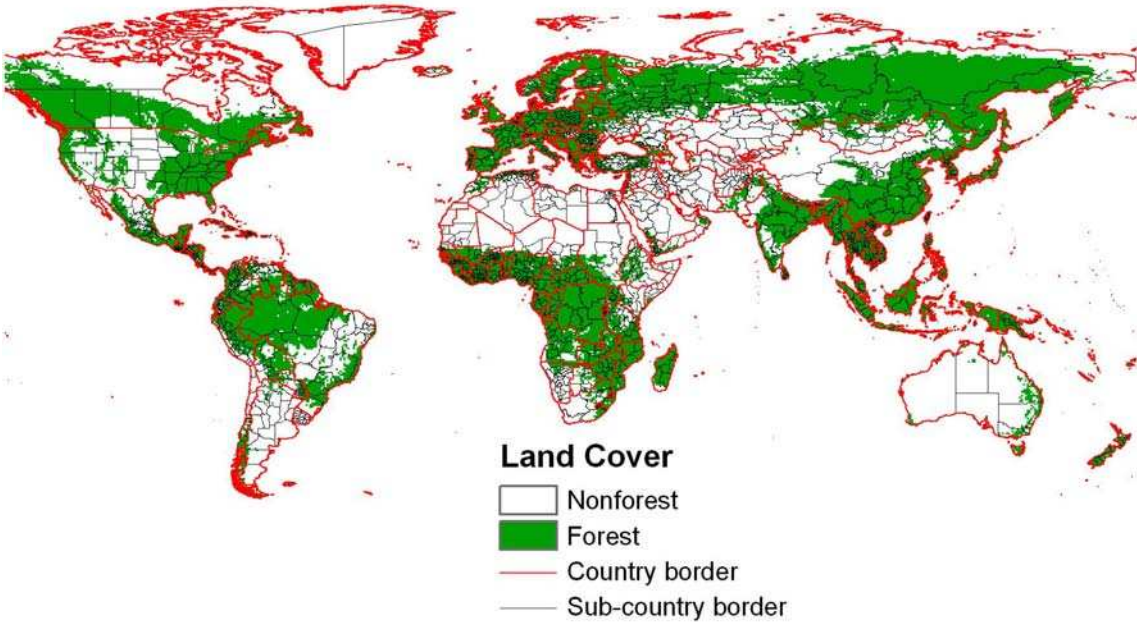


Figure 1: Forest cover from 8,000 years ago (UNEP-WCMC).

After reclassifying each dataset to forest and non-forest land, forest area was calculated for each country-scale administrative unit (red borders, Figure 1). For each country, forest loss is calculated as (1 – forest cover/potential forest) * 100. Table 3 presents the results using both the Ramankutty and Foley data as well as the UNEP-WCMC data. For the Ramankutty and Foley potential forest column, the savanna category is included as forest. Most of the forest loss results are similar to Pahari and Murai's results, with the exception of the Former Soviet Union, which differs substantially due to the exclusion of the former Soviet states in central Asia in the updated work. The remainder of the paper only presents results from the UNEP-WCMC dataset.

Table 3: Forests (%) comparison with Pahari and Murai (1999).

Country	Pahari and Murai (1999)			GLC 2000	Ramankutty and Foley		UNEP-WCMC	
	Potential forest	Forest cover	Forest loss	Forest cover	Potential forest	Forest loss	Potential forest	Forest loss
Brazil	97.54	66.68	31.64	45.61	85.70	46.78	53.96	15.47
Peru	91.95	53.63	41.67	53.22	62.82	15.28	67.15	20.74
Bolivia	92.39	47.22	48.89	47.01	66.01	28.78	59.93	21.55
Ghana	100.00	42.23	57.77	35.22	97.95	64.05	89.08	60.46
Cameroon	97.88	43.50	55.56	67.40	99.09	31.98	83.83	19.60
Zimbabwe	74.84	23.16	69.05	34.94	98.86	64.66	87.04	59.86
Bangladesh	100.00	8.10	91.90	3.69	98.67	96.26	90.12	95.91
Thailand	99.53	25.99	73.89	17.77	98.63	81.98	86.41	79.43
Malaysia	97.27	53.18	45.33	53.78	99.61	46.00	86.68	37.95
India	82.28	21.85	73.44	18.41	75.36	75.58	64.19	71.33
Nepal	83.81	37.25	55.55	36.73	69.60	47.24	65.94	44.31
USSR (Russia)[a]	41.87	37.96	9.34	46.25	78.49	41.07	62.71	26.24
France	99.28	25.87	73.94	22.73	97.44	76.67	85.28	73.35
UK	98.98	9.63	90.27	3.52	99.94	96.48	72.90	95.17

[a] Pahari and Murai use the USSR, the other data are aggregated to Russia.

The regional regression approach of Pahari and Murai was then applied to the forest loss variable derived from the UNEP-WCMC data. Since their six regions, however, do not include several relevant countries, these were added to yield six modified regions. Figure 2 shows the regression results for each region. Also, countries where the data show negative forest loss (afforestation) were excluded from the analysis (see Appendix A for a complete list of the modified Pahari and Murai regions).

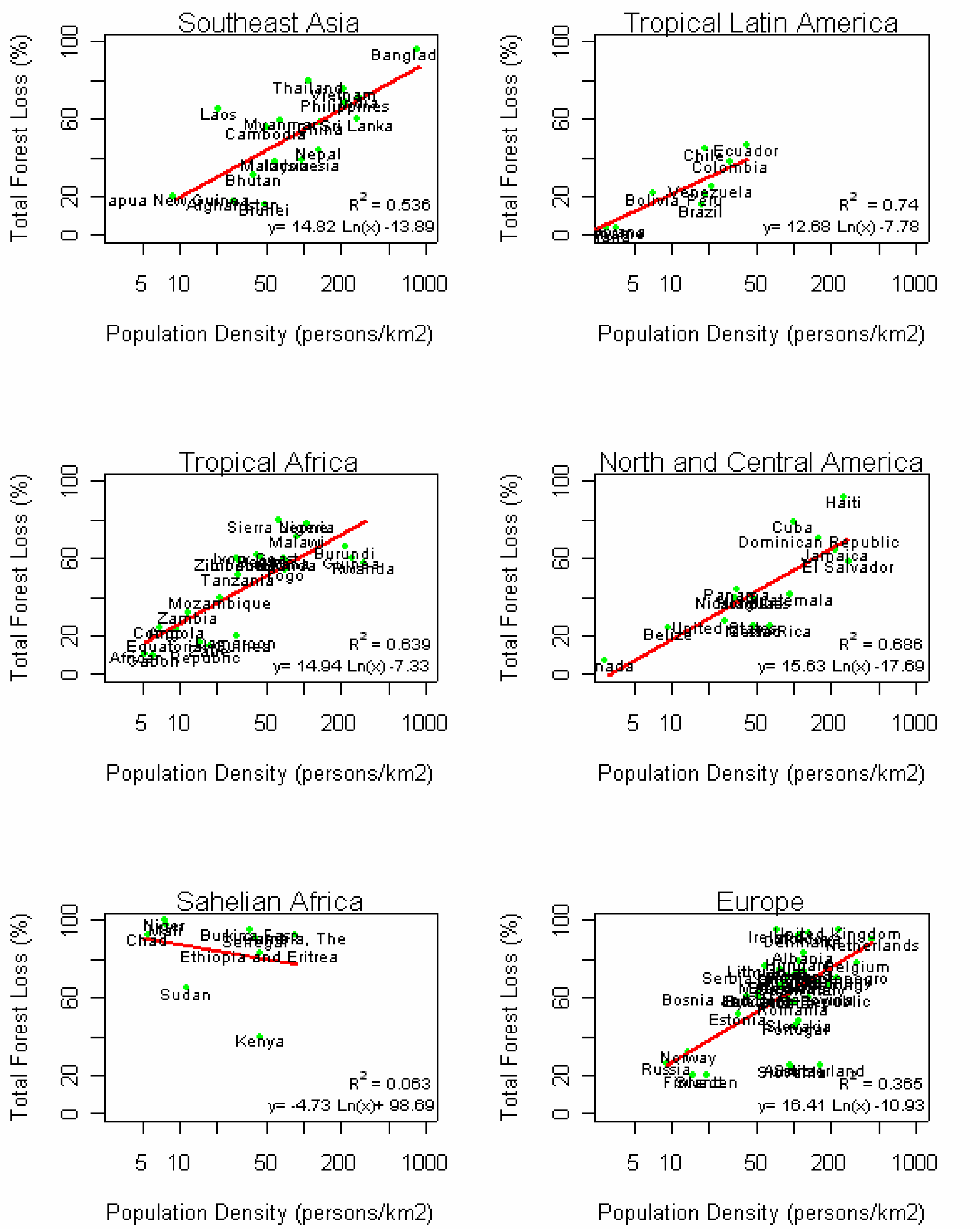


Figure 2: Scatterplots and OLS fit lines for comparison with Pahari and Murai (1999).

Though these regional results differ from Pahari and Murai's, five of the six regions are quite similar. The exception is the Sahelian Africa region. This region remains plagued with the problem of forest classification in the savanna transition zone between the Sahara and tropical Africa. The initial model for tropical Africa was also influenced by this problem due to the savanna regions on its southern fringe. For tropical Africa, the problem was addressed by removing Namibia and Botswana from the analysis, countries that registered high fractions of forest loss. Since both of these countries have only a small portion of their land area forested, any change in the historical classification can result in large swings in the total deforestation measure. In Pahari and Murai's study, for instance, these countries registered 0% forest loss, compared to 82% (Botswana) and 98% (Namibia) with the UNEP-WCMC data.

Regression model results from Pahari and Murai are shown in Table 4 alongside the regression parameters from Figure 2. Whereas Figure 2 reports raw R^2 values for comparison with Pahari and Murai, Table 4 reports the adjusted R^2 values for comparison with the multivariate regression model.

The multivariate regression model of Table 4 adds three new country-scale variables in an effort to improve the more simplistic bivariate model. Two of these are control variables, the other is an explanatory variable.

First, the Herfindahl index of population density was calculated for each country. This index is a simple measure ($\sum x^2 / (\sum x)^2$) of equality meant to capture the extent of urbanization and uneven population distribution for each country. Countries with high levels of urbanization may have a different impact on forests when compared with countries with less urbanization and therefore more direct interaction with forests. The index was calculated using the 1990 IIASA 0.5 degree global population density grid (Grübler, 2004). The natural logarithm was then applied to generate a more normal statistical distribution.

The other control variable measures the fraction of usable land area that was originally forested. So for each country, the UNEP-WCMC forest area was divided into the total land area minus the non-usable land cover categories (bare areas, water bodies, and snow and ice). Though some bare areas are usable with irrigation inputs, their long-term potential is doubtful (Houghton, 2001). Inclusion of this percent original forest variable is meant to control for countries with relatively low population densities and high levels of deforestation, such as the Sahelian countries where land cover classification uncertainty weakens the relation.

The third additional variable is the natural logarithm of GDP per capita. These data were obtained from the World Bank (2004) website for the year 2000. The expectation for this explanatory variable is that countries with higher levels of GDP per capita will have lower deforestation levels. Lofdahl (2002), for instance, shows that GDP per capita acts to ameliorate deforestation, as wealthy countries push their environmental costs to developing countries through trade. This relation is far from clear, especially when applied to a measure of deforestation spanning 8,000 years. Other research shows high per capita income to correlate with greater deforestation or exhibit a non-linear relation, as in an environmental Kuznets curve (Cropper and Griffiths, 1994; Kaimowitz and Angelsen, 1998).

Table 4: Comparison of country-scale regional models.

Model		Southeast Asia		Tropical Africa		Sahelian Africa		Latin America		Northern and Central America		Europe	
		Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Pahari	Intercept	-19.560		7.845		12.305		-7.020		-29.643		0.728	
	In(PopDens)	16.042		15.206		16.872		16.896		21.637		14.719	
	R^2	0.638		0.717		0.638		0.672		0.824		0.523	
Comparison	Intercept	-13.890	.413	-7.330	.440	98.689	.003[b]	-7.777	.292	-17.688	.197	-10.933	.519
	In(PopDens)	14.816	.001[c]	14.944	.000[c]	-4.727	.515	12.676	.001[b]	15.632	.000[c]	16.405	.000[c]
	R^2	0.505		0.622		-0.071		0.708		0.660		0.347	
Multivariate	Intercept	-87.777	.097	-65.326	.178	205.067	.192	126.766	.014[a]	56.934	.509	44.100	.201
	In(PopDens)	12.276	.002[b]	17.865	.000[c]	-11.460	.291	26.659	.000[c]	12.165	.012[a]	17.129	.000[c]
	In(Herf.)	-7.454	.045[a]	-1.530	.513	3.918	.534	16.197	.002[b]	0.590	.917	1.272	.690
	Pct. forest	1.068	.025[a]	0.403	.086	0.601	.072	-0.258	.113	-0.122	.759	-0.218	.401
	In(GDP/cap)	-5.875	.234	0.963	.808	-19.003	.450	-16.451	.006[b]	-6.209	.298	-4.087	.096
	Adj-R^2	0.646		0.630		0.553		0.957		0.651		0.383	

[a] Statistically significant at the 0.05 level.
[b] Statistically significant at the 0.01 level.
[c] Statistically significant at the 0.001 level.

Regional model results using these additional inputs show varying degrees of improvement (Table 4). For regions that were already relatively well predicted in the simple population density model, the additional variables resulted in only moderate improvement; though the model for Latin America improves remarkably, explaining almost 96% of the variance of long-term deforestation. Sahelian Africa also improves significantly, mostly from the contribution of the percent original forest variable. This again highlights the problem of quantifying deforestation in the Sahel.

In terms of individual parameters, none of the additional inputs to the model show a consistent influence. The explanatory variable, GDP per capita, generally shows that wealthy countries have experienced less deforestation, though this variable is only significant for Latin America. Much of the variation associated with GDP per capita is controlled for simply by taking such a regional approach. (The global multivariate regression, for instance, shows GDP per capita significant at the 0.01 level with a negative sign.) The Herfindahl index and percent original forest do not consistently contribute to the models.

4.2 Sub-country Models

Though the above models provide a good description of deforestation at the country-scale, they fail to capture any sub-country variation. This is especially concerning for large countries such as Russia, China, Canada, and the United States. To reduce this problem, a sub-country map from ESRI (2002) was obtained. This map consists of over 2500 administrative units with global coverage.

Based on the above analysis, a modified version of the multiple regression model was applied. For this model, two variables, population density (Figure 3) and the control variable, fraction of original forests, were used to predict long-term deforestation. Average population density was calculated for each areal unit based on the 0.5 degree global IIASA grid (Grübler, 2004). The percent forests control variable was retained largely due to its significant influence in improving the Sahelian Africa regional model.

The sub-country analysis further differs from the country-scale regional approach by instead using geographically weighted regression (GWR) models (Fotheringham *et al.*, 2002) in place of six regional regression models. Since the country-scale results in substantial regional differences, it is appropriate to allow the model parameters to vary over space, a key strength of GWR. Another advantage of using GWR is that explicit regional boundaries (which are often arbitrary) need not be defined. Instead, a regression model is calculated for the centroid of each areal unit of analysis based on a distance decay function. This conforms with the first law of geography, that near things are more related than far things (Tobler, 1970). By allowing model parameters to vary over space, a more geographically nuanced picture of deforestation can be created, while still addressing the problem from the global scale.

Since even these sub-country areal units vary greatly in size, the GWR models were configured to use an adaptive kernel bandwidth.[1] This allows the weighting of surrounding points to decrease more gradually when the regression points are widely spaced, and more rapidly for closely spaced points.

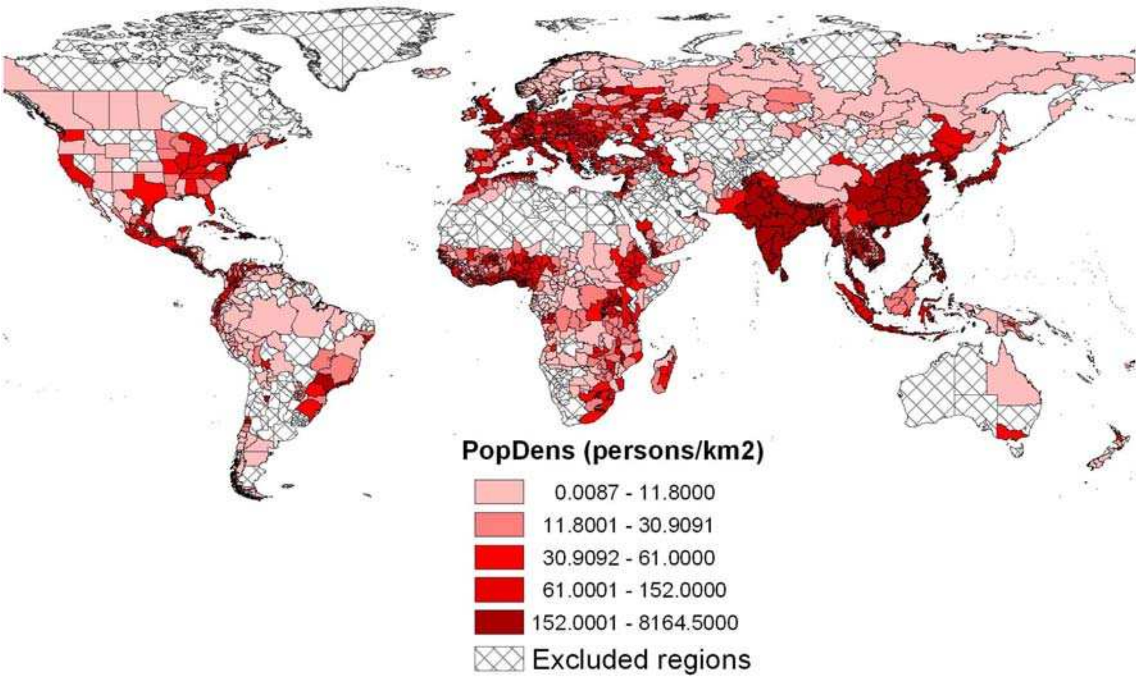


Figure 3: Population density for the year 2000.

For each areal unit, the natural log of population density and fraction of original forest area were calculated. Areas with no population or no original forest were excluded from the analysis. The dependent variable, cumulative deforestation (using the UNEP-WCMC and GLC 2000 data), was re-calculated for each of the sub-country units (Figure 4). Areal units registering negative deforestation were also excluded from the analysis, with the assumption that classification errors dominate these areas. This leaves a total of 1793 units for analysis. Note the higher levels of total deforestation in the problem areas of the African savanna.

---

[1] The adaptive kernel uses a variable bandwidth according to a bi-square function where the weight w for data point j at regression point i is given by:

$$w_{ij} = [1-(d_{ij}/b)^2]^2 \qquad \text{when } d_{ij} \leq b$$

$$w_{ij} = 0 \qquad \text{when } d_{ij} > b$$

where b is the bandwidth (beyond which no data points influence the regression) and d is the distance between i and j. The bandwidth is variable and calculated such that the number of data points contributing to any one model is constant. For this analysis, the Akaike Information Criterion (AIC) is used to automatically determine the local sample size (Fotheringham *et al.* 2002). In the results presented here, the number of nearest neighbors contributing to each model is 92.

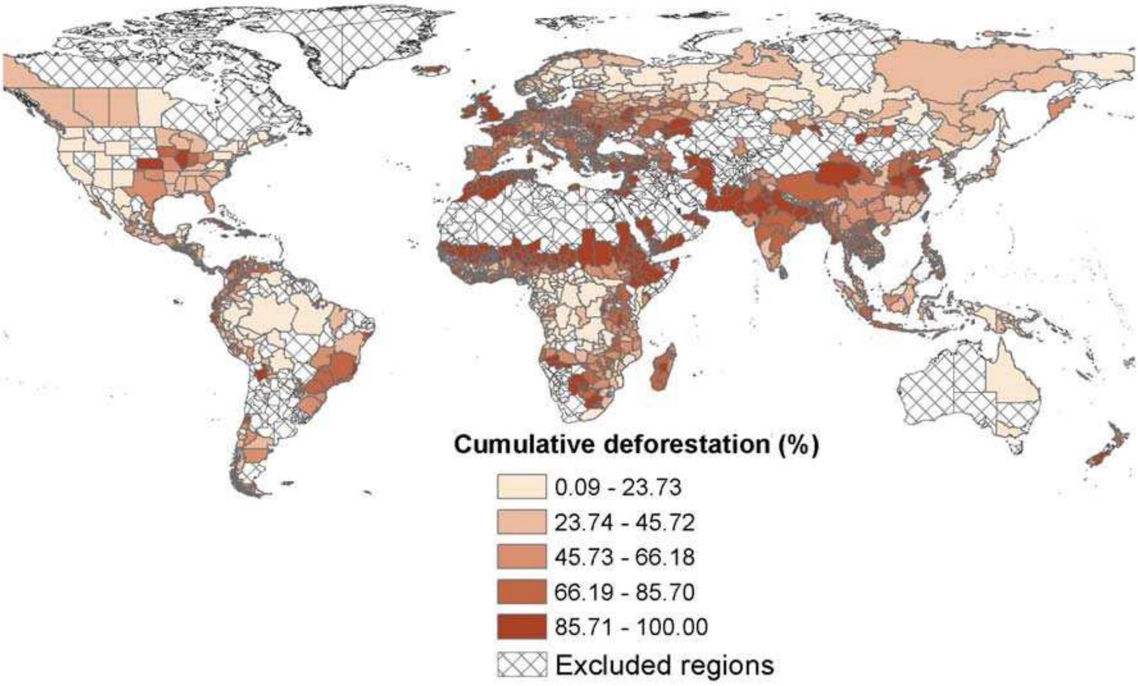


Figure 4: Cumulative deforestation through the year 2000.

Model results for both the single global regression model and the range of estimates for all 1793 regression models are presented in Table 5. The global model results confirm population density as a significant predictor of long-term deforestation. Percent original forest also contributes to the model, though less substantially. Overall, the global scale model explains about 12% of deforestation.

Table 5: Sub-country regression models.

Global Model Parameters		**Coeff.**	**Std. Error**	**T-value**
	Intercept	55.190	2.570	21.475
Adj-R^2	In(PopDens)	6.450	0.438	14.739
0.124	Pct. Forest	-0.220	0.025	-8.641
GWR Estimates		**Lower Quartile**	**Median**	**Upper Quartile**
	Intercept	23.833	70.566	98.000
Adj-R^2	In(PopDens)	0.376	4.873	9.975
0.547	Pct. Forest	-0458	-0.150	0.066

In contrast, the GWR results explain 55% of the variation in deforestation levels (Table 5). Figure 5 shows the spatial variation of the local R-square values. This map essentially represents the level of confidence for predicting deforestation. The tropical regions in South America, Africa, and Southeast Asia tend to have at least 50% of the variation explained by the models. In contrast, there is much lower confidence in the model results for much of North America, Central America, southern Africa, and Siberia.

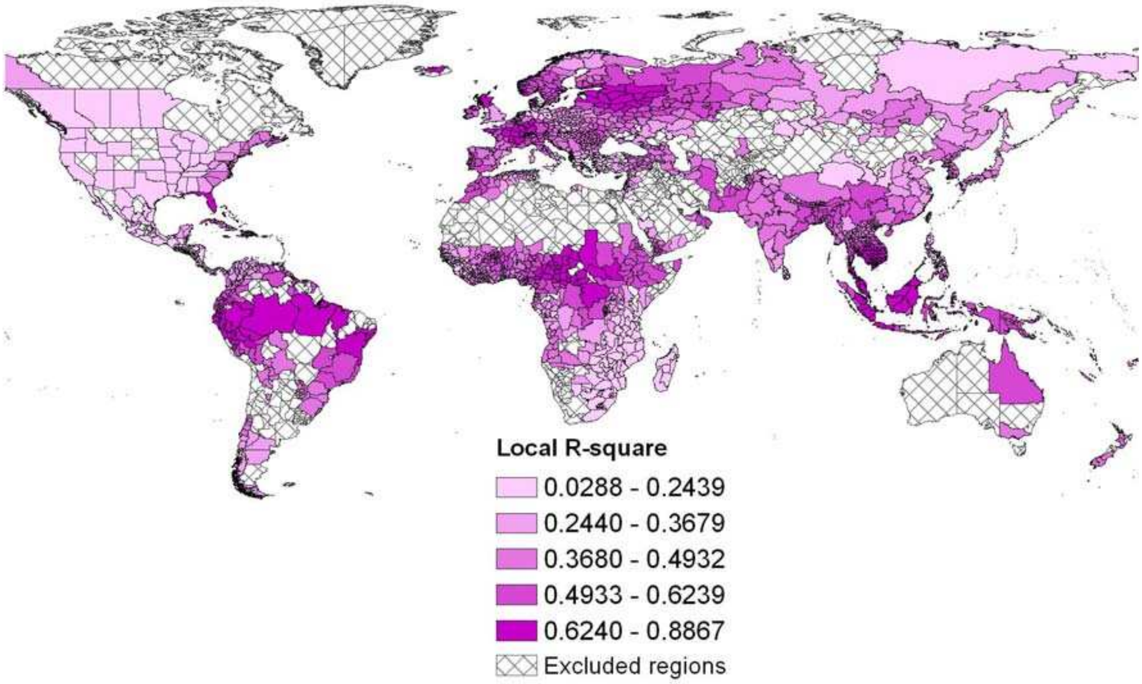


Figure 5: GWR local R-squares for the sub-country models.

Examination of the explanatory variable, population density, shows that while some of the parameters are negative (Figure 6), most of the parameters are positive (Table 5), as expected. Areas with higher population density parameters are more sensitive to changes in population density. South America, tropical Africa, and Southeast Asia all exhibit a statistically significant relationship between population density and deforestation (Figure 7). The T-values of Figure 7 are mapped such that white areas are not statistically significant, lightly shaded areas are significant at the 0.05 level, and areas in dark blue or dark red are significant at the 0.01 level.

The area of northern Africa and the Iberian Peninsula and the region surrounding the Caspian Sea stand out as significantly defying expectations (Figure 7). The inverse relation found in the first area of the western Mediterranean most likely reflects a mismatch in areal unit with underlying population pressures. This is therefore a manifestation of the modifiable areal unit problem (MAUP), where different spatial aggregations can cause results to widely vary (Openshaw and Taylor, 1979; Fotheringham and Wong, 1991). In these areas, most of the population is along the coast, while most of the deforestation has occurred inland. For the northern top of Africa, the original UNEP-WCMC forest stretches along a narrow band, just inland from the coast (Figure 1). A relatively dense coastal population was thus forced to go further inland, beyond its administrative unit, to consumer forest resources. For the region surrounding the Caspian Sea, the inverse relationship between population density and deforestation seems to reflect a dearth of forests, both historically and in 2000. The region to the northwest of the Caspian Sea corresponds to the steppe of southern European Russia and eastern Ukraine. This region is quite suitable for agriculture (Ramankutty *et al*., 2002) and can therefore support its population with little need to deforest.

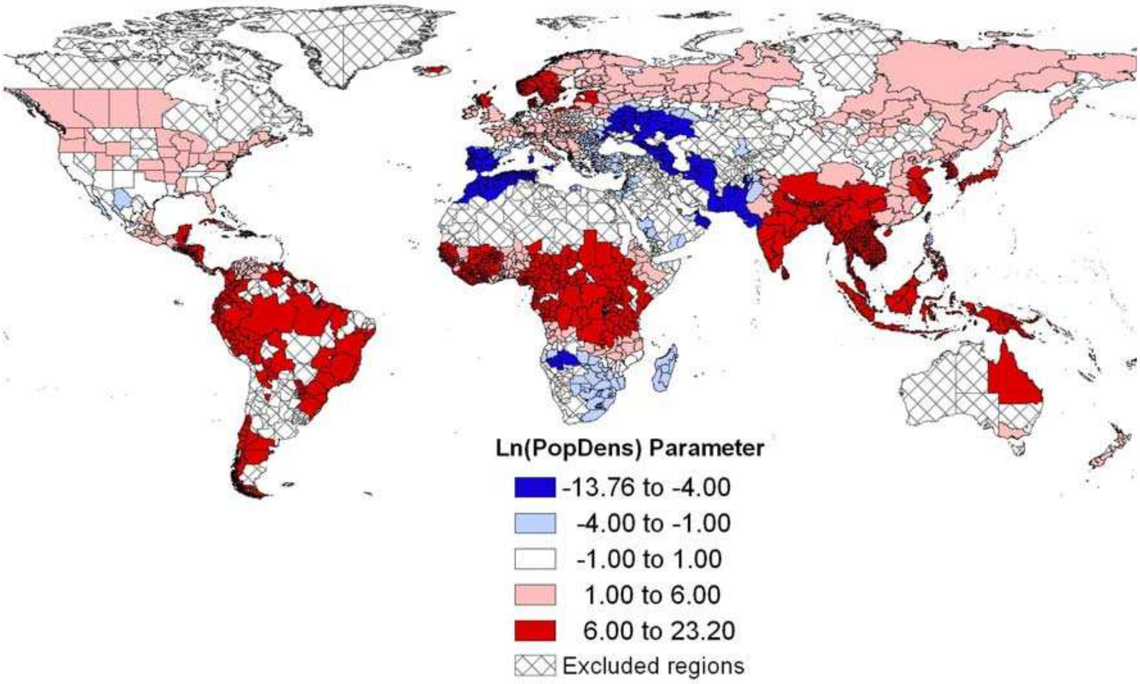


Figure 6: GWR population density parameters.

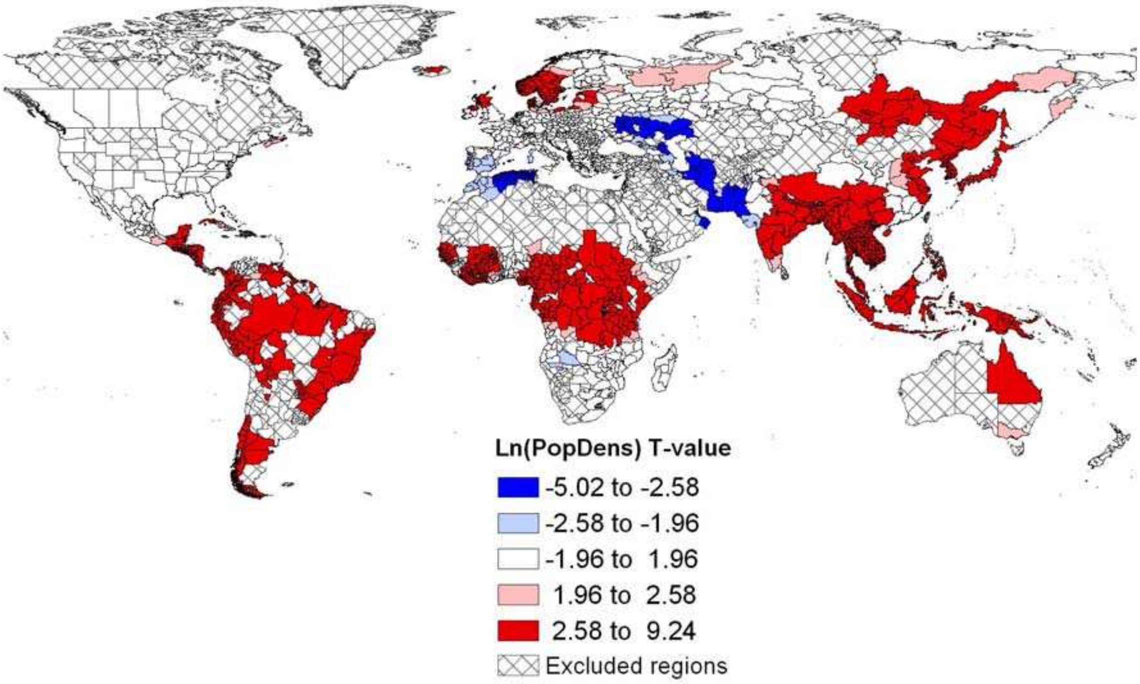


Figure 7: GWR T-values for population density.

Similarly, the region to the southeast of the Caspian Sea towards India also lacks any substantial forests. But here, the few historical forests that did exist have been cleared, yielding deforestation rates over 85% for the area, even though absolute numbers of forest loss are relatively small. This, coupled with low population density help explain how low numbers of people are correlated with high levels of deforestation.

The other input to the model is the percent original forest for each areal unit. This was included primarily to control for classification problems in the savanna zones bordering tropical Africa. Figure 8 shows this variable to significantly contribute to the explanatory power of the models not only in most of Africa, but also southern Europe, northwest Russia, eastern United States, and portions of Southeast Asia.

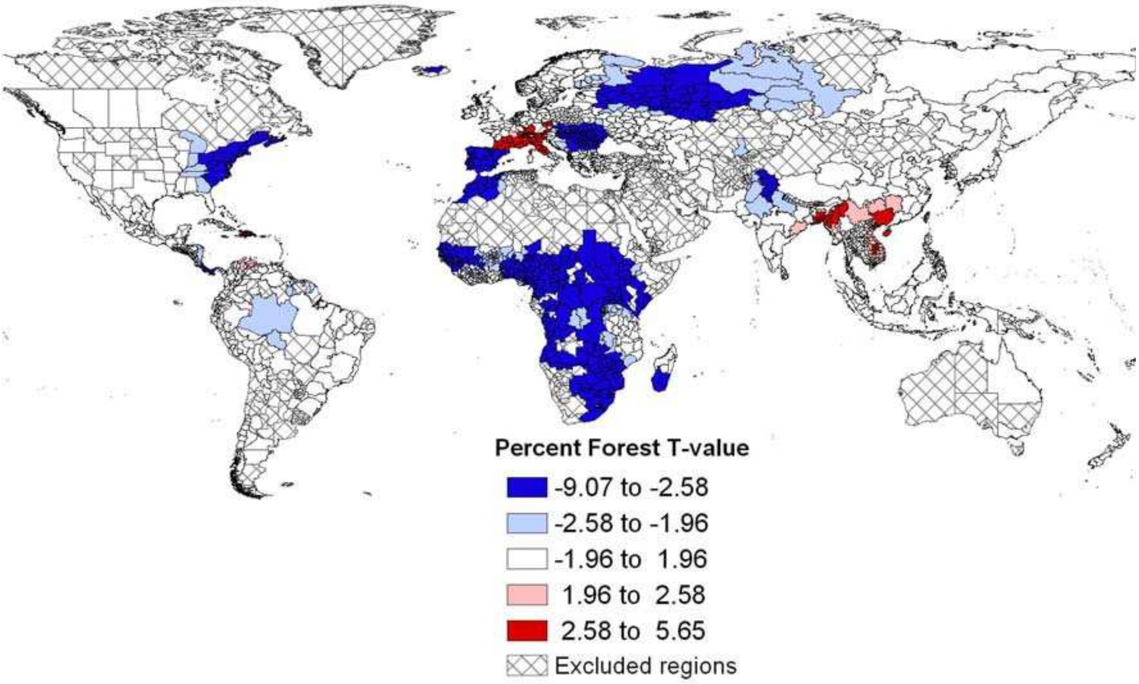


Figure 8: GWR T-values for percent original forest.

4.3 Sub-country Projections

With the GWR models established, it is possible to simulate deforestation to the year 2100. This is done by first calculating projected population densities for each areal unit according to the extremes of the United Nations' population estimates. This is done for both the B1 (low population growth) and A2 (high population growth) scenarios using disaggregated 0.5 degree gridded IIASA data (Grübler, 2004). The local model parameters were then used to predict additional deforestation for each of the areal units of the model. Model residuals were also added to the estimates under the assumption that model errors remain constant over time.

Projections are presented both in map and tabular form. Figures 9–12 show both the UN population density projections and corresponding projected deforestation. In Figures 9 and 11, for instance, change in population density is calculated for the B1 and

A2 scenarios, respectively, by subtracting 2000 values from 2050 values. For the deforestation measure, the projected cumulative deforestation for 2050 is subtracted from the cumulative deforestation for the year 2000. This means that negative map values indicate afforestation.

When evaluating the projection maps, it is important to consider both the magnitude of the population density parameter (Figure 6) as well as the explanatory power of the models for a given region (Figure 5). For the B1 scenarios (Figures 9 and 10, Table 6), population densities and deforestation peak close to 2050. At this peak, the model results show deforestation most severe in tropical Africa and portions of Southeast Asia. By 2100, however, population declines in southern Asia actually result in widespread processes of afforestation. In central and South America, population pressures can be expected to result in deforestation through 2100 for coastal areas, while the interior Amazon region remains stable or increases in forest area.

As expected, A2 scenario results are not as optimistic both for 2050 and 2100 (Figures 11 and 12, Table 6). For these population projections, more deforestation is projected in South America and Southeast Asia.

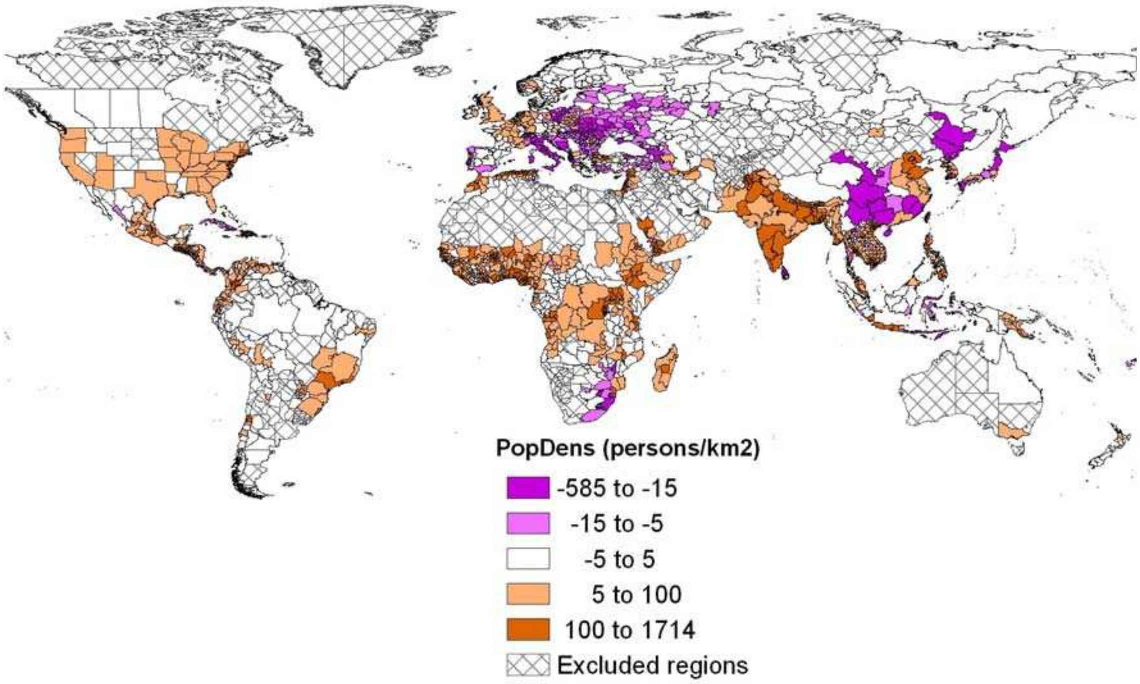
The areas whose models exhibit counter-intuitive parameter behavior continue to show unexpected results. Each of the projected scenarios show northern Africa experiencing deforestation, even though population projections suggest an increased demand for forest resources. Similarly, continued population declines in the southern portions of the Russian Plain are projected to result in not less, but more deforestation. Though some of these regions have lower predictive power (Figure 5), they are not uniformly weak.

Aggregated results by SRES region (ECS, 2004), are reported in Table 6. In addition to the raw historical and year 2000 forest areas, projected change numbers for the two scenarios are also reported relative to the 2000 figures. For all scenarios, Sub-Saharan Africa is projected to lose the most area of current forests, ranging from over 30 million ha (B1, 2100) to close to 50 million ha (A2, 2050). The Latin America and Caribbean region is also projected to experience substantial deforestation in three of the scenarios. However, by 2100 in the B1 scenario, 2.6 million ha are projected to revert to forest from their 2000 level. At the other extreme, the region projected to gain the most forests is the Former Soviet Union, with an average gain of some 6.5 million ha over all four projections.

5 Conclusions

Attempts to predict the future are necessarily speculative and even require a bit of arrogance. The modeling results presented here do not fully characterize how human actions affect global deforestation, both today or in the future. What they do represent, however, is a method for understanding the spatial variation of how one underlying force, population density, affects long-term deforestation. By allowing model parameters to vary over space, the different ways in which humans modify their landscape through a wide array of proximate forces can be captured by the common driving force of population density.

(a) B1 change in population density (2050–2000)



(b) B1 percent deforestation (2000–2050).

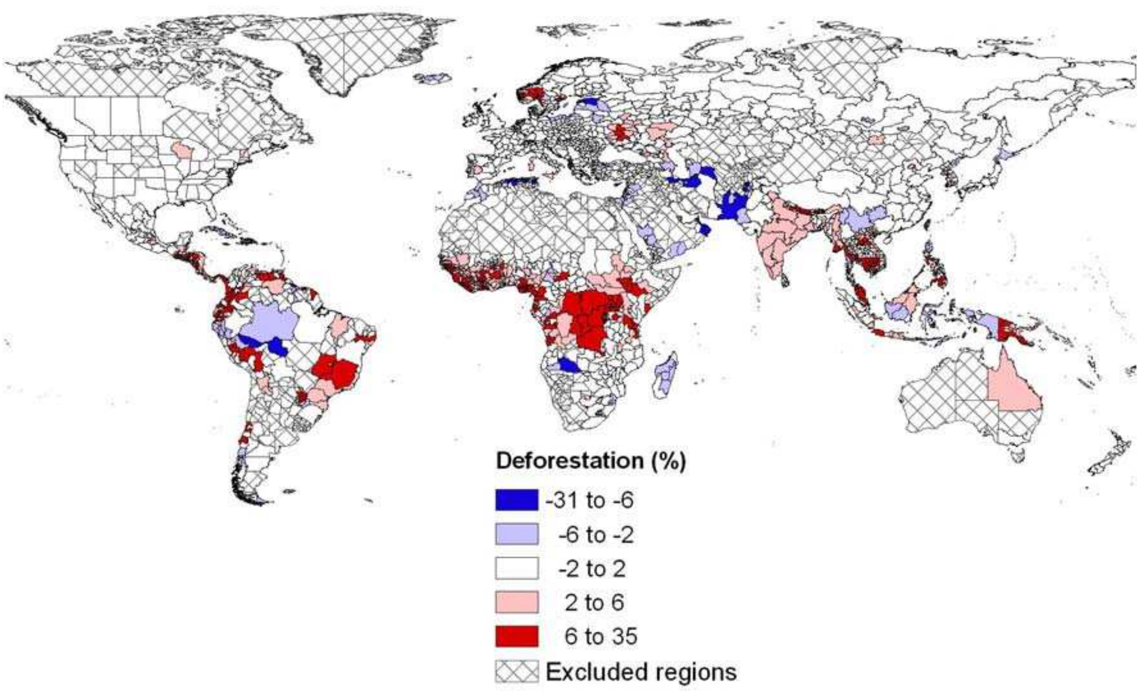
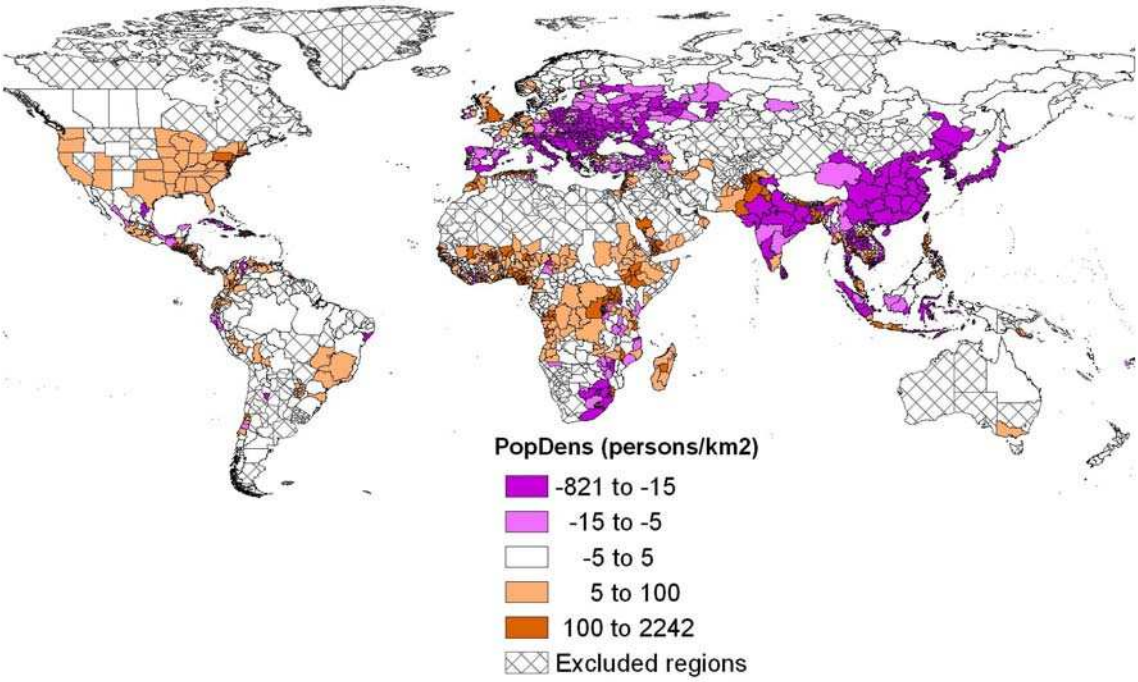


Figure 9: B1 population and deforestation projections through 2050.

(a) B1 change in population density (2100–2000).



(b) B1 percent deforestation (2000–2100).

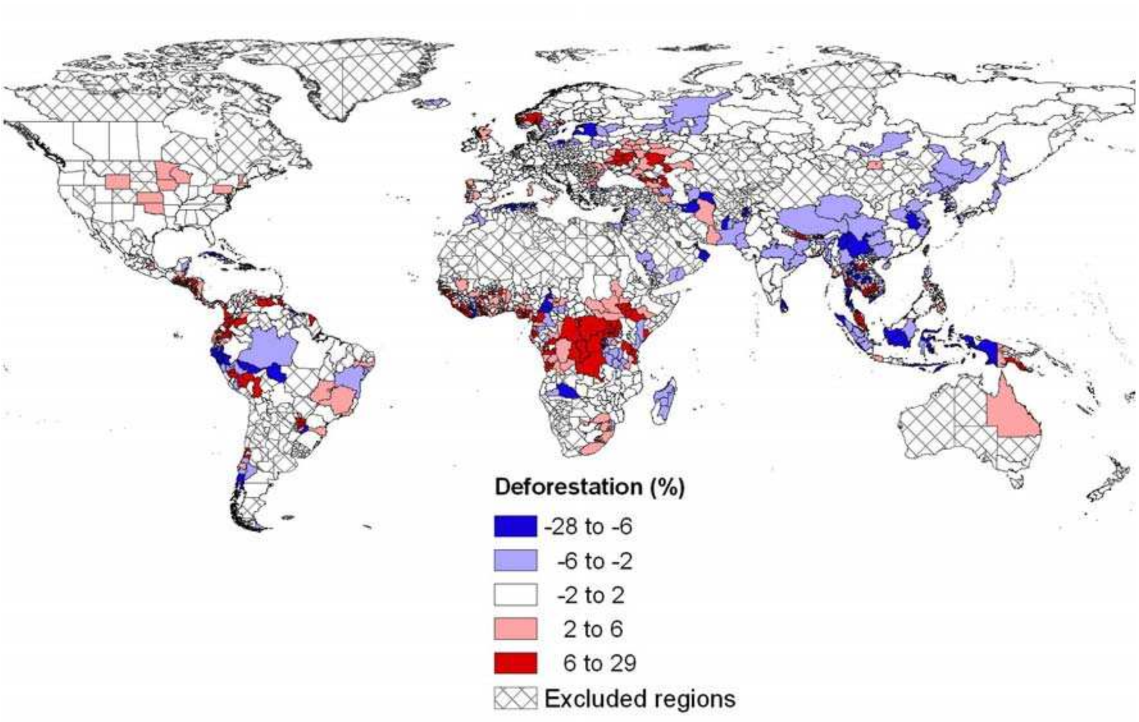
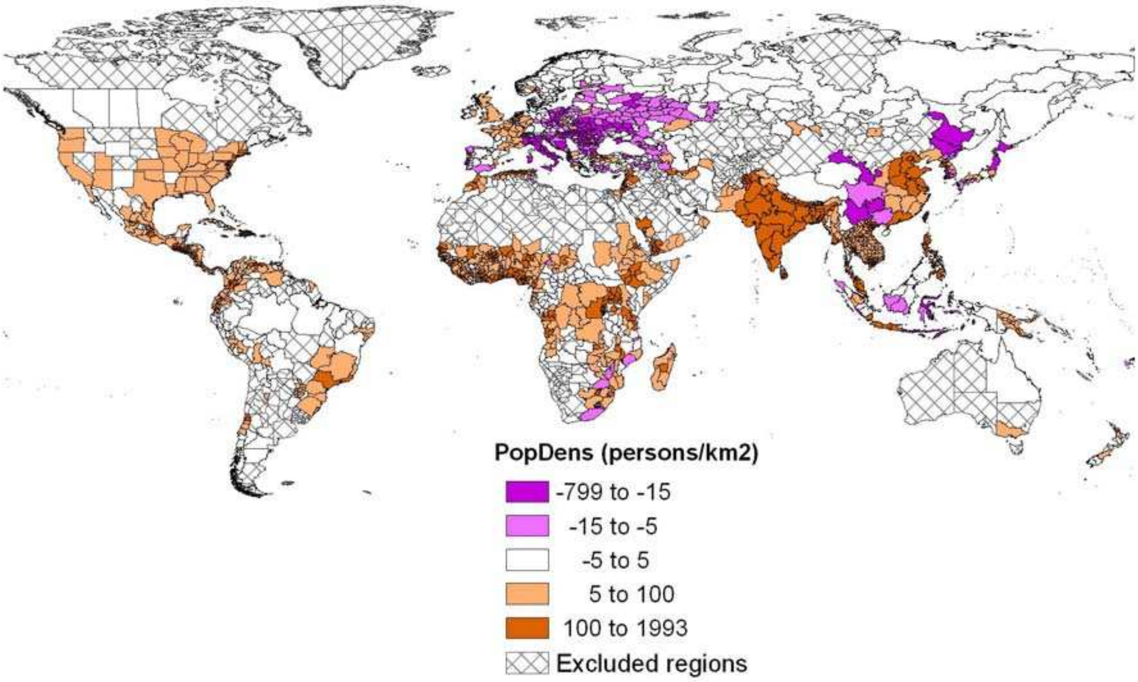


Figure 10: B1 population and deforestation projections through 2100.

(a) A2 change in population density (2050–2000).



(b) A2 percent deforestation (2000–2050).

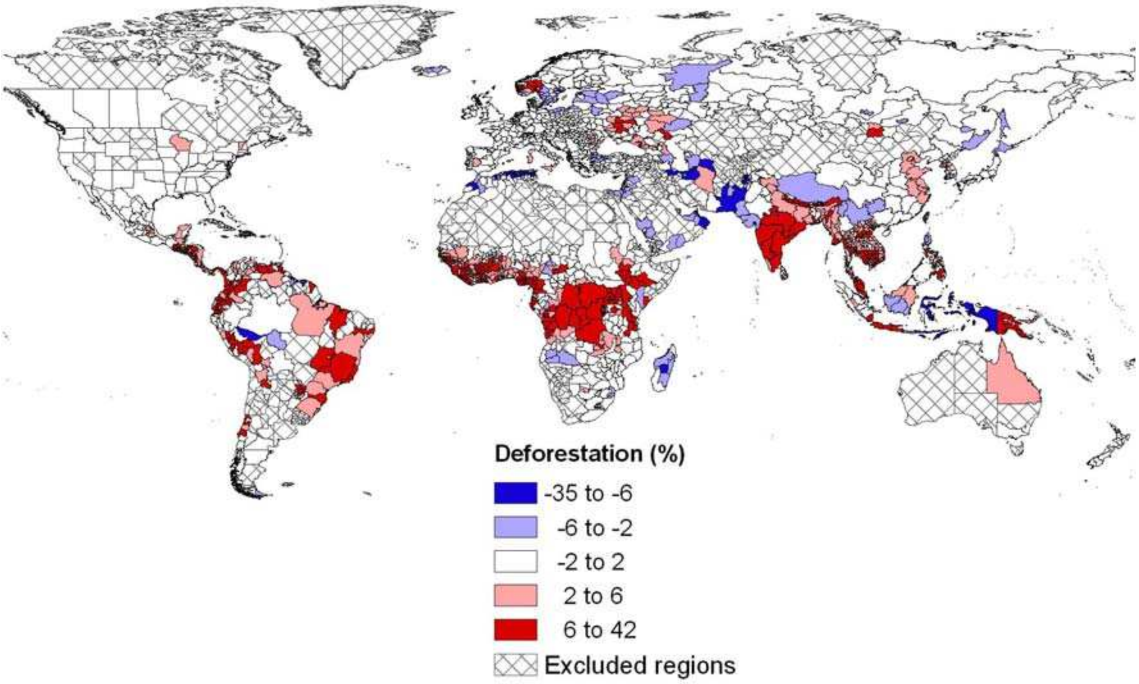
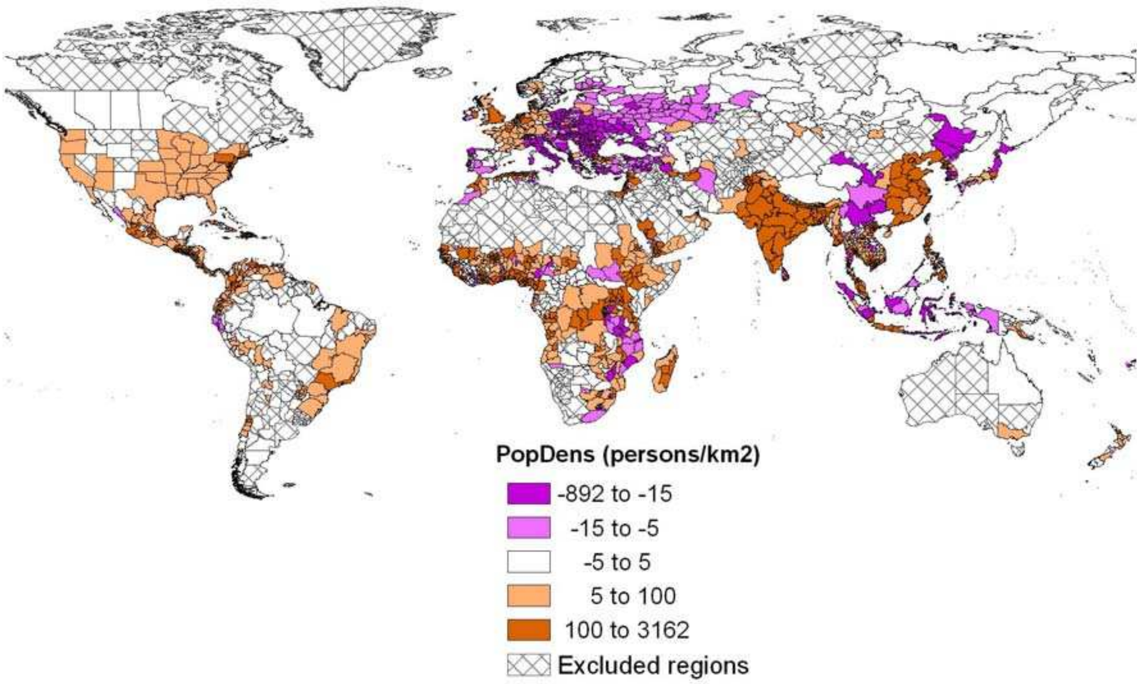


Figure 11: A2 population and deforestation projections through 2050.

(a) A2 change in population density (2100–2000).



(b) A2 percent deforestation (2000–2100).

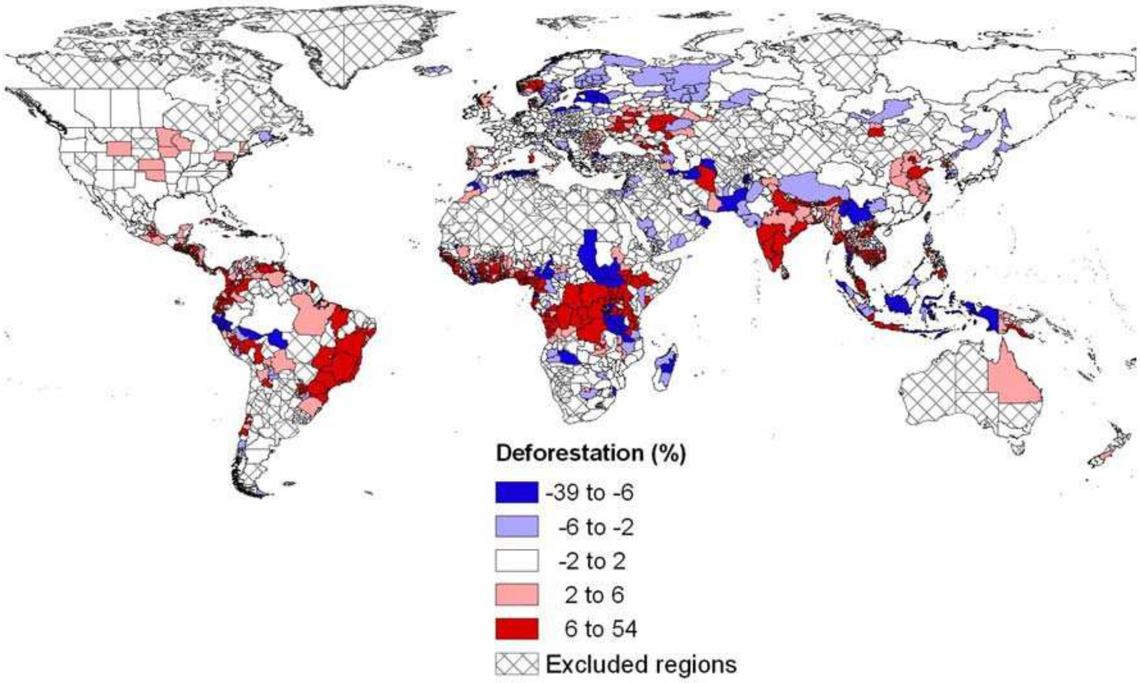


Figure 12: A2 population and deforestation projections through 2100.

Table 6: Forest area and projected deforestation (1,000 ha) by region.

Region	Past and Recent		B1 Projected Deforestation		A2 Projected Deforestation	
	UNEP-WCMC	GLC 2000	2050 (Δ)	2100 (Δ)	2050 (Δ)	2100 (Δ)
North America	822,671	678,817	3,839	5,733	4,057	5,192
Western Europe	322,620	131,038	884	1,059	121	737
Pacific OECD	112,584	118,097	532	185	672	828
Central and Eastern Europe	94,656	31,904	-124	-372	-159	-407
Former Soviet Union	1,105,838	786,928	-4,801	-7,104	-5,708	-8,625
Centrally Planned Asia, China	511,559	207,327	917	-12,378	4,118	4,366
South Asia	262,470	74,224	5,254	-3,478	10,943	11,515
Other Pacific Asia	366,602	195,904	6,187	-9,288	6,430	-5,127
Middle East and North Africa	100,146	23,040	-632	-383	-2,016	-5,950
Latin America and Caribbean	1,016,760	805,912	11,147	-2,601	25,178	28,963
Sub-Saharan Africa	1,118,485	601,067	39,821	30,785	48,955	47,732
Total	***5,834,391***	***3,654,258***	***63,023***	***2,157***	***92,589***	***79,224***

Geographically weight regression proved to be particularly effective in explicitly characterizing how processes of deforestation vary from one region to the next. Though parameters can still be adversely affected by the size and shape of the areal unit, this information can still be useful for understanding how and why relationships vary over space. So, whereas population density and deforestation may be highly correlated when the data are aggregated to the whole of a country (e.g., United States), the relationship may break down when aggregated to sub-country areal units (e.g., individual US states).

The deforestation projections presented here rely on two assumptions. First, that population growth over the next hundred years will fall in the range of the UN population projections, and second, that the underlying relation between population density and deforestation will remain largely intact. If these assumptions hold, then the simulation results suggest that even though the Brazilian Amazon has recently received more attention in the press and academic research (Geist and Lambin, 2001; Lambin *et al.*, 2003; Economist, 2004; Laurance *et al.*, 2004), Sub-Saharan Africa might experience twice as much deforestation over the next 100 years. This conclusion is supported by the scenarios presented here, in addition to the prior work of Pahari and Murai (1999). In a review of 152 cases of tropical deforestation, only 19 (13%) were in Africa, while over half (78) were in Latin America (the remaining 36% were located in Asia) (Geist and Lambin, 2001). Though these numbers reflect the greater deforestation rates occurring in the Brazilian Amazon, especially in the 1990s, they also reflect the lack of datasets and research for Africa (Lepers, 2002; Lambin *et al.*, 2003). The dearth of attention given to Africa not only means few studies exist to provide baseline knowledge, but also that potentially rapid changes might occur with little global awareness.

Further improvements to this modeling approach could take several forms. One possibility is to include measures of ecological variation to control for differences in potential land use. Also, the dependent variable could be altered to instead measure forest area instead of deforestation (Uusivuori *et al.*, 2002). Other additional socioeconomic inputs to the model, especially at the sub-country scale, do not hold much prospect, however, since global scale data are not available, both as inputs for model creation as well as for future deforestation projections.

References

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers, Dordrecht; Boston.

CIESIN/IFPRI/WRI (2000). Gridded Population of the World (GPW), Version 2. Center for International Earth Science Information Network (CIESIN), International Food Policy Research Institute (IFPRI) and World Resources Institute (WRI), Columbia University. Available at: http://sedac.ciesin.columbia.edu/plue/gpw (accessed 25 June 2004).

Cropper, M. and C. Griffiths (1994). The Interaction of Population Growth and Environmental Quality. *The American Economic Review*, **84**(2): 250–254.

ECJRC (2003). Global Land Cover 2000 Project. European Commission Joint Research Center (ECJRC). Available at: http://www.gvm.jrc.it/glc2000/ProductGLC2000.htm (accessed on 18 June 2004).

Economist (2004). The Brazilian Amazon: Asphalt and the Jungle. *The Economist***,** July 22.

ECS (2004). Definition of the Four World Regions and the 11 MESSAGE World Regions. Environmentally Compatible Energy Strategies (ECS) Program, International Institute for Applied Systems Analysis, Laxenburg, Austria. Available at: http://www.iiasa.ac.at/Research/ECS/docs/11worldregions.html, (accessed on 24 August 2004).

Elvidge, C.D., K.E. Baugh, J.B. Dietz, T. Bland, P.C. Sutton and H. . Kroehl (1999). Radiance Calibration of DMSP-OLS Low-light Imaging Data of Human Settlements. *Remote Sensing of Environment* **68**(1): 77–88.

ESRI (2002). Data and Maps. Environmental Systems Research Institute Inc. (ESRI), Redlands, CA.

Fotheringham, A.S. and D.W.S. Wong (1991). The Modifiable Areal Unit Problem in Multivariate Statistical Analysis. *Environment and Planning A* **23**: 1025–1044.

Fotheringham, A.S., C. Brunsdon and M. Charlton (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley, Chichester.

Geist, H.J. and E.F. Lambin (2001). What Drives Tropical Deforestation? LUCC Project Report Series No. 4, University of Louvain, Belgium.

Goldewijk, K.K. (2001). Estimating Global Land Use Change Over the Past 300 Years: The HYDE Database. *Global Biogeochemical Cycles* **15**(2): 417–434.

Grübler, A. (2004). Spatial Patterns of Economic and Demographic Change. Internal Greenhouse Gas Initiative Workshop, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Houghton, R.A. (2001). Forests and Agriculture. In: G.M. Woodwell (ed.), *Forests in a Full World,* Yale University Press, New Haven, 36–50.

Kaimowitz, D. and A. Angelsen (1998). *Economic Models of Tropical Deforestation: A Review*. Center for International Forestry Research (CIFOR), Bogor, Indonesia.

Kapos, V. (2000). Original Forest Cover Map. United Nations Environment Programme-World Conservation Monitoring Centre (UNEP-WCMC). Available at: http://www.unepwcmc.org/forest/original.htm (accessed on 16 August 2004).

Lambin, E.F., B.L. Turner, H.J. Geist, S.B. Agbola, A. Angelsen, J.W. Bruce, O.T. Coomes, R. Dirzo, G. Fischer, C. Folke, P.S. George, K. Homewood, J. Imbernon, R. Leemans, X. Li, E.F. Moran, M. Mortimore, P.S. Ramakrishnan, J.F. Richards, H. Skanes, W. Steffen, G.D. Stone, U. Svedin, T.A. Veldkamp, C. Vogel and J. Xu (2001). The Causes of Land-use and Land-cover Change: Moving Beyond the Myths. *Global Environmental Change* **11**(4): 261–269.

Lambin, E.F., H.J. Geist and E. Lepers (2003). Dynamics of Land-use and Land-cover Change in Tropical Regions. *Annual Review of Environment and Resources* **28**: 205–241.

Laurance, W.F., A.K. Albernaz, P.M. Fearnside, H.L. Vasconcelos and L.V. Ferreira (2004). Deforestation in Amazonia. *Science* **304**: 1109–1111.

Lepers, E. (2002). Synthesis of Knowledge of Rapid Land-cover and Land-use Change. Millenium Ecosystem Assessment, University of Louvain, Louvain-la-Neuve, Belgium.

Lofdahl, C.L. (2002). *Environmental Impacts of Globalization and Trade: A Systems Study*. MIT Press, Cambridge, MA.

Maddison, A. (2004). *The World Economy: Historical Statistics*. Organisation for Economic Cooperation and Development (OECD), Paris.

Mather, A.S. and C.L. Needle (2000). The Relationships of Population and Forest Trends. *The Geographical Journal* **166**(1): 2–13.

Meyer, W.B. and B.L. Turner (1992). Human Population Growth and Global Land-use/Cover Change. *Annual Review of Ecology and Systematics* **23**: 39–62.

Openshaw, S. and P.J. Taylor (1979). A Million Or So Correlation Coefficients: Three Experiments on the Modifiable Areal Unit Problem. *Statistical Applications in the Spatial Sciences*. Pion Ltd., N. Wrigley, London, 127–144.

Pahari, K. and S. Murai (1999). Modeling for Prediction of Global Deforestation Based on the Growth of Human Population. *ISPRS Journal of Photogrammetry and Remote Sensing* **54**(5–6): 317–324.

Ramankutty, N. and J.A. Foley (1999). Estimating Historical Changes in Global Land Cover: Croplands From 1700 to 1992. *Global Biogeochemical Cycles* **13**(4): 997–1027.

Ramankutty, N., K.K. Goldewijk, R. Leemans, J. Foley and F. Oldfield (2001). Land Cover Change Over the Last Three Centuries Due to Human Activities. *IGBP Global Change Newsletter* **47**: 17–19.

Ramankutty, N., J.A. Foley, J. Norman and K. McSweeney (2002). The Global Distribution of Cultivable Lands: Current Patterns and Sensitivity to Possible Climate Change. *Global Ecology and Biogeography* **11**(5): 377–392.

Sutton, P., D. Roberts, C. Elvidge and K. Baugh (2001). Census from Heaven: An Estimate of the Global Human Population Using Night-time Satellite Imagery. *International Journal of Remote Sensing* **22**(16): 3061–3076.

Tobler, W.R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography* **46**(2): 234–240.

Uusivuori, J., E. Lehto and M. Palo (2002). Population, Income and Ecological Conditions as Determinants of Forest Area Variation in the Tropics. *Global Environmental Change* **12**(4): 313–323.

Wallerstein, I. (1974). The Rise and Future Demise of the Capitalist World System: Concepts for Comparative Analysis. *Comparative Studies in Society and History* **16**: 387–418.

Williams, M. (1990). Forests. In: B.L. Turner, W.C. Clark, R.W. Kates, J.F. Richards, J.T. Mathews and W.B. Meyer (eds.), *The Earth as Transformed by Human Action*. Cambridge University Press with Clark University, Cambridge; New York, 179–201.

Appendix A: Modified Pahari and Murai Regions

Europe
Albania
Austria
Belgium
Bosnia and Herzegovina
Byelarus
Bulgaria
Denmark
Ireland
Estonia
Czech Republic
Finland
France
Germany
Greece
Croatia
Hungary
Italy
Latvia
Lithuania
Slovakia
Luxembourg
Moldova
Macedonia
Netherlands
Norway
Poland
Portugal
Romania
Russia
Slovenia
Spain
Serbia and Montenegro
Sweden
Switzerland
United Kingdom
Ukraine

Tropical Africa
Angola
Benin
Burundi
Congo
Zaire
Cameroon
Central African Republic
Equatorial Guinea
Gabon
Ghana
Guinea
Ivory Coast
Liberia
Malawi
Mozambique
Nigeria
Rwanda
Sierra Leone
Togo
Tanzania
Uganda
Zambia
Zimbabwe

Sahelian Africa
Chad
Ethiopia and Eritrea
Gambia
Kenya
Mali
Niger
Senegal
Sudan
Burkina Faso

North and Central America
Belize
Canada
Costa Rica
Cuba
Dominican Republic
El Salvador
Guatemala
Haiti
Honduras
Jamaica
Mexico
Nicaragua
Panama
United States

Tropical Latin America
Bolivia
Brazil
Chile
Colombia
Ecuador
French Guiana
Guyana
Suriname
Peru
Venezuela

Southeast Asia
Afghanistan
Bangladesh
Myanmar
Bhutan
Brunei
Cambodia
Sri Lanka
China
Indonesia
India
Laos
Malaysia
Nepal
Papua New Guinea
Philippines
Thailand
Vietnam