Predicting the Location of Deforestation: The Role of Roads and Protected Areas in North Thailand

Maureen Cropper, Jyotsna Puri, and Charles Griffiths

ABSTRACT. *Using plot level data, we estimate a bivariate probit model to explain land clearing and the siting of protected areas in North Thailand in 1986. The model suggests that protected areas (national parks and wildlife sanctuaries together) did not reduce the likelihood of forest clearing; however, wildlife sanctuaries may have reduced the probability of deforestation. Road building, by reducing impedance-weighted distance to market, has promoted clearing, especially near the forest fringe. We simulate the impact of further road building to show where road building is likely to have greatest impact and where it is likely to threaten protected areas.* (JEL Q23, Q28, R40)

I. INTRODUCTION

Concern over the rate at which forests are being converted to agriculture has given rise to a literature that quantifies the impact of forces that drive deforestation. The literature has focused on two questions: (1) What factors affect the *location* of deforestation? and (2) What factors affect the *rate* of deforestation? Each question has policy significance. It is clearly important to know *where* deforestation is likely to occur, especially if it is in environmentally sensitive areas, and it is also important to know *how fast* the process is taking place.

This paper focuses on the first question. We estimate an equilibrium model of land use in North Thailand in the mid-1980s, using coarse-resolution (1:1,000,000) plot-level data. The purpose of the model is to predict where deforestation is likely to occur and to examine the impact of two government policies that can affect the location of deforestation: the establishment of protected areas, and road building.

Protected areas are often suggested as a means of conserving tropical ecosystems and have, at least on paper, been created in many tropical developing countries. In 1985, Thailand declared that 15% of its land area should be set aside for conservation or protected forests. By 1986, 10% of the country's land lay within protected areas. Fifty-two percent of the land in protected areas was devoted to national parks and 42% to wildlife sanctuaries.[1] Whether such areas can, in fact, protect biodiversity depends on their size and location, and on how they are managed. Protected areas are less likely to experience encroachment if they have the political support of surrounding communities, and if these communities can produce sufficient income without encroaching upon the protected area. This suggests that understanding the reasons for the success or failure of protected areas requires on-the-ground knowledge, and is best evaluated using a case study approach.

The contribution we make to the topic is to evaluate statistically whether protected areas have reduced the probability of deforestation in national parks and wildlife sanctuaries in Thailand. Other authors who have tackled this issue (Chomitz and Gray 1996; Dei-

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[1] The remaining 8% of protected areas included arboretums, botanical gardens, and reserved areas.

ninger and Minten 1996) have estimated a land use model that predicts the probability that land located in protected areas is cleared. The fraction of land predicted to be cleared is then compared with the fraction of land actually cleared to determine the impact of protected areas on clearing.

This approach does not, however, allow one to determine whether the impact of protected areas on clearing is statistically significant, or to test hypotheses about its magnitude. We estimate a bivariate probit model to explain the probability that a plot of land is cleared and the probability that it lies within a protected area. Protected area status enters the clearing equation, and variables that affect the designation of an area as protected (but not the clearing decision) are used to identify the coefficient of protected area status. This allows us to control for the selectivity problem inherent in single-equation models of land use: In a single-equation model of clearing, the coefficient of protected area status is likely to overstate (in absolute value) the impact of protected areas on clearing. This is because protected areas are likely to be located in places that have not yet been cleared.

The second topic on which we focus is the impact of roads on the land-clearing decision. Qualitatively, the impact of roads on land clearing is well understood: Road building facilitates access to markets, and thus raises the probability that forests will be cleared for agriculture. Understanding the *quantitative* impact of road building on clearing is, however, crucial for policy. Suppose a government wishes to build a road to a proposed national park. Where should the road be located to reduce the likelihood of development en route to the park? As Chomitz and Gray (1996) emphasize in their study of the impact of roads on agricultural development in Belize, the impact of roads depends on the topography of the area, and on soil quality. One goal of our study is to show where road building in North Thailand is likely to have the greatest impact on the probability that forests are cleared, and to identify the impact of further road building on protected areas.

To investigate the issues discussed above, we have assembled a GIS database on land use, roads, physiographic variables (slope, elevation, and soil quality), populated places, and population density for the 17 provinces of North Thailand. The data also include protected area boundaries, and provincial and district boundaries. The model of land clearing and protected area status estimated with these data is described in section 2. Section 3 contains a more detailed description of the data and our sampling strategy. Econometric results are presented in section 4. We conclude the paper by showing how our model can be used to estimate the threat of encroachment in protected areas.

II. A MODEL OF LAND CLEARING AND PROTECTED AREA STATUS

Economic theory predicts that forested land will be cleared if the profits from clearing land exceed the profits from leaving land under forest cover. We follow Chomitz and Gray (1996) (see also Nelson and Hellerstein 1997) in assuming that the profit from land use k on plot i, R_{ik}, may be defined as the difference between the value of outputs and inputs Q_{ik} and X_{ik} at their respective location-specific prices P_{ik} and C_{ik},

$$R_{ik} = P_{ik}Q_{ik} - C_{ik}X_{ik}. \qquad [1]$$

Chomitz and Gray (1996) demonstrate that when output is a Cobb-Douglas function of X_{ij} and plot characteristics, $s_{1i}, s_{2i} \ldots$

$$Q_{ik} = S_{ik}X_{ik}^{\beta_k} \textit{ with } 0 < \beta_k < 1 \qquad [2]$$

$$S_{ik} = \lambda_0 s_{1i}^{\lambda_{1k}} s_{2i}^{\lambda_{2k}} \ldots \qquad [3]$$

R_{ik} may be written

$$R_{ik} = \left(\frac{1 - \beta_k}{\beta_k}\right) C^{\beta_k/(1-\beta_k)} (P_{ik}S_{ik}\beta_k)^{1/(1-\beta_k)}. \qquad [4]$$

By taking logs and collecting coefficients, this can be transformed into an expression of the form

$$\ln R_{ik} = \alpha_k + \delta_k \ln P_{ik} + \theta_k \ln C_{ik} + \sum_n \mu_{nk} \ln s_{ni}. \qquad [5]$$

Empirically, we distinguish between two forms of land use, agriculture and forestry and note that plot i will be devoted to agriculture if $R_{i1} > \ln R_{i0}$.

In practice, data on input and output prices are unavailable at the plot level. We assume that both P_{ik} and C_{ik} vary with the impedance-weighted distance of the plot from the nearest market (Cost$_i$), and, also, with the population density of the district in which the plot is located (Population density$_i$). District population affects P_{i1} by shifting the demand for agricultural output, and C_{i1} by shifting the demand and supply curves of labor. We use district population density, rather than population, to control for the fact that districts vary in area.

Plot characteristics $\{s_{ni}\}$ that affect the profitability of clearing include slope, elevation, measures of soil quality, and the plot's protected area status. Since the government has the right to evict persons living in parks or wildlife sanctuaries, there is at least some threat of expropriation if output is grown in these areas. The province in which the plot is located is also likely to affect the profitability of agriculture. Provincial dummy variables capture differences in rainfall and may proxy differences in tenure security. Representing protected area status by $Y_{2i} = 1$, if a plot lies in a protected area (and $= 0$ otherwise), and all other factors that influence the profitability of conversion (including distance to markets and population density) by vector $\mathbf{Z}_i$, a plot will be cleared if $\mathbf{Z}_i B_1 + \gamma Y_{2i} > 0$.[2] In our empirical model, $\mathbf{Z}_i$ includes the slope of the plot, its elevation, population density in the district in which the plot is located, the natural logarithm of impedance-weighted to market, provincial dummy variables, and dummy variables for soil categories.

There is no well-developed theory to explain which plots of land are designated protected areas; however, political and economic considerations suggest that land where the opportunity costs of protection are low (land of low agricultural value) would be more likely to be selected than land of high agricultural value. This suggests that the factors, $\mathbf{Z}_i$, that affect the profits of clearing land (the opportunity cost of protection) should enter the equation to explain protected area status. The benefits of protecting a plot should, however, depend on different factors. Areas that serve as habitat to endangered species or that contain fragile ecosystems clearly yield higher benefits from preservation than areas that are ecologically unremarkable. Riverine forests constitute fragile ecosystems that are often home to diverse species. We posit that location near rivers increases the chance that a plot is protected.

The econometric model that we estimate is thus given by

$$Y_{1i}^* = \mathbf{Z}_i B_1 + \gamma Y_{2i} + e_{1i}$$
$$Y_{1i} = 1 \text{ if } Y_{1i}^* > 0; = 0 \text{ otherwise} \quad [6]$$

$$Y_{2i}^* = \mathbf{Z}_i B_2 + \alpha W_i + e_{2i}$$
$$Y_{2i} = 1 \text{ if } Y_{2i}^* > 0; = 0 \text{ otherwise} \quad [7]$$

where the plot is cleared ($Y_{1i} = 1$) if the net profits from clearing plot i (Y_{1i}^*) are positive, and the plot lies in a protected area ($Y_{2i} = 1$) if the net benefits from protecting plot i (Y_{2i}^*) are positive. W_i indicates that the plot is located near a river (watershed dummy). We estimate this structural model as a bivariate probit model, assuming that e_{1i} and e_{2i} are jointly normally distributed.[3] This allows us to estimate the impact of protected area status on the probability that a plot is cleared.

The model is estimated for two definitions of protected area: national parks and wildlife sanctuaries (hereafter referred to as "protected areas"), and wildlife sanctuaries only. The focus on wildlife sanctuaries is prompted by anecdotal evidence that the Thai government has made stronger efforts to prevent encroachment in wildlife sanctuaries than in national parks.

[2] If P_{ik} and C_{ik} are exponential functions of population density and distance to market, then these variables will enter Z_i linearly. Likewise, if $\{s_{ni}\}$ are an exponential function of plot characteristics they will enter Z_i linearly.

[3] To reduce the problem of spatial autocorrelation, we sample plots at intervals of 5 km. We have also estimated the model including average values of slope, elevation, and distance to market within a 10-km radius of plot i. The coefficients of these variables measured for plot i are robust to the inclusion of the average values of the variables on surrounding plots.

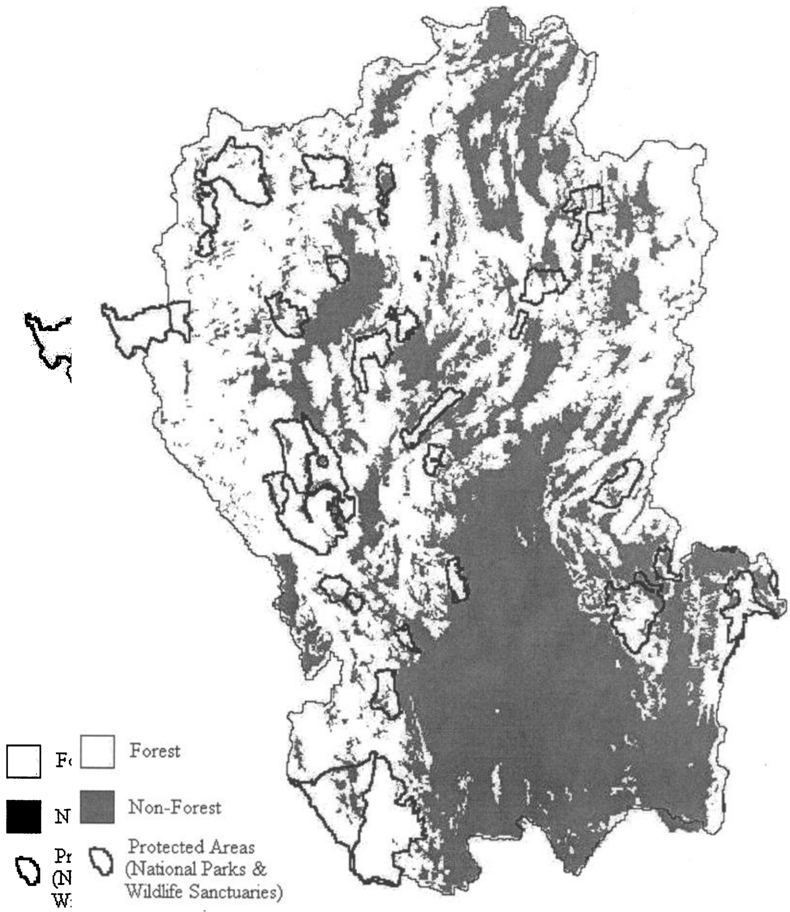

FIGURE 1
FOREST AND PROTECTED AREAS MAP OF NORTH THAILAND, 1986

III. STUDY AREA AND DATA

The area we have chosen for this study—the 17 provinces that constitute North Thailand—remains heavily forested, especially the Upper North portion of the region.[4] Protected areas constituted 11% of the region in 1986, the year of our study (see Figure 1), and continue to be established. North Thailand is the second poorest of the four regions of Thailand, and road building is part of the government's strategy to reduce rural poverty. Between 1973 and 1985, extensive road building increased road density in North Thailand by 57% (Cropper, Griffiths, and Mani 1999). The policy issues raised in the introduction are, therefore, relevant to North Thailand.

Data

We model the land clearing decision in North Thailand in 1986 using coarse resolution data. Land use information comes from a 1:1,000,000 Land Development Department map that originally contained 15 land use categories. Urban areas and water were omitted from the study area and the remaining land uses classified as "forest" or "non forest." The term "clearing," as used in section 2, is thus synonymous with "non forest."

Physiographic factors that should influ-

[4] The Upper North consists of the provinces of Chiang Mai, Chiang Rai, Nan, Lampang, Lamphun, Mae Hong Son, Uthai Thani, Tak, and Phrae.

ence the profitability of clearing include the soil characteristics of the plot, its slope, and its elevation. All soils in North Thailand are classified by the FAO Soil Map of the World as falling in one of 12 soil categories, defined on the basis of soil texture and slope class (Acrisol, Fluvisol, Gleysol, etc.). We represent these soil categories using a series of dummy variables.[5] Elevation (in meters) was obtained at a resolution of 30 arc seconds, and the slope of each plot was calculated as the maximum difference between the elevation of the plot and the elevation of each of neighboring plot. (The sources of our data are described in the Appendix.)

To compute ease of access to markets, we digitized a 1982 road map of Thailand (1:1,000,000 scale), distinguishing between paved and unpaved roads. The locations of market towns were obtained from the Digital Chart of the World. To calculate the impedance-weighted distance from each plot to the nearest market town, travel along a paved road was assigned an impedance factor of 1, travel along an unpaved road an impedance factor of 2, and travel from a plot to a road a factor of $[100 + (\text{Slope of Plot})^2]$. An algorithm was used to compute the shortest distance from each point to the nearest market town.[6] River distances were computed in a similar fashion.

Population, a proxy for the demand for agricultural products and for labor supply, is measured at the district level using 1990 census data. Population density is calculated using 1990 district boundaries. Because each district is large relative to the size of a plot, we treat district population density as exogenous to the pixel.

Protected area boundaries, obtained from the IUCN, indicate that 14.4% of our sample points lie within protected areas (parks and wildlife sanctuaries), while 9.1% lie within wildlife sanctuaries. The percent of protected areas remaining under forest cover is 87% whereas it is 70% for all sample points.

Sampling Strategy

All layers of the GIS database were converted to a resolution of 100 square meters, which resulted in over 28,000,000 data points. We sampled points systematically, at 5-km intervals, which yielded 6,550 observations. The three provinces that contained no protected areas were dropped from estimation of the protected area equations, while the five provinces that contained no wildlife sanctuaries were dropped from those equations (see Table 1). Exact collinearity between protected areas and four soil categories (and between wildlife sanctuaries and the same soil categories) necessitated that observations in these soil categories also be dropped (see Table 1). The means and standards deviations of variables for each of the protected area and wildlife sanctuary samples are presented in Table 1.

IV. ECONOMETRIC RESULTS

Determinants of Land Clearing in North Thailand

We begin by examining how well our model explains land clearing in North Thailand (see Tables 2 and 3). North Thailand is a mountainous area, characterized by parallel hills and valleys that run north to south (see Figure 2). Steep slopes and high elevations have helped to protect much of the area from clearing. Indeed, 70% of the study area was classified as forested in 1986. The model of Table 2 correctly predicts land use ($Y_{1i} = 0$) for 91% of the sample points under forest cover. The model predicts clearing less accurately—only 57% of cleared plots are correctly predicted to be cleared. When the model does predict clearing, however, it is correct 75% of the time (see Table 3).

The quantitative impacts of factors that affect the probability of clearing are shown in columns (4) and (5) of Table 2. Phyisographic factors have a significant impact on clearing: Calculated at the means of explanatory variables, the elasticity of probability of clearing with respect to the slope of the plot

[5] The distribution of more familiar soil properties (nitrogen or phosphorous context) is known for all plots in a soil category; however, it is not known at the level of an individual plot.

[6] Costdistance is a module in Arc/Info™ that calculates for each cell the least accumulative cost of travel from a set of source cells, over a cost surface.

TABLE 1
SUMMARY STATISTICS

	North Thailand Sample	Protected Area Sample	Wildlife Sanctuary Sample
Variable	Mean or proportion (S.D)	Mean or proportion (S.D)	Mean or proportion (S.D)
Total no. of observations	6,550	4,946	4,355
Cleared land	0.425	0.307	0.263
Slope of plot (degrees)	3.54 (3.87)	4.24 (3.94)	4.46 (3.94)
Elevation (meters)	472.54 (352.13)	546.32 (645.06)	578.93 (341.15)
Population density 1990 (people/km^2)	63.44 (67.14)	45.64 (53.78)	42.56 (55.63)
Cost82 (impedance-weighted distance to nearest market)	546.92 (621.68)	636.45 (676.85)	652.96 (700.85)
Watershed dummy	0.600	0.569	0.562
Protected area dummy	0.108	0.144	0.263
Wildlife sanctuary dummy	0.069	0.091	0.151
Province dummy (Chiang Rai)	0.062	province omitted	province omitted
Province dummy (Chiang Mai)	0.134	0.164	0.186
Province dummy (Mae Hong Son)	0.077	0.102	0.116
Province dummy (Phayao)	0.037	0.029	0.033
Province dummy (Nan)	0.069	0.091	0.104
Province dummy (Lampang)	0.075	0.095	0.108
Province dummy (Phrae)	0.040	0.047	0.054
Province dummy (Lamphun)	0.026	0.025	0.029
Province dummy (Uttaradit)	0.046	0.054	0.061
Province dummy (Tak)	0.103	0.136	0.155
Province dummy (Sukhothai)	0.040	0.035	province omitted
Province dummy (Phitsanulok)	0.062	0.059	0.067
Province dummy (Phetchaboon)	0.072	0.085	province omitted
Province dummy (Khamphaeng Phet)	0.047	0.034	0.039
Province dummy (Phichit)	0.026	province omitted	province omitted
Province dummy (Nakhon Sawan)	0.045	province omitted	province omitted
Province dummy (Uthai Thani)	0.039	0.044	0.050
Soil dummy (Af60-1/2ab)	0.119	0.147	0.136
Soil dummy (Ag16-2a)	0.007	0.009	0.010
Soil dummy (Ag17-2ab)	0.086	category omitted	category omitted
Soil dummy (Ao107-2bc)	0.062	0.056	0.049
Soil dummy (Ao90-2/3c)	0.479	0.598	0.634
Soil dummy (I-Lc-Bk-c)	0.029	0.038	0.038
Soil dummy (Je72-2a)	0.045	category omitted	category omitted
Soil dummy (Lc100-c)	0.012	0.016	0.018
Soil dummy (Lg39-3ab)	0.046	category omitted	category omitted
Soil dummy (Ao108-2ab)	0.068	0.090	0.079
Soil dummy (Nd65-3ab)	0.043	0.047	0.036
Soil dummy (Vp64-3a)	0.005	category omitted	category omitted

is - 0.48, and the elasticity with respect to elevation is - 0.61.[7] Soil quality also matters. Sixty percent of the observations in our sample lie in FAO soil category Ao90-2/3c, which is the omitted soil category in our models. This soil type is distinguished by shallow soils, with low potassium content found on steep slopes. The few pockets of better soil in North Thailand have a higher probability of being cultivated. For example, the marginal effect of moving from FAO soil unit Ao90-2/3c to FAO soil unit Lc100-c is to increase the probability of cultivation by

[7] If we calculate the elasticity at means of forested plots, the elasticities with respect to slope and elevation are much higher: -0.66 and -0.84, respectively. Our discussion here focuses on the models reported in Table 2. Results for the clearing equations in Table 4 are qualitatively and quantitatively similar to those in Table 2.

TABLE 2

Bivariate Probit Model Estimated Using Protected Area Sample

Dependent variable Cleared Land ($Y1 = 1$)	Equation [6]				Equation [7]			
Independent variable	Coefficient	Z	Marginal Effect[a]	Elasticity	Coefficient	Z	Marginal Effect	Elasticity
Slope (degrees)	−0.088	−10.652	−0.027	−0.475	0.034	5.297	0.005	0.272
Elevation (ms.)	−0.001	−8.095	−0.0003	−0.614	0.001	9.058	0.0001	0.917
Population density 1990 (people/km2)[b]	0.003	4.532	0.001	0.154	0.001	2.297	0.0002	0.09
Log (Cost82)[c]	−0.191	−9.729	−0.059	−0.24	0.192	7.477	0.028	0.362
Provincial dummy (Chiang Mai)	−0.12	−1.085	−0.039		0.363	1.422	0.063	
Provincial dummy (Mae Hong Son)	−0.725	−5.573	−0.179		1.052	4.163	0.253	
Provincial dummy (Phayao)	−0.341	−2.249	−0.094		1.042	3.748	0.265	
Provincial dummy (Nan)	−0.278	−2.453	−0.082		−0.574	−1.737	−0.059	
Provincial dummy (Lampang)	−0.493	−4.4	−0.133		0.501	1.865	0.096	
Provincial dummy (Phrae)	−0.394	−3.099	−0.105		1.381	5.217	0.388	
Provincial dummy (Lamphun)	−0.491	−2.769	−0.123		1.851	6.395	0.579	
Provincial dummy (Tak)	−0.343	−3.061	−0.095		1.197	4.755	0.292	
Provincial dummy (Sukhothai)	−0.288	−2.101	−0.079		1.331	4.678	0.373	
Provincial dummy (Phitsanulok)	0.384	2.916	0.141		1.446	5.454	0.407	
Provincial dummy (Phetchaboon)	0.746	6.46	0.274		0.855	3.216	0.194	
Provincial dummy (Kamphaeng Phet)	0.03	0.213	0.014		1.334	4.752	0.374	
Provincial dummy (Uthai Thani)	−0.107	−0.687	−0.02		2.176	8.253	0.68	
Soil dummy (Af60-1/2ab)	0.326	4.773	0.108		−0.452	−4.29	−0.052	
Soil dummy (Ag16-2a)	0.563	2.263	0.224		1.397	6.103	0.406	
Soil dummy (Ao107-2bc)	−0.17	−1.677	−0.05		0.175	1.473	0.028	
Soil dummy (I-Lc-Bk-c)	0.101	0.761	0.038		0.573	5.193	0.116	
Soil dummy (Lc100-c)	0.947	5.75	0.361		0.309	1.921	0.054	
Soil dummy (Ao108-2ab)	0.215	2.536	0.071		−0.52	−3.326	−0.055	
Soil dummy (Nd65-3ab)	−0.062	−0.599	−0.018		−0.06	−0.387	−0.007	
Watershed dummy[b]					0.188	3.543	0.026	
Protected area dummy (1986)[b]	−0.077	−0.332	−0.059					
Constant	1.295	8.87			−4.098	−14.01		
Rho					−0.068	0.309		
Log Likelihood	−3,714.743							
No. of observations	4,946							

[a] Marginal Effects calculated from univariate reduced-form equations.

[b] Watershed dummy = 1 if the impedance-weighted distance to the nearest river is less 3 km, assuming no primary roads. Protected area dummy = 1 if pixel lay in a Protected Area in 1986. Population density is measured at the district level.

[c] Cost is measured as units of primary road traveled, in km.

TABLE 3
ACCURACY OF BIVARIATE PROBIT MODEL IN PREDICTING CLEARING
(PROTECTED AREA SAMPLE)

Actual → Predicted ↓	Cleared	Forested	Percentage of predictions correct
Cleared	**872**	296	75%
Forested	657	**3,133**	83%
Percentage correctly predicted	57%	91%	

Note: Diagonal (bold) figures show correct predictions.

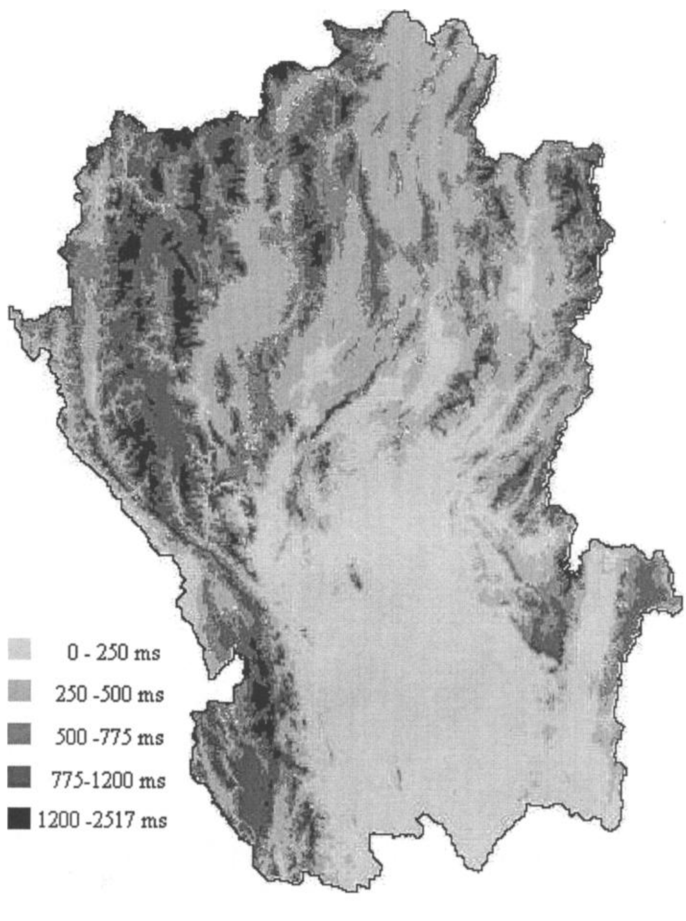

FIGURE 2
ELEVATION MAP OF NORTH THAILAND

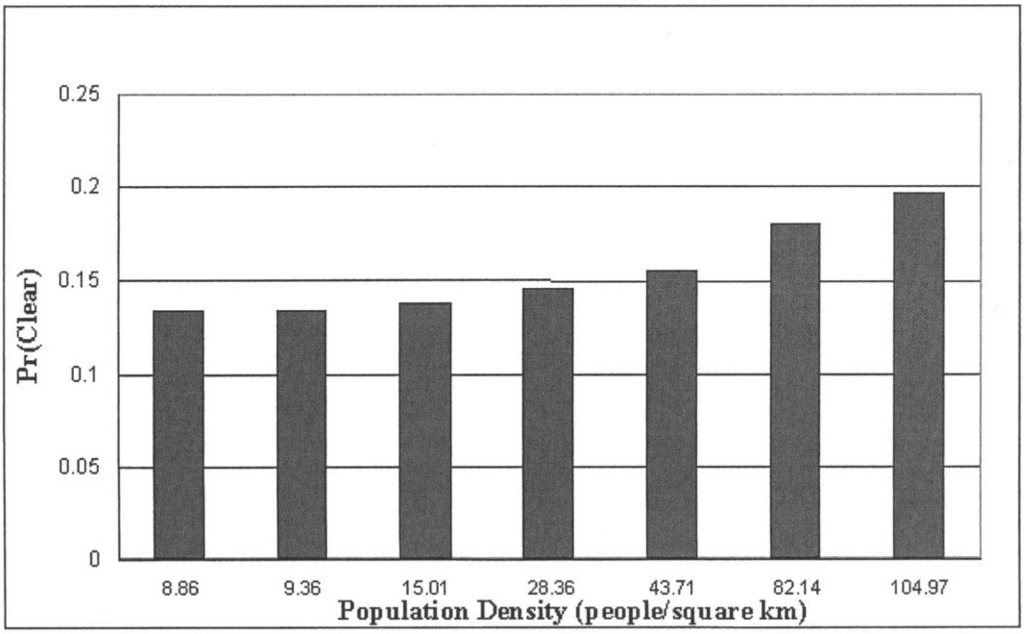

FIGURE 3
IMPACT OF POPULATION DENSITY ON PROBABILITY OF CLEARING, EVALUATED AT FOREST MEANS

36%. The latter soil is distinguished by finely textured soils that drain well, have good chemical properties, and are well-suited to growing sugarcane and rice. In general, the soil categories that significantly increase the probability of clearing are loamy, occur at greater depth than soils in the reference category, and are found on flat or moderately undulating plains.

Deininger and Minten, in their study of deforestation in Mexico, note that physiographic factors alone explain land clearing almost as well as a model to which socioeconomic variables—specifically, population density and market access—are added. The same is true of North Thailand. If we exclude population density and impedance-weighted distance from the model, the percent of observations correctly predicted by the model hardly changes: the percent of observations correctly predicted by the clearing equation falls from 81.1% to 80.7%.

Nonetheless, population density and market access do have a statistically significant impact on clearing. Figures 3 and 4 show the impact of changes in these variables on the probability of clearing, when all other variables are held at their mean values for plots in forest areas. In forest areas mean population density is approximately 40 persons per square kilometer. Doubling this density (and holding all other variables at their means in forest plots) increases the probability that a plot is cleared from about 0.15 to 0.18 (see Figure 3). This relatively modest effect can be explained by the fact that higher population density has two opposing effects on clearing—increases in population density may imply higher agricultural prices, which should encourage clearing, but may also reflect higher wages, which should discourage clearing.[8]

The impact of roads is much larger, especially at the forest fringe. Consider a forest

[8] As a referee noted, increases in rural population density may reduce agricultural wages through the factor proportions effect.

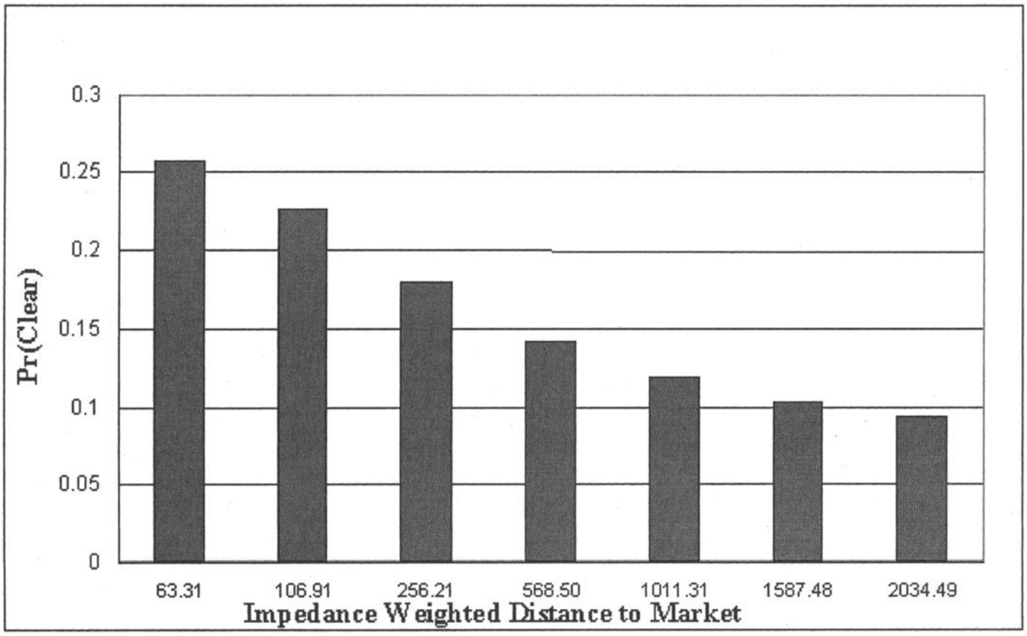

FIGURE 4
IMPACT OF IMPEDANCE-WEIGHTED DISTANCE ON PROBABILITY OF CLEARING, EVALUATED AT FOREST MEANS

plot that is 2.5 km from the nearest paved road and 6 km along the road to the nearest market (i.e., with an impedance-weighted distance of 256). As Figure 4 shows, bringing this plot 1.5 km closer to a paved road (i.e., reducing impedance-weighted distance by 150) increases the probability of clearing from 0.18 to 0.23, that is, by 5%. The impact of changes in the road network is further explored in section 5 below.

Determinants of the Location of Protected Areas and Wildlife Sanctuaries

As one would expect, the variables that increase the probability that a pixel is cleared in general reduce the probability that it lies within the boundary of a protected area (see Table 2) or wildlife sanctuary (see Table 4). Steeper slopes, higher elevations, and locations farther from market centers increase the chance that land is designated a protected area. The same is true for wildlife sanctuaries, although slope and elevation have a smaller quantitative impact on the siting of wildlife sanctuaries than they do on all protected areas. Higher population density in a district increases the probability that a pixel within the district lies in a protected area, although the effect is quantitatively small. This may reflect a desire to locate national parks near population centers. By contrast, higher population density reduces the probability of siting a wildlife sanctuary in a district. Our results in Tables 2 and 4 support Dixon and Sherman's (1990) observation that, in developing countries, areas of low agricultural value are more likely to be designated protected areas in order to avoid political conflict. This point is brought home by estimating univariate probit versions of equation [6] (without either protected area or wildlife sanctuary dummy variables) and using them to predict the probability that plots in protected areas and wildlife sanctuaries are cleared. The average predicted probability of

TABLE 4

BIVARIATE PROBIT MODEL ESTIMATED USING WILDLIFE REFUGE SAMPLE

Dependent variable Cleared Land (Y1 = 1)	Equation [6]				Equation [7]			
Independent variable	Coefficient	Z	Marginal Effect[a]	Elasticity	Coefficient	Z	Marginal Effect	Elasticity
Slope (degrees)	−0.09	−10.111	−0.026	−0.561	0.019	2.514	0.001	0.191
Elevation (ms.)	−0.001	−6.861	−0.0002	−0.02	0	2.997	0.00003	0.459
Population density 1990 (people/km2)[b]	0.003	4.509	0.001	0.163	−0.008	−4.401	−0.0005	−0.753
Log (Cost82)[c]	−0.179	−8.4	−0.051	−0.25	0.292	9.198	0.017	0.638
Provincial dummy (Chiang Mai)	−0.199	−1.781	−0.053		0.321	1.251	0.061	
Provincial dummy (Mae Hong Son)	−0.734	−5.602	−0.159		0.868	3.485	0.17	
Provincial dummy (Phavao)	−0.341	−2.218	−0.084		1.438	5.116	0.388	
Provincial dummy (Nan)	−0.335	−2.942	−0.084		−0.472	−1.456	−0.006	
Provincial dummy (Lampang)	−0.571	−5.046	−0.131		0.047	0.161	0.032	
Provincial dummy (Phrae)	−0.405	−3.264	−0.097		0.55	1.793	0.113	
Provincial dummy (Lamphun)	−0.66	−3.73	−0.138		1.398	4.562	0.378	
Provincial dummy (Tak)	−0.342	−3.06	−0.088		0.94	3.786	0.179	
Provincial dummy (Phitsanulok)	0.379	2.913	0.12		0.835	3.003	0.175	
Provincial dummy (Khamphaeng Phet)	0.048	0.341	0.013		0.778	2.439	0.17	
Provincial dummy (Uthai Thani)	−0.021	−0.135	−0.009		1.972	7.59	0.578	
Soil dummy (Af60-1/2ab)	0.277	3.748	0.085		−0.572	−3.881	−0.022	
Soil dummy (Ag16-2a)	0.619	2.703	0.212		0.057	0.221	0.003	
Soil dummy (Ao107-2bc)	−0.202	−1.686	−0.052		−0.343	−1.553	−0.015	
Soil dummy (I-Lc-Bk-c)	0.012	0.076	−0.002		0.729	6.158	0.077	
Soil dummy (Lc100-c)	0.949	5.647	0.34		0.377	2.271	0.03	
Soil dummy (Ao108-2ab)	0.41	4.312	0.131		−0.15	−0.701	−0.008	
Soil dummy (Nd65-3ab)	−0.104	−0.848	−0.029		0.266	1.427	0.017	
Watershed dummy[b]					0.133	2.052	0.007	
Wildlife sanctuary dummy (1986)[b]	−0.334	−1.296	−0.077					
Constant	1.211	8.055			−4.037	−12.746		
Rho					0.018	0.017		
Log Likelihood	−2890.715							
No. of observations		4,355						

[a] Marginal Effects calculated from univariate reduced-form equations.

[b] Watershed dummy = 1 if the impedance-weighted distance to the nearest river is less than 3 km, assuming no primary roads. Wildlife sanctuary area dummy = 1 if pixel lay in a wildlife sanctuary in 1986. Population density is measured at the district level.

[c] Cost is measured as units of primary road traveled, in km.

clearing is 0.165 for protected areas and 0.125 for wildlife sanctuaries. These numbers are much lower than the average predicted probability of clearing for all sample points, which are 0.308 for the protected area sample and 0.26 for the wildlife refuge sample.

Impacts of Protected Areas and Wildlife Sanctuaries on Land Clearing

We turn now to the impact of protected areas on the probability that land is cleared. The coefficient of the protected area dummy in the clearing equation in Table 2 is insignificant, suggesting that protected areas had no statistically significant impact on forest clearing in North Thailand.[9] A much different impression is obtained from a univariate probit model with the same variables as equation [6]. In the univariate probit model (not shown) the coefficient of the protected area variable = -0.199, with a standard error of .076. The impact of switching $Y_{2i} = 1$ from $Y_{2i} = 0$ is to reduce the probability of clearing by 6 percentage points. This erroneous conclusion occurs because areas designated as protected are less likely to be cleared in the first place.

Measuring the impact of protected areas using the Chomitz and Gray/Deininger and Minten approach also leads to a different conclusion than Table 2. Their approach is to estimate a single equation probit model for clearing and then use this to predict the probability that pixels in protected areas are cleared. If we estimate a single equation model for clearing (without the protected area or watershed dummies) the average probability that protected areas are cleared equals 0.165. This is higher than the fraction of protected areas actually cleared (0.132). The analysis of Table 2 however indicates that this difference is not statistically significant.

The story is somewhat different for wildlife sanctuaries. In the single-equation version of equation [7] in Table 4, wildlife sanctuaries have a much larger impact on clearing (coefficient = -0.303 with standard error = 0.104) than do all protected areas. In Table 4, the coefficient of wildlife sanctuaries is approximately the same as in the single equation model (-0.334), but has a larger standard error (0.257). Had we been able to identify a better instrument for wildlife sanctuaries than the watershed dummy, we would very likely have estimated the impact of wildlife sanctuaries with greater precision. We therefore conclude that there is weak evidence to suggest that wildlife sanctuaries may have deterred deforestation in North Thailand.

These results are consistent with anecdotal evidence (Albers 1999). National parks in Thailand are designed without formal buffer zones to separate parks from adjacent land uses. Park boundaries often become de facto buffer zones, a result supported by our analysis. By contrast, anecdotal evidence suggests a deliberate policy to prevent encroachment in wildlife sanctuaries.

V. POLICY IMPLICATIONS OF THE MODELS

In this section we use the model to answer two questions of policy relevance for North Thailand. Which protected areas are under the greatest threat of encroachment? And what is the likely impact on protected areas of increased road building?

We define the areas of North Thailand under greatest threat of deforestation as those areas under forest cover in 1986 ($Y_1 = 0$) for which the predicted probability of clearing exceeds one-half. Two hundred ninety-three sample points are so threatened, and are plotted on Figure 5. Most of these points are clustered in the low-lying portions of the lower half of the region. This is not surprising given the importance of slope and elevation in explaining clearing. Although only 8 of the 293 points lie strictly within the boundaries of protected areas, most of the points are clustered near protected areas. The national parks of Nam Nao and Thung Salaeng Luang, near the southeastern border of North Thailand are surrounded by areas un-

[9] Following the suggestion of a referee, we also used the length of time a pixel had been designated protected to explain the probability of clearing. This variable was, however, insignificant.

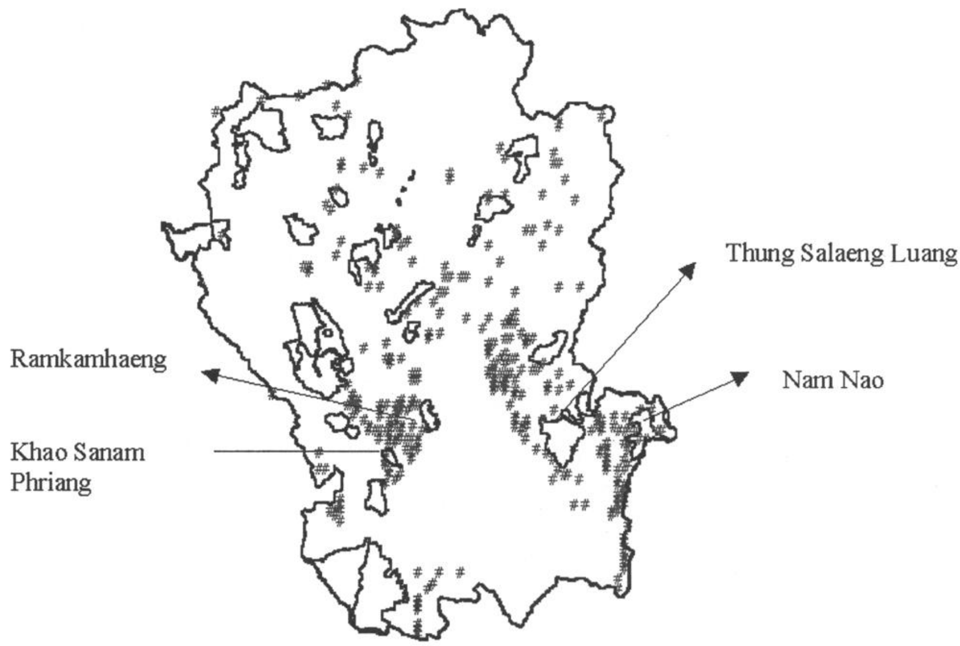

FIGURE 5
AREAS PREDICTED TO BE CLEARED

der high threat of conversion, as are the Khao Sanam Phriang wildlife sanctuary and the Ramkamhaeng national park, located to the west. We note, in the case of Thung Salaeng Luang, that three-quarters of the area of the park under forest cover in 1986 had a probability of clearing greater than or equal to 0.4.

To show how further road building might affect deforestation, we use equation [6] (Table 2) to compute the impact of a 100-unit reduction in impedance-weighted distance to market on the probability of clearing for all our sample points. This is equivalent to bringing a paved road one kilometer closer to each point. We then identify the areas where such an improvement in access raises the probability of clearing above 0.5. There are 207 such points. These points (along with the points predicted to be cleared in Figure 5) are plotted in Figure 6. Not surprisingly, the plots that we predict will be cleared as a result of road building are often clustered near the plots predicted to be cleared in Figure 5. In some cases we predict that road-building will result in clearing within protected area boundaries. In other cases, road building will lead to development around a park or wildlife sanctuary, suggesting the likelihood of eventual encroachment. This is especially true for the national parks labeled in Figure 6.

What are the policy implications of these exercises? Analyses such as ours can suggest where effort should be placed if the goal of protected area management is to prevent deforestation within park boundaries. While our work says little about what tools are likely to be effective in preventing encroachment, it suggests where these tools should be applied. Our models also suggest where road building is likely to increase the threat of encroachment in protected areas, but also where it will not. There are, for example, areas in Figure 6 where improved access to markets is likely to encourage land clearing (and may thereby achieve other objectives, such as reducing poverty), but where protected areas are not threatened.

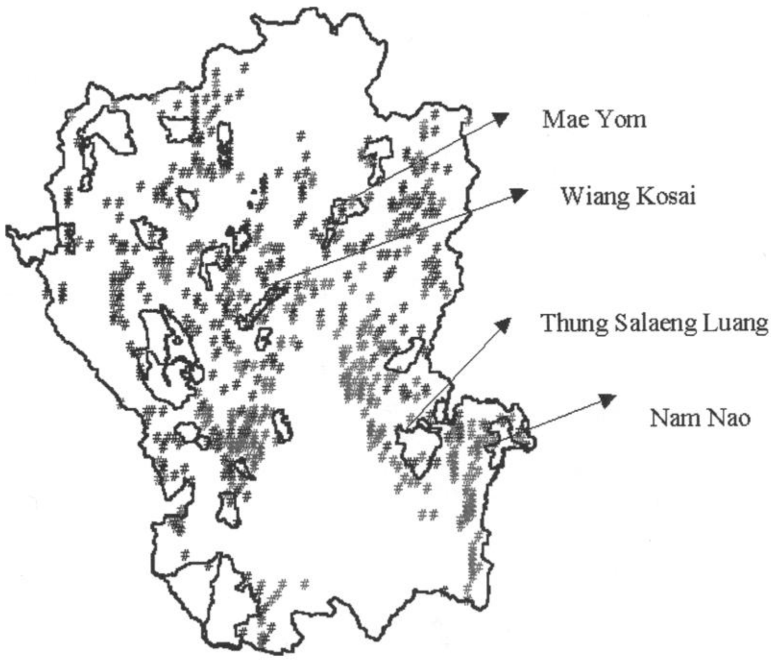

FIGURE 6
AREAS PREDICTED TO BE CLEARED AFTER A 100 UNIT REDUCTION IN IMPEDANCE-WEIGHTED DISTANCE

APPENDIX

SOURCES AND LAYERS COMPRISING THE GIS DATABASE

Data Layer	Source	Year	Attribute Categories
Land Use	Land Development Department Bangkok, Thailand	1986	15 land use categories
Political Boundaries	University of New Hampshire	1990	17 Provinces and 168 districts
Elevation	Digital Elevation Model (EROS web site) http://edcwww.cr.usgs.gov	NA	1 meter intervals
Rivers	Digital Chart of the World	Unknown	Perennial and non-perennial waterways
Roads	Digitized from paper maps provided by the Land Development Department, Thailand	1982	Paved and unpaved roads
Soil	FAO	1972	12 FAO soil categories
Population	Housing and Population Census, Thailand	1990	Population at the district level
Populated Places	Digital Chart of the World	Unknown	620 populated places in study area
Slope	Derived from the Elevation Map		Derived using ''slope'' module in IDRISI
Protected Areas	IUCN (World Conservation Union)/ The World Bank	1991	National Parks (IUCN category No. II) & Wildlife Sanctuaries (IUCN category No. IV)

PROPERTIES OF SOILS OF THAILAND (%)

FAO Soil Category	Too Wet	Infertile	Sandy	Loamy	Clayey	Slope 1–8%	Slope 8–30%	Slope >30%	Depth > 100cms
Af60-1/2ab	10	20	30	70	0	25	75	0	100
Ag16-2a	70	30	0	100	0	70	30	0	100
Ag17-1/2ab	55	20	15	85	0	35	65	0	100
Ao107-2bc	0	20	0	100	0	0	75	25	90
Ao90-2/3c[a]	0	10	0	65	35	0	25	75	20
I-Lc-Bk-c	0	0	0	100	0	16	50	34	66
Je72-2a	40	0	0	100	0	100	0	0	100
Lc100-c	0	0	0	100	0	0	25	75	10
Lg39-3ab	70	0	0	60	40	60	40	0	100
Ao108-2ab	10	60	0	90	10	30	70	0	100
Nd65-3ab	0	0	0	50	50	30	65	5	90
Vp64-3a	10	10	0	40	60	75	15	10	40

Source: FAO/UNESCO Soil Map of The World.
[a] Is the comparison Soil Category.
Note: These 12 categories of soils are an exhaustive list of soils occurring in North Thailand. The numbers in the table show the percentage of each soil category in all of Thailand with the property shown in the column.

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