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FIRE IN THE BRAZILIAN AMAZON: A SPATIALLY EXPLICIT MODEL FOR POLICY IMPACT ANALYSIS*

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ABSTRACT. This article implements a spatially explicit model to estimate the probability of forest and agricultural fires in the Brazilian Amazon. We innovate by using variables that reflect farm-gate prices of beef and soy, and also provide a conceptual model of field management and deforestation fires to simulate the impact of road-paving, cattle exports, and conservation area designation on the occurrence of fire. Our analysis shows that fire is positively correlated with the price of beef and soy, and that the creation of new conservation units may offset the negative environmental impacts caused by the increasing number of fire events associated with early stages of frontier development.

1. INTRODUCTION

Much international attention has recently focused on a specific form of environmental degradation, namely the widespread destruction caused by fire in

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tropical regions (Lambin, Geist, and Lepers, 2003). Fires that blaze out of control, so-called wildfires, have been of particular concern in recent years. During the El Niño Southern Oscillation (ENSO) episode of 1997–1998, they destroyed 80,000 km^2 of forest in Indonesia (Ruitenbeek, 1999), 8,500 km^2 across Mexico (Galindo et al., 2003), and 10,000 km^2 of primary forest in Roraima, a State in the Brazilian Amazon (Barbosa and Fernside, 2000). Although wildfires occur more often during ENSO episodes, fire represents a yearly threat to tropical forests such as found in the Amazon basin, where a rapidly expanding frontier is bringing human populations and their agricultural practices into pristine natural areas (Uhl et al., 1989; Uhl and Kauffman, 1990; Cochrane et al., 1999; Nepstad et al., 1999). In this part of the world, fire is the primary agricultural technology used by poor farmers and large ranchers alike to clear and prepare land for pasture or crops, and its accidental spread from intentional burn sites represents the main source of ignition for wildfires in the region.

Recent studies have attempted to estimate the environmental impacts of Brazil's development plans in the Amazon Basin (Laurance et al., 2001; Nepstad et al., 2001). Such studies have provided the policy context for research addressing the relationship between land cover and use of fire by farmers and ranchers (Uhl and Kauffman, 1990; Cochrane and Souza, 1998; Nepstad et al., 1999; Sorrensen, 2004) and social capital and fire contagion at the community level (Simmons et al., 2004). Nevertheless, modeling efforts to date have been limited in their capacity to predict future fire-related events because they fail to take into account key economic factors affecting land use. In the present paper, we attempt to rectify this shortcoming by considering the all-important role of market access to the use of agricultural technology, and by specifying a statistical model that can predict the likelihood of fire across the basin as a function of geo-referenced economic information. Our approach allows for spatial simulation of the potential impact of public policy changes on fire use, and subsequent wildfire vulnerability.

The paper is organized as follows. First, the conceptual model for spatially relating fire use to human land use is presented. Second, detailed descriptions of the methodology and data sources are provided. Lastly, we provide analyses of simulations of three different potential scenarios. The first scenario evaluates the effect of paving two highways (BR-163 and BR-230) on fire probability. The second scenario evaluates the impact of opening up the region to the exportation of beef. The third scenario explores the effect of recent plans for establishment of conservation units in the Amazon on the spatial changes in fire use.

2. BACKGROUND

Fire is probably one of mankind's most ancient agricultural tools (Stewart, 1956; Sauer, 1958), and even today its use represents the primary land management approach of an estimated four million Amazonian farmers who use it to facilitate land clearing, transform organic matter from vegetation into fertilizer, and control invasions of grasses and shrubs that compete with crops for

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nutrients.Despite widespread knowledge and understanding of fire management techniques (Sorrensen, 1998), few farmers invest the labor and capital necessary to employ them, and instead rely on nearby moist forests to contain the blaze (Wetzler and Omi, 1991; Nepstad et al., 2001). As a result, fire from intentional burn sites frequently escapes control and spreads to adjacent forests, or neighboring agricultural lands, causing unintended damage. Selective logging exacerbates forest vulnerability to fire by damaging residual trees, increasing debris on the forest floor, opening the forest canopy to desiccation, and altering the forest microclimate (Uhl and Kauffman, 1990; Cochrane et al., 1999; Nepstad et al., 1999). Finally, road building aggravates fire vulnerability by causing forest fragmentation, and enhancing forest accessibility to the myriad of agents seeking to exploit the region's vast resources.

Clearly, the use of fire, and the destructive potential of accidental fire, bears some relationship to the farming system and land cover in question (Walker et al., 2000; Sorrensen, 2004). Walker et al. (2000) suggests that accidental fire is most likely in areas dominated by subsistence farmers and ranchers who are dependent on fire, and least likely in areas with perennial plantations where fire represents a threat to production (Nepstad et al., 1999). Sorrensen (2004) suggests a link between exposure to accidental fire, and the frequency and intensity of biomass burning employed by land managers. Initial clearing of forest for annuals production (i.e., rice, beans, and corn) requires intense yet infrequent fires, while pasture maintenance results in frequent, low intensity fires. Finally, fire itself plays a role in crop choice and type of farming system selected by a farmer or rancher. Where use of fire is common, land managers will be hesitant to plant perennials and may instead opt for pasture-based farming to minimize risk. Compounding matters, pasture-based farming, which is a fire-dependent technology, may actually intensify fire ignitions and, thus, increase vulnerability to fire.

Although use of fire is a cost effective mode of weed control and fertilization, its misuse generates both substantial cost and environmental externalities. The average damage suffered by large farmers (i.e., greater than 5,000 ha) from uncontrolled fire amounts to about US$11,000 per farmer (Nepstad, 2001). During *fire season* in the Amazon, when farmers and ranchers burn because conditions are dry, fires have far-reaching regional impacts with smoke causing airport closures, numerous traffic accidents, and many respiratory illnesses. Overall, the economic costs of fire in the Brazilian Amazon are estimated to be $102 million or 0.2 percent of the regional GDP (Seroa da Mota et al., 2002). The Roraima wildfires of 1998 alone accounted for the loss of 12,000 head of cattle and 30 percent of region's crops estimated at US$36 million (Barbosa and Fernside, 2000).

In response to the widespread use of fires and associated damages, the Brazilian government initiated a series of fire prevention programs beginning with the *Sistema Nacional para a Prevenção e Combate de Incêndios Florestais* (PREVFOGO) established in the aftermath of the 1997 El Niño fires, and followed by the *Monitoramento de Quemadas e Prevenção e Controle de Incêndios*

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Florestais no Arco do Desflorestamento na Amazônia (PROARCO). In addition to these programs, regulations were instituted to control the agricultural applications of fire by putting in place a permitting process designed to ensure proper fire containment strategies are practiced, and that burning only occurs within the appropriate physical and climatic parameters (IBAMA, 2005). Finally, in 1998, new environmental laws made the starting of a forest fire illegal and punishable by two to four years in jail, or six months to one year if started *without malice* (Brazilian Environmental Crimes Law 9.605 of 2/12/98).

Despite these programs, concern lingers that problems associated with fire will be aggravated by large-scale infrastructure improvements in the Amazon as proposed in *Avança Brasil*, which calls for the expansion and paving of over 6,000 km of highway in the Amazon, the digging of canals and rechannelization of Amazonian tributaries, and the construction of numerous hydroelectric dams (Laurance et al., 2001; Nepstad et al., 2001). The ultimate objective of these improvements is to reduce transportation costs for agricultural products, thereby enhancing Brazil's competitive advantage in the global market for agricultural products such as soybeans. Nevertheless, environmental impacts are likely to be great. This paper adds to the environmental assessment literature in this regard by addressing infrastructure impacts on fire, taking into account economic considerations that have the potential to impact land use choices and the behavior of independent land managers. In this paper, we account for important economic considerations, and predict the likelihood of fires as a function of geo-referenced economic information.

3. CONCEPTUAL MODEL

Our conceptual model accepts the premise that the occurrence of fire is dependent on land use, number of potential ignitions, and environmental conditions such as vegetation type and climate. For instance, undisturbed forests far from frontier settlements are generally free from fire given their distance from farmers who depend on fire technology. On the other hand, forestlands at the agricultural frontier are at risk for fire because farmers and ranchers are likely to burn trees to clear and fertilize land, which also leaves adjacent forest vulnerable to accidental fire spread from intentional burn sites. Of course, environmental conditions affect both accessible and inaccessible areas independently. Indeed, remote, undisturbed forests that receive relatively little rainfall may show a relatively high risk of fire due strictly to lightning strikes. Finally, the likelihood of fire in a particular area is a function of the number of ignition sources, which in turn is a function of the number of properties found there.

We conceptualize fire as a probabilistic event affecting individual land parcels as functions of fire-inducing characteristics. Let F be the event that fire occurs on some arbitrary parcel, or pixel, which could be covered by forest or agricultural land use. Then the probability that F occurs, or $\Pr(F)$, is the union of the probability of the mutually exclusive events that the fire is a field maintenance fire or a forest fire, $\Pr(F_m \cup F_f)$. Field maintenance and

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forest fire events are mutually exclusive because they occur in different settings. Field maintenance fires, in the control of pasture weeds for example, occur on already cleared agricultural lands, L_a. What we refer to as forest fires consist of two types, also mutually exclusive, deforestation fires, F_d, and wildfires due to accidental lightning strikes and unintentional ignitions spreading accidentally from property-bound acts of deforestation and burning, F_w; both of these occur on forested lands, L_f. The probability of fire on an arbitrary pixel may then be written as

$$\Pr(F) = \Pr[(F_m \cup F_d \cup F_w)]$$

For the Amazon basin, F_w events are relatively uncommon, since most of the land is covered by tropical moist forest. Even though incidence of lightning storms are high in tropical regions, "natural fires" are an infrequent element of disturbance given that such strikes are more often than not accompanied by rain, which extinguishes the flame before wildfires ensue (Cochrane et al., 1999; Ramos-Neto et al., 2000; Stott, 2000) Indeed, most wildfires in tropical forested regions occur along forest edges in areas of active deforestation where land has been degraded, and within close proximity to farmers dependent on fire technology (Cochrane, 2003).[1] Thus, we take F_w as the null set, $\emptyset$, and rewrite the fire probability as,

$$\Pr(F) = \Pr[(F_m \cup F_d \cup \emptyset)] = \Pr[(F_m \cup F_d)]$$

We also assume that the Amazon basin consists of only agricultural lands and forest, in which case the universe of pixel types may be written as $\Omega = L_a \cup L_f$.[2] Hence, further manipulation of the probability yields,

$$\Pr(F) = \Pr[(F_m \cup F_d) \cap (L_a \cup L_f)] = \Pr[(F_m \cap L_a) \cup (F_d \cap L_f)]$$

given the associative properties of event unions, and the fact that field maintenance fires do not occur in forest, and deforestation fires do not occur in agricultural lands. Rewriting the above equation for estimation purposes, let y be a binary variable reflecting whether or not a fire occurs on some arbitrary pixel, where $y = 1$ if a fire occurs, and $y = 0$ if not. Similarly, let y_m and y_d represent field maintenance and deforestation fire events, respectively. Then

[1]Lightning strikes can be considered spatially random events but the character of burning is not random, since it is correlated with rainfall, humidity, forest fragmentation, and vegetative fuel loads (Mutch, 1970; Stott, 2000). Hence, even persistent natural fires are related to the agricultural use of land.

[2]Some of the basin consists of cerrado, the Brazilian savanna. Cerrado is generally converted to agricultural land before tropical moist forest, so it can be reasonably assumed that many of the agricultural pixels in our sample were originally cerrado. Cerrado, although considered a type of savanna, consists of dry and seasonal forests, as well as shrubbier grasslands. Thus, cerrado can be deforested.

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$$\Pr[y = 1] = \Pr[L_a]\Pr[y_m = 1 \mid L_a] + \Pr[L_f]\Pr[y_d = 1 \mid L_f]$$

Define latent variables y_m^* and y_d^* such that

$$\text{(1)} \qquad \Pr[y_m = 1 \mid L_a] = \Pr\left[y_m^* > 0\right] \quad \text{and} \quad \Pr[y_d = 1 \mid L_f] = \Pr\left[y_d^* > 0\right], \quad \text{and}$$

$$\Pr[y = 1] = \Pr[L_a]\Pr\left[y_m^* > 0\right] + \Pr[L_f]\Pr\left[y_d^* > 0\right].$$

Letting y_m^* and y_f^* be linear functions of observable variables, X, write

$$y_m^* = X_m\beta_m + e_m \quad \text{and} \quad y_f^* = X_f\beta_f + e_f$$

where the β's are associated coefficients and the e's are error terms. In the estimation, we consider four primary variable types reflecting market access, physical conditions, institutional environment, and nearness to ignition sources. Of prime importance to agricultural activity—and therefore the use of fire—are market access variables represented in the present application by farm-gate prices for cattle and soy, the two main commercial products from the region. Specifically, we assume optimal land use under a Thunian concept linking market centers for beef and soy to location-specific production. This implies decreasing intensity of production—and farm-gate prices—with distance from the market, as well as larger holdings. Since inputs such as fertilizers, pesticides, and capital are relatively expensive in low income settings, fire is widely used by farmers and ranchers alike. Thus, in general, the density of both field maintenance and deforestation fire events diminishes with distance, if only because there are fewer people on the land per unit area given the increased size of holdings.[3]

Although farmers and ranchers use fire as a technology of production, it is a physical phenomenon depending on physical conditions. In particular, climate variables such as the amount of precipitation and the moisture holding potential of soils affect the likelihood of fire occurrence. Also affecting the likelihood is the institutional environment in which land parcels are located. In the Amazon basin, for example, conservation areas and indigenous reserves might be expected to experience lower fire risk given both Brazilian law and the farming practices of native populations. As for deforestation fires, in addition to physical conditions, these will also be linked to market access variables, given such fires are set for agricultural purposes. Specifically, in forest areas farmers (and ranchers) burn trees both to clear land for agricultural production and to provide a ready source of nutrients for their low technology farm systems. For

[3]The fact that farms are smaller closer to markets in the Brazilian Amazon is an empirical observation from agricultural census tracts (Chomitz and Thomas, 2001). The Thünian model predicts higher farm intensity (i.e., larger inputs/land ratio) as one moves closer to the market but there is not an equivalent theoretical necessity for smaller farm size units (Dunn Jr., 1954; Nerlove and Sadka, 1991). Alonso (1964) and Fujita (1989) adapt von Thünen to urban spaces, explicitly defining lot size as a variable. Fujita shows that lots sizes, or property sizes, increase with distance from the urban core.

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this type of fire we also include a distance to deforested land since given this is likely to reflect localized conditions of accessibility.

Thus, the latent variables are given as

$$y_m^* = \beta_b^m P_b + \beta_s^m P_s + \beta_t^m P_t + \mathbf{v}\boldsymbol{\beta}_v^m + e_m \quad \text{and}$$
$$y_d^* = \beta_b^d P_b + \beta_s^d P_s + \beta_t^d P_t + \beta_d X_d + \mathbf{v}\boldsymbol{\beta}_v^d + e_d$$

where P_b and P_s are farm-gate prices for beef and soybeans respectively, P_t is the level of protection (conservation units, indigenous lands), X_d is distance from already deforested land, $\mathbf{v}$ is a vector of other control variables (e.g., rainfall, soil conditions, vegetation type, etc.), and the β's, including those in $\boldsymbol{\beta}_\mathbf{v}$, are associated parameters. We now assume an identical normally distributed error term ($e_m = e_d = e$) and that coefficients are the same for field maintenance and deforestation fires, given that agricultural reasons motivate the burning of trees.[4] Observing that the distance variable can be added to the latent variable, y_m^*, because for agricultural pixels it will be 0, and defining $y_m^* = y_d^* \equiv y^*$, we have

$$y^* = Z + e, \quad \text{where} \quad Z = \beta_b P_b + \beta_s P_s + \beta_t P_t + \beta_d X_d + \mathbf{v}\boldsymbol{\beta}_v$$

Substituting for y_m^* and y_d^* in Equation (1) and noting that $\Pr[L_a] + \Pr[L_f] = 1$ yields $[y = 1] = \Pr[y^* > 0]$, the probability of fire may now be given as

$$\mathrm{P}(y = 1 \mid \mathbf{x}) = \mathrm{P}(y^* > 0 \mid \mathbf{x}) = \mathrm{P}(e > -\mathbf{x}\boldsymbol{\beta} \mid \mathbf{x}) = \boldsymbol{\Phi}(\mathbf{x}\boldsymbol{\beta})$$

where $\boldsymbol{\Phi}(\cdot)$ is the cumulative normal density function, $\mathbf{x} \equiv (P_b, P_s, P_t, X_d, \mathbf{v})$, and $\boldsymbol{\beta} \equiv (\beta_b, \beta_s, \beta_t, \beta_d, \boldsymbol{\beta}_\mathbf{v})$.

With its present structure, the model has little or no explanatory power to predict fire in forested regions dominated by pure subsistence farming, where market conditions do not strongly affect the intensity of land, the size of holding, or the agricultural decision-making of resident populations. Fortunately, pure subsistence farming is rarely observed in the Amazon basin (Walker, 2003). Further limitations include its inability to address the impact of landscape configuration and disturbance or drought histories on fire vulnerability. Landscape fragmentation at scales finer than our 5 × 5 km analysis can be directly linked to the probability of fire (Cochrane, 2001; Cochrane and Laurance, 2002), with recurrent fires (Cochrane and Schulze, 1998) becoming more prevalent as a system of positive feedbacks makes fires endemic in a region (Cochrane et al., 1999). In addition, intense droughts or long-term moisture deficits can reduce the water available to vegetation, and thereby lead to large areas of intact forest becoming susceptible to fire in some years (Nepstad et al., 1999).

[4] Assuming the same coefficients may seem strong. We conducted a sensitivity test estimating for two samples, with and without agricultural pixels. The results, presented in Table 3, indicate the reasonableness of the assumption.

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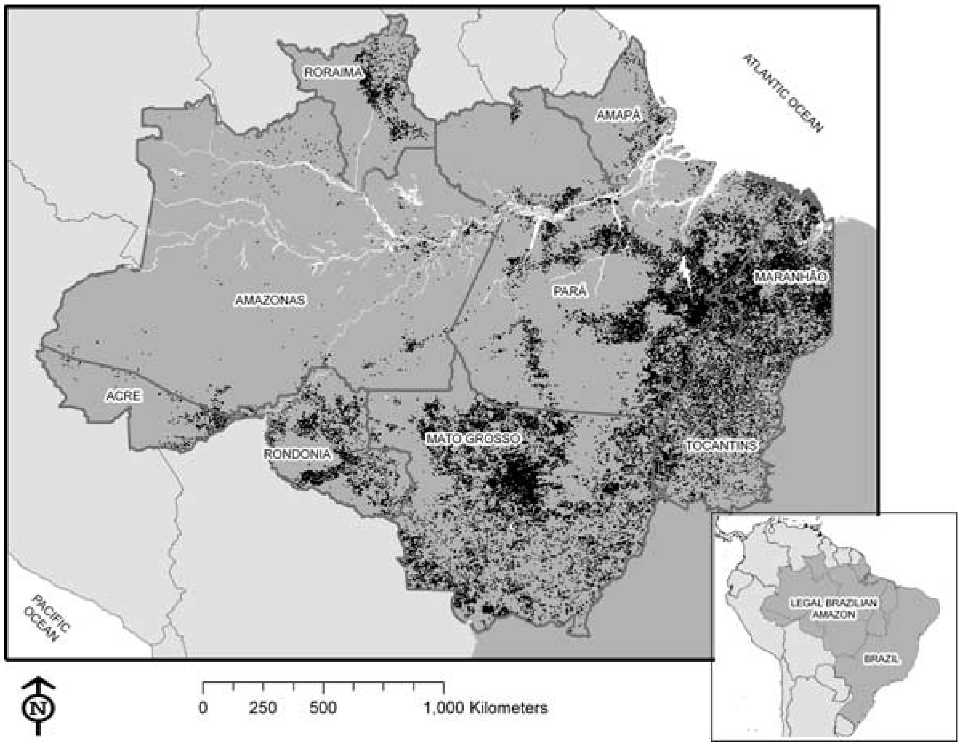

FIGURE 1: Hot Spots Detected by AVHRR Sensors Between January and December 2001.

4. ESTIMATION OF THE MODEL

Model Variables and Data Sources

The data used in the probit regression were derived from a series of digital maps covering the entirety of the Legal Brazilian Amazon,[5] which were incorporated as data layers within a geographic information system (GIS). Each layer was divided into 5×5 km cells in a raster environment, with each cell representing an observation in the statistical analysis ($n = 201{,}352$). The following is a discussion of the model variables and data sources.

The dependent variable, *Fire*, is a discrete variable reflecting whether fire occurred in a cell (1 = yes and 0 = no). Hot spot maps, obtained from the Brazilian Space Agency, *Instituto Nacional de Pesquisas Espaciais* (INPE) website (http://www.cptec.inpe.br/products/queimadas/), were used to identify the presence of fire (Figure 1). The information on this map is derived from imagery from

[5]The Legal Brazilian Amazon comprises the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins, Mato Grosso, and Maranhão west of the 44° meridian.

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the Advanced Very High Resolution Radiometer (AVHRR) sensors on NOAA weather satellites. These sensors measure the amount of thermal energy being emitted or reflected from the Earth. They provide temperature estimates for a grid of nominal 1 km pixels. Although not designed for fire detection, the AVHRR data has been widely adopted for fire monitoring purposes. Depending on the algorithms and thresholds used, the AVHRR data can identify hot spots, represented as geo-referenced points, which are thought to be the consequence of fire. The techniques used by INPE provide fire detection for fire greater than or equal to 30 m in length and half a meter in depth (INPE, 2001). INPE receives and processes data from two satellites with a temporal resolution of 12 hours each, which provide four images every day of the same area. While certain low intensity, understory fires might pass undetected, clouds and other atmospheric interferences are less likely to mask the results (Cochrane, 2003). In this analysis, we used hot spot information for the entirety of 2001. The distribution of the number of possible fire detections by cell was highly skewed and asymmetrical. Of the 201,352 sample cells, approximately 84 percent had no detected hot spots. Cells with between one and four detected hot spots comprised 13 percent of the pixels, those with five to nine represented 2.5 percent of the pixels, and those with more than 10, amounting to 1,001 cells, represented a limited 0.5 percent of the total sample in 2001. For the dependent variable *Fire*, if hot spots were detected in a cell, the value was coded one, if not it was coded zero.

Two important economic measures were included in the analysis as independent variables, (1) *Farmgate price of beef (Reais\$/ton)* and (2) *Farmgate price of soybean (Reais\$/ton)*. These independent variables are used as proxies for land rents from extensive, ranching, and intensive, soybean cultivation, land uses. The farmgate price (P) at a given cell i is the price (M) paid at markets (e.g., slaughter houses, ports, soybean processing plants, grainaries, etc.) at locations j minus the costs of transportation (CT) from i to j using existing infrastructure. For each cell i, the farmgate price is therefore defined as:

$$\mathrm{P}_i = \mathrm{Max}(\mathrm{M}_j - \mathrm{CT}_{ij} : j = 1, \dots, k).$$

Here, k is given as 55, representing 42 slaughterhouses and 13 soy processing plants.

Prices of beef and soybeans paid at slaughter houses and processing plants, as well as transportation costs, were established through field interviews (Costa et al., 2001). The transportation costs (CT) between any i and j were calculated within ArcView using the CostDistance function. We assign a “friction value” for each cell, which represents the costs of traversing the cell (Table 1). The friction value varies according to the mode of transportation (e.g., truck, boat, train) and quality and type of infrastructure (e.g., paved or unpaved roads, rivers, railways). For example, transport of cattle by truck on an unpaved road was R\$ 0.39 ton^{-1} km^{-1} in 2000, while the cost for similar transport on paved roads was R\$ 0.133 ton^{-1} km^{-1}. These costs were taken from Verissimo et al. (1998) and Costa et al. (2001). The CostDistance function calculates the cumulative

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TABLE 1: Transportation Costs According to Different Modes of Transportation and Infrastructure Quality

Mode/Type	$R\$$ ton^{-1} km^{-1}
Water	0.10
Asphalted road	0.13
Dirty road	0.39
Natural bed—savanna	1.30
Natural bed—forest	2.60

cost of transportation from each source (e.g., slaughter houses, ports, etc.) to each cell. Hence, the farmgate price for soybean and ranching incorporates three variables: distance to markets, transportation costs, and product prices. Such prices may be endogenous to deforestation, since they are higher near towns with beef and soy processing facilities, and such towns could be located in areas attractive to deforestation. However, we control for this possible effect with variables reflecting resource quality (soils and rainfall, see below), as is often done in deforestation studies (e.g., Chomitz and Gray, 1996). In addition, we note that there are relatively few destinations ($n = 55$), many of them probably already located in previously deforested areas, relative to the recent time period of the analysis.

Finally, a variety of control variables were included in the model as follows. *Distance to deforested area* was included to capture the fact that deforestation tends to "sprawl" from previously deforested areas (Chomitz and Thomas, 2003). To calculate this measure, we used a map of deforestation up to 1991 provided by IBGE (1997), and we constructed a Euclidean distance-to-deforestation layer applying the FindDistance function in ArcView spatial analyst module. *Annual precipitation (mm)* was included to account for the variation in precipitation across the basin. The rainfall data were provided by the CAMREX project at the University of Washington. In the analyses, rainfall amounts were interpolated between meteorological stations (Chomitz and Thomas, 2001) and each 5×5 km cell was given a precipitation value equal to the mean annual rainfall value that occurred between 1970 and 1996. As shown in Table 2, there is a sharp difference in terms of fire evident at the 2000 mm level. For cells with less than 2000 mm average rainfall, 28.5 percent of the cells showed evidence of fire in 2001 compared with only 8.5 percent of cells with greater than 2000 mm average precipitation. Furthermore, although cells with less than 2000 mm rain comprise less than 38 percent of the basin, they contained more than 67 percent of the cells with detected hot spots.

An additional control variable is a dummy variable reflecting whether the cell was in a *Protected area* (1 = yes and 0 = no), as identified on an IBGE (1997) map. If a cell was in a protected area, including parks, national forests, and indigenous reservations, it was expected that it would be less vulnerable to fire because legislation protects these areas from logging, agriculture, and

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TABLE 2: Counts of Cells with and without Hot Pixels Detected, by Categories

	No fire	Hot pixel	Total
State			
AC	5,733	383	10,517
AP	5,350	389	5,739
AM	62,387	723	6,116
RR	8,081	938	10,897
RO	7,486	2,065	9,551
TO	6,981	3,916	9,019
MA	5,294	5,223	36,277
PA	41,616	8,510	50,126
MT	26,173	10,104	63,110
Rainfall			
1.2–1.4 m	363	102	465
1.4–1.6 m	2,290	1,139	3,429
1.6–1.8 m	20,517	9,332	29,849
1.8–2.0 m	31,145	11,197	42,342
2.0–2.2 m	30,323	5,414	35,737
2.2–2.4 m	41,752	2,815	44,567
2.4–2.6 m	18,105	1,339	19,444
2.6–2.8 m	11,503	689	12,192
2.8–3.0 m	5,770	152	5,922
3.0–3.2 m	2,805	67	2,872
3.2–3.4 m	3,408	3	3,411
3.4–3.6 m	1,120	2	1,122
Soil limiting factors			
Seasonal excess water	259	135	394
Salinity/alkalinity	1,654	236	1,890
Impeded drainage	9,036	237	9,273
Shallow soils	6,102	591	6,693
Low organic matter	2,380	647	3,027
High P,N & organic retention	2,651	687	3,338
High aluminum	1,216	1,335	2,551
Excessive nutrient leaching	5,998	1,520	7,518
Minor root restricting layer	11,952	2,962	14,914
Low water holding capacity	8,364	3,379	11,743
Low nutrient holding capacity	83,700	6,156	89,856
Seasonal moisture stress	35,789	14,366	50,155
Vegetation			
Campinarana	3,319	48	3,367
Forest-campinarana	7,995	312	8,307
Pioneer	4,024	601	4,625
Forest-cerrado	11,569	4,027	15,596
Cerrado	21,224	8,465	29,689
Forest	120,970	18,798	139,768
Land status			
Protected area	47,799	2,299	50,098
Non protected area	121,302	29,952	151,254

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ranching, and subsequently deforestation and wildfire. In addition, many of the fire prevention measures (i.e., PREVFOGO) have concentrated their efforts in conservation areas. Dividing the cells with hot spots among protected areas (e.g., parks, national forests, indigenous reservations), Table 2 shows that in unprotected lands, which comprise 75 percent of the Amazon, 20 percent had evidence of fire accounting for nearly 93 percent of all cells with possible fires. The protected areas, conversely, held only 7 percent of the fire cells, with only 5 percent having potential fires.

A set of dummy variables was created to represent *Soil limiting factors*, which may impede agricultural activity, influence forest cover, and impact fire vulnerability. The soil-limiting factor variables were derived from a map generated by the Soil Survey Division of World Soil Resources of the U.S. Department of Agriculture (Eswaran and Reich, 1999). The twelve dummy variables (1 = present and 0 = absent) included: (1) low organic matter; (2) seasonal excess water; (3) minor root restricting layer; (4) impeded drainage; (5) seasonal moisture stress; (6) high aluminum; (7) excessive nutrient leaching; (8) low nutrient leaching capacity; (9) high P, N, and organic retention; (10) low water-holding capacity; (11) salinity/alkalinity; and (12), shallow soils. According to Table 2, distribution of the cells with fire evidence by limiting soil factors shows that 44 percent of all detected pixels are within regions limited by seasonal moisture stress. When normalized by numbers of total cells, the most fire prone are soils with high aluminum content in which 52 percent showed evidence of fire.[6] At the other extreme, poorly drained soils had less than 3 percent of cells with any possible fires.

Dummy variables were also created to account for *vegetation*, each type associated with different degrees of fire vulnerability. The IBGE (1997) vegetation cover type map, which provides the vegetation cover type prior to deforestation, was used in the analyses. We created dummy variables (1 = yes and 0 = no) for each of the six vegetation types used in first level classification schemata of IBGE, including: (1) forest, (2) savanna, (3) campinarana grasslands, (4) forest-savanna, (5) campinarana-forest, and (6), pioneer species. When distributed by vegetation type, Table 2 shows that 58 percent of all cells with fire fall within forest. Another 39 percent fall within cerrado or cerrado-forest transition areas. When normalized by area, 13 percent of forest cells show evidence of fire, while 29 percent of cerrado and 26 percent of transition areas show it.

Finally, State dummy variables account for potential institutional variation in fire regulation enforcement and state-instituted policy. As shown in Table 2, suspected fires concentrated primarily within states along what is referred to as the *Arc of Deforestation* (Nepstad et al., 1999). In absolute terms, Mato Grosso and Pará had the most fire detections, comprising 31 percent and 26 percent respectively, followed by Maranhão (16 percent) and Tocantins. When normalized by area (cells per state) to provide a density of fire detections, Maranhão

[6]Oxisols (yellow and red-yellow latosols) are the major soil unit in these areas.

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showed fire detections in nearly 50 percent of all cells. Tocantins (35 percent) and Mato Grosso (28 percent) also had high densities of fire detection. In comparison, Amazonas, the state with the lowest density fire detection, had only 1.1 percent of its cells showing evidence of possible fire.

Data Sampling and Estimation Procedure

The possibility of fire spread from one grid cell to an adjacent one can bias the parameters estimation owing to severe spatial autocorrelation in the dependent variable. To reduce potential problems of spatial autocorrelation, we subsampled the data systematically by selecting cells from every third row and column throughout the basin (Anselin, 2002). A 15 km distance between sampled cells is sufficient to isolate individual, noncontagious fire events since no large scale incident was reported in 2001, to our knowledge. In addition, although some properties are quite large in the region and range into the hundreds of square kilometers in size, these are the exception and not the rule. Thus, fire adjacency across pixels attributable to unified management decisions is likely to be nil in the sample.

The resulting subset, 22,362 observations, was used in the subsequent regression analyses. We also included the column and row cell number to the set of independent variables to capture the spatial trend in the data and further reduce spatial correlation (Chomitz and Gray, 1996). The probit variance matrix was calculated using the Huber–White method, which is robust to dependencies in the error term.[7]

5. REGRESSION RESULTS

Table 3 provides the results from two probit regression analyses. Of particular importance for this paper is the statistical and practical significance of the economic indicators and key control variables, which represent important elements of the conceptual model presented. In Model 1, first column, where we use pixels located in both agricultural and forested areas, the estimated model predicts that *Fire* is directly related to the price of cattle and soybean. Figure 2 shows the change in the probability of having fire if the price of cattle is changed with all other variables held constant at average levels. For example, increasing the price from R$600 to R$700/ton would increase the probability of having fire by 3.3 percent. This change in the fire probability may seem small in absolute terms, but since the unconditional probability of fire is 16 percent this actually represents a 20.6 percent increase in the likelihood of fire.

In comparison, the predicted effect of an increase in the price of soybean is non-monotonic, with an initial decrease in the probability of fire followed by subsequent increases for continued price increases. The range of prices at

[7]The use of a robust matrix in a probit estimation can be justified as a result of possible dependence over space, not because the response model is misspecified or heteroskedastic.

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TABLE 3: Probit Regression Results of Fire in the Amazon

Variables	Model 1[a] ($n = 22{,}362$)	Model 2[b] ($n = 21{,}443$)
Farmgate price of beef (R/ton)	0.007	0.007
	(0.001)	(0.001)
Farmgate price of beef (R$/ton)^2	−0.000004	−0.000004
	(1.22E−06)	(1.19E−06)
Farmgate price of soy (R$/ton)	−0.005	−0.005
	(0.0007)	(0.0007)
Farmgate price of soy (R$/ton)^2	0.00002	0.00002
	(2.44E−06)	(2.49E−06)
Annual precipitation (mm)	0.002	0.002
	(0.0008)	(0.0009)
Annual precipitation (mm)^2	−0.000001	−0.000001
	(1.98E−07)	(2.07E−07)
Distance to deforested area in 1991 (km)	−0.007	−0.007
	(0.0005)	(0.0005)
Distance to deforested area in 1991 (km)^2	0.00002	0.00002
	(2.02E−06)	(2.07E−06)
Protected area	−0.605	−0.614
	(0.039)	(0.039)
Seasonal excess water	0.568	0.337
	(0.259)	(0.292)
Minor root restricting layer	0.303	0.280
	(0.099)	(0.100)
Impeded drainage	−0.276	−0.318
	(0.131)	(0.132)
Seasonal moisture stress	0.237	0.207
	(0.092)	(0.092)
High aluminum	0.122	0.102
	(0.121)	(0.124)
Excessive nutrient leaching	0.369	0.318
	(0.111)	(0.114)
Low nutrient holding capacity	0.253	0.212
	(0.094)	(0.094)
High P, N, & organic retention	0.060	0.087
	(0.124)	(0.132)
Low water holding capacity	0.200	0.163
	(0.101)	(0.102)
Salinity/alkalinity	0.025	0.023
	(0.166)	(0.166)
Shallow soils	−0.004	−0.051
	(0.119)	(0.123)
Forest	0.396	0.371
	(0.214)	(0.216)
Forest-campinarana	0.638	0.621
	(0.225)	(0.226)

(Continued)

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TABLE 3: Continued

Variables	Model 1[a] (n = 22,362)	Model 2[b] (n = 21,443)
Pioneer	0.247	0.190
	(0.233)	(0.235)
Savanna	0.018	−0.003
	(0.219)	(0.221)
Forest-savanna	0.317	0.302
	(0.218)	(0.220)
Acre	−0.240	−0.215
	(0.112)	(0.118)
Amazonas	−1.042	−1.005
	(0.096)	(0.099)
Roraima	−0.805	−0.745
	(0.128)	(0.132)
Pará	−0.264	−0.268
	(0.097)	(0.101)
Amapá	−0.609	−0.560
	(0.147)	(0.151)
Tocantins	−0.174	−0.214
	(0.111)	(0.116)
Maranhão	−0.136	−0.199
	(0.128)	(0.133)
Mato Grosso	−0.176	−0.193
	(0.065)	(0.069)
Xcoord	0.002	0.002
	(0.0002)	(0.0003)
Ycoord	−0.001	−0.0002
	(0.0003)	(0.0003)
Constant	−5.348	−5.338
	(1.036)	(1.075)
Log-likelihood	−7208	−6621
Pseudo R^2	.274	.285

Notes. Standard errors between parentheses below estimated parameters.
[a]Sample of pixels containing agricultural and forested areas.
[b]Sample containing only pixels outside deforested area in 1991.

which we usually observe soybean selling is closer to the upper bound shown in the graphic (>R$200/ton). Therefore, this result contradicts one of our initial hypotheses that higher prices of soybeans are associated with lower probabilities of fire. In fact, the results may suggest that higher soybean prices create greater incentive for the clearing of land to plant soybeans. Therefore, those fires may be related to new clearings (deforestation) and not necessarily with intensification of agricultural practices.

With regards to *distance to deforested area in 1991*, results were both statistically and substantively significant with the average probability of fire in

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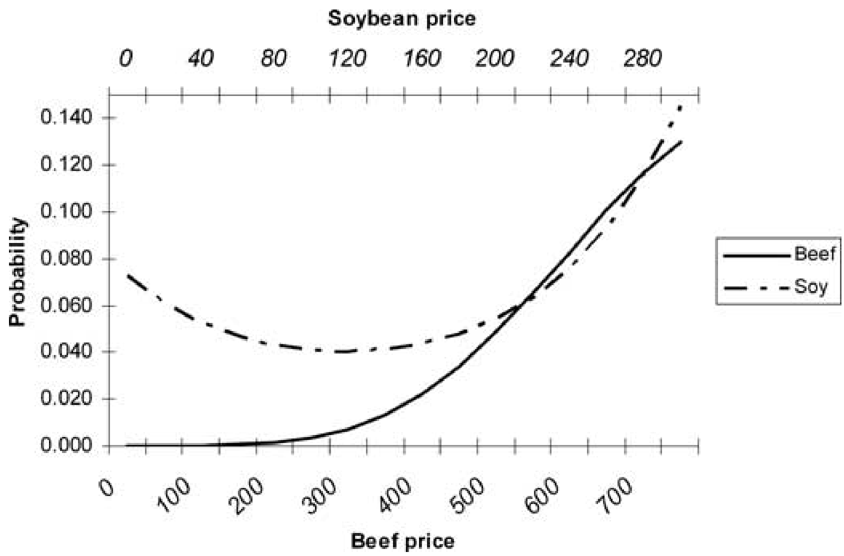

FIGURE 2: Probability of Fire Occurrence with Respect to Farmgate Prices of Soy and Cattle.

deforested areas estimated at 9 percent. However, this probability decreases with distance to only 3 percent at 156 km. The estimated parameters of the level and squared terms are negative and positive respectively, indicating that the probability of fire decreases as we move away from deforested areas, but eventually increases at very large distances, which seems to be an artifact of the quadratic form used since 94 percent of fire events were observed within 150 km from deforested area in 1991 and the maximum observed value for this variable was 1092 km.

Annual precipitation was also statistically significant, with increasing levels of mean annual rainfall suppressing fire probability (Figure 3).[8] This effect could be both direct and indirect. The direct effect is obvious, higher rainfall levels reduce the chance of vegetation becoming dry and hence flammable. The indirect effect is not as clear, but may arise from the decrease in agricultural productivity that has been observed in areas of the Amazon with high rainfall. The poor agricultural potential may decrease forest clearing for agriculture, and, consequently, reduce the potential of accidental fires spreading from planned burn sites. For example, Chomitz and Thomas (2001) determined that the average stocking density of cattle was 0.38 head/ha for areas with mean rainfall of 1600 mm, but only 0.27 head/ha in regions with 2300 mm of annual

[8]The rainfall gradient increases north and westward and one reviewer raised the concern that the row and column number variables might be capturing part of this effect. We ran a regression without the coordinate variables and the results change only slightly. Hence, we are confident that the rainfall effect is not underestimated.

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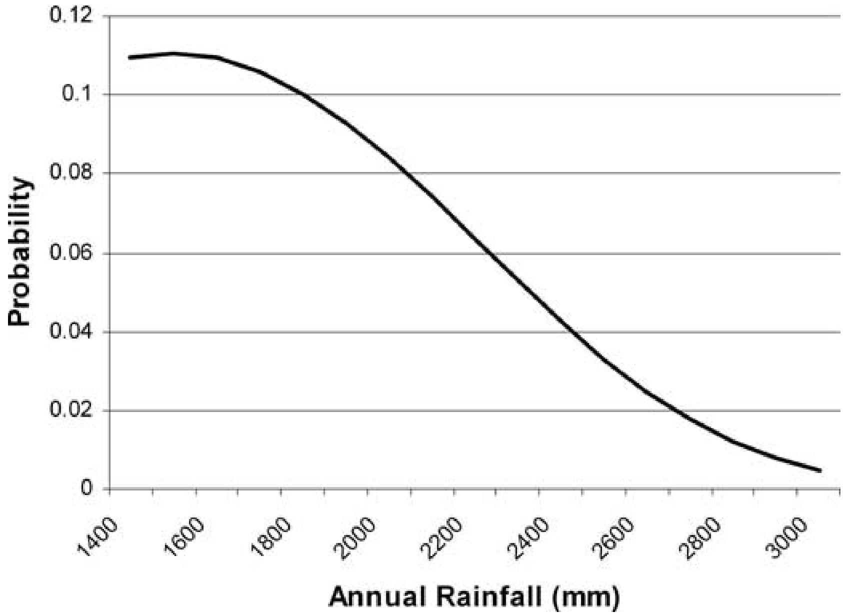

FIGURE 3: Probability of Fire Occurrence with Respect to Annual Rainfall.

rainfall with other factors, like distance to roads, held constant. Under these conditions, the creation of new pastures would be less likely in areas experiencing high rainfall. Our model agrees with this supposition and predicts a 5 percent decrease in the likelihood of fire over the 1,600 *versus* 2,300 mm rainfall interval.

As Table 3 shows, *Protected areas* was statistically significant with land under federal protection, such as indigenous reserves, military bases, and conservation areas, experiencing on average 5.4 percent less chance of fire. This represents a 33 percent decrease from the unconditional probability. Obviously, the human population density of protected areas is very low, and in some areas human settlement or use is strictly prohibited. In the case of indigenous populations, slash-and-burn agriculture is practiced on a small scale, but cattle grazing, and the concomitant demand for pasture, is virtually nonexistent. In the next section, we will simulate the effect of creating additional conservation units upon the probability of fire.

The *soil-limiting factors* also proved to be statistically significant, although the interpretation of the coefficients is difficult. Interpretation of results are further complicated because they must be considered with respect to the omitted dummy variable "low organic matter." In general, the results show that the soil-limiting factor most associated with increased chance of fire was "seasonal excess water," which was approximately 9 percent more likely to experience fire than the omitted dummy category. We believe that this surprising result is due to the concentration of rainfall in these areas during a heavy wet season

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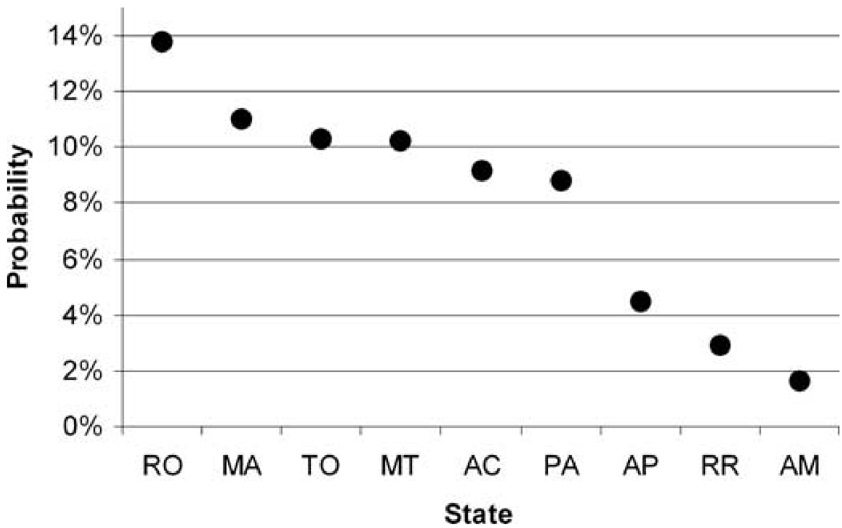

FIGURE 4: Mean Probability of Fire Occurrence in Legal Amazonia States.

with a comparably intense dry season thereafter. During these dry periods, forests are cleared and pasture maintenance fires are set. The interpretation of the vegetation effects upon fire is similarly complicated. In this case, results show that the "Floresta-campinara" class has an 11 percent greater chance of experiencing fire than the omitted "Campinarana" class.

Finally, the *State* dummy variables proved to be very significant (Figure 4), both statistically and substantively. Only Maranhão and Tocantins were not statistically different from the omitted state (Rondonia) in their probability of experiencing fire. Rondonia, with a 14 percent likelihood of fire, was the most fire prone state when all other factors were held constant at mean value. The Amazonian states of Amapá, Roraima, and Amazonas showed very low probability of fire. For example, the probability of observing fire in Amazonas was only 1.65 percent evaluated at mean value. These results lend support to our contention that differences in state policies, such as those aimed at environmental enforcement, might influence deforestation and fire.

In our conceptual model, we assumed the same set of parameters for field maintenance and deforestation fires. We tested this assumption by running a separate regression using a subset of pixels that are located outside deforested areas of 1991. The results presented in the second column of Table 3 indicate that the parameters are indeed very similar, particularly for the continuous independent variables.[9]

[9]We also ran a third regression using pixels at least 15 km far from nearest deforested area in 1991. The results are similar to the ones reported in column two and are available upon request to the first author.

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TABLE 4: Accuracy of Predictions of Base Model

		Actual		
		No fire	Fire	Total
Estimated	No Fire	116,580	3,589	120,169
	Fire	52,521	28,662	81,183
	Total	169,101	32,251	201,352
% correct predictions*		69%	89%	72%

*Using 0.1601 as the cutoff probability (sample unconditional probability).

To evaluate the overall accuracy of the probit model for making fire predictions, an unconditional "cut-off rate" was used (i.e., probabilities larger than 0.16 were considered to predict fire, otherwise no fire was predicted). As Table 4 shows, the probit model correctly predicted 69 percent of the 2001 fires, indicating that the model variables increase our capacity to predict fire when compared to the unconditional probability prediction. Overall, the model over predicts fire occurrence in 31 percent of the cells (i.e., predicted fires in cells, which did not actually have fire). The cases with "under-prediction" are less, only 11 percent. The spatial accuracy of the predictions varied considerably between states, with nearly 100 percent of fires accurately predicted in states experiencing high densities of fire, such as Mato Grosso, Maranhão, Tocantins, and Rondônia; although there was a generally high level of "over-prediction" (commission errors) in these States as well. The opposite was observed in states that had low levels of fire, like Amapá and Amazonas. In these locations, nearly all regions of "no-fire" were correctly predicted, but there were substantial omission errors for fire occurrence.

6. SIMULATIONS

Figure 5 shows the estimated probability of fire for each 5×5 km cell in Amazônia based on the estimated parameters from the probit regression. As this figure reveals, fire probability across the Amazon basin varies greatly from virtually no probability of fire in the western states to probabilities as high as 85 percent in the eastern and southern reaches of the basin. Nevertheless, the probability of fire is not stagnant, and may be greatly influenced by infrastructure improvements, expanded markets for agricultural products, and changes in environmental policy. In this section, we use the estimated parameters from the probit model to simulate the potential impact of economic and environmental policy changes to fire probability. In particular, we consider how the reduction of transport costs brought about by road paving (simulation 1), and the expansion of international markets for beef exports resulting from the eradication of hoof-and-mouth disease (simulation 2), may exacerbate fire occurrence. We also simulate how environmental policy directed at increasing land in conservation (simulation 3) may, in turn, mitigate fire vulnerability.

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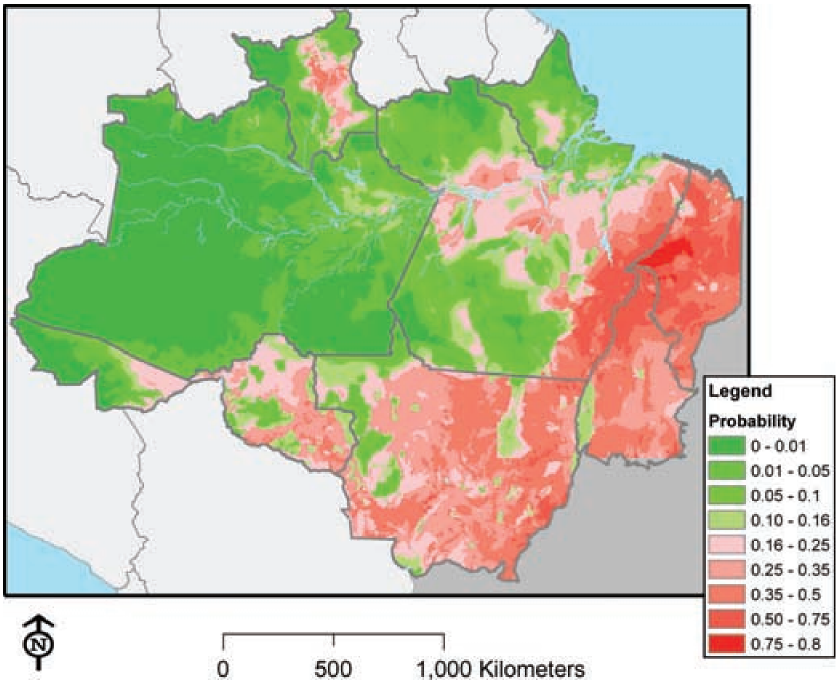

FIGURE 5: Estimated Probability of Fire in Amazonia—Base Case Scenario.

Scenario 1. Paving of BR-230 (Transamazon Highway) and BR-163 (Cuiabá–Santarém Highway). The federal government in Brazil has again begun investing in the improvement of infrastructure throughout the Amazon as part of the *Avança Brasil* Program. The motive for paving the BR-163 highway is to facilitate the expansion of the agricultural sector in the center-west portion of the Amazon, primarily the state of Mato Grosso. This investment will reduce the transportation time and costs of getting soybeans to external markets, making this land-use more competitive. The paving of the Transamazon highway (BR 230) is intended to take advantage of the hydroelectric potential of the Xingu River. Plans to construct a hydroelectric dam at Monte Belo were recently restarted after the energy rationing that was necessary during 2001 in Brazil. Overall, investments in infrastructure improvement are concentrated in the state of Pará.

Recent studies have tried to model the impact of these construction projects and infrastructure improvements on deforestation (Laurance et al., 2001) and fire (Nepstad et al., 2001), using observed deforestation rates along existing roads to extrapolate potential effects of new investments. However, these approaches fail to consider how future development may be impacted by economic changes resulting from decreased transportation cost.

For this simulation, the effects of paving both the BR-163 and BR-230 highways were estimated by accounting for the change in the “friction” term

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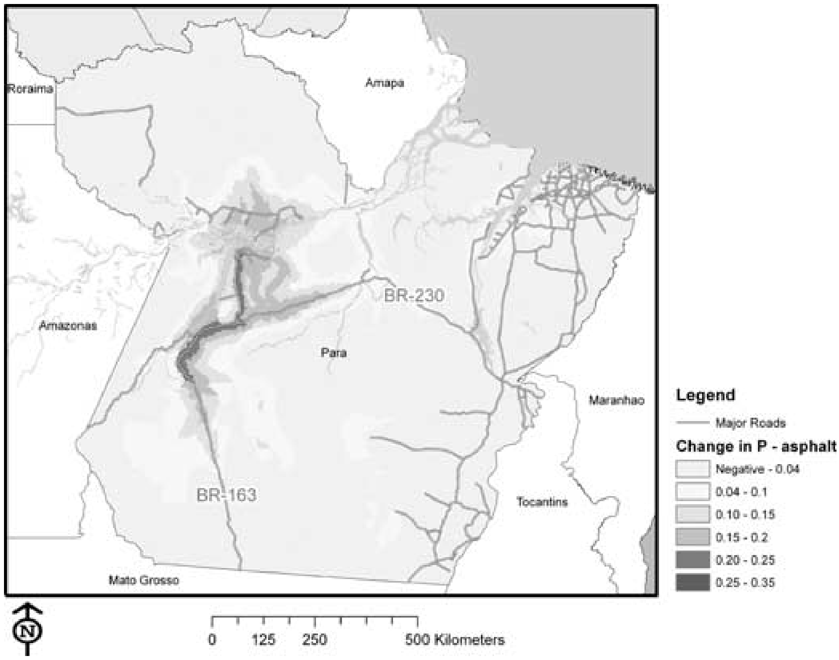

FIGURE 6: Estimated Change in Probability of Fire in Pará State with the Paving of BR-163 and BR-230.

for each road upon the economic possibilities in the affected regions. In other words, paving of the roads makes it easier to get products to markets by reducing the transportation costs with a consequent increase in farmgate prices. For example, the transport cost of cattle was changed from R\$ 0.390 ton^{-1} km^{-1} to R\$ 0.133 ton^{-1} km^{-1} when a dirt road was paved. Similar calculations were made for soybeans. Two new variables were created (Pb^* and Ps^*) within the *ArcView* GIS environment, which were substituted for the original indicators (Pb and Ps) in the initial regression, allowing a revised probability function of:

$$pr\hat{o}b_i = \Phi(\hat{\beta}_1 Pb_i^* + \hat{\beta}_2 Ps_i^* + \hat{\beta}_1 Pt_i + \mathbf{v}_i \hat{\beta})$$

where the $\hat{\beta}$*'s* are the estimated regression parameters presented in Table 3.

Figure 6 shows the impact of the road-paving projects on the probability of fire throughout the state of Pará, where the majority of the affected roads are situated. The probit model predicts that, in the absence of other changes, the road improvements will result in an increase of 13 percent in the number of cells classified with a probability of fire above 16 percent in Pará, as compared to the base model scenario (22,979 cells *versus* 20,391). Obviously, the areas adjacent to the BR-163 and BR-230 highways will be the most affected. This effect is most pronounced along the BR-163 highway where fire probabilities greater

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than 20 percent are expected. With the exception of Rondônia, which is also expected to experience a 13 percent increase in cells with fire, no other states are predicted to have significant changes due to these projects. The net result for the whole Amazon is predicted to be a 4 percent increase in the number of cells experiencing fire.

Scenario 2. Paving of Roads and Beef Export. At the time of the initial survey work on agricultural prices in 2001, beef from the Amazon region could not be exported to other countries because of hoof-and-mouth disease. However, there have been intense and ongoing efforts to control this disease though vaccination and strict regulation of cattle movement in the region. Indeed, as of 2006, four states including Tocantins, Mato Grosso, Acre, and Rondonia, were cleared by the World Organization for Animal Health (OIE) to export beef to the European Union. In the near future, Pará state is likely to become free of hoof-and-mouth disease, and permitted to sell beef to the world market.

Over the last decade, beef prices external to the region have stayed on average 17 percent above local prices (ABIEC, 2002). Consequently, it is likely that the price paid to beef producers will increase in the near future. To take into account a potentially modest increase in beef prices, we simulated the effect of a 10 percent increase in beef prices at the principal export markets of the Amazon (Belém, Santarém, and Manaus) on fire probability. For example, the price of live cattle in Belém in the base model was R$ 1.13 kg^{-1}; therefore, a 10 percent increase in the price would result in a new price of R$ 1.25 in the simulation. This scenario also maintains the paved status of the BR-163 and BR-230 highways, as specified in simulation 1. Again, we calculated a new farmgate beef price variable using *ArcView* and substituted this new variable (let it be called Pb^e) for the previous using the same estimated parameters.

With both paved roads and increased beef prices, the likelihood of fire increases substantially. The main state impacted would be Pará, with a 43 percent increase in the number of cells with fire when compared to the base-case scenario. Rondonia would still show a 13 percent increase owing to the paving of roads. The states of Mato Grosso, Tocantins, Roraima, Acre, and Maranhão are not affected. The state of Amazonas is predicted to have an increase from 77 to 227 in the number of cells with fire, which is a large relative increase for the state, but a small change in terms of area affected in the Amazon (Figure 7).

Scenario 3. Paving of Roads, Beef Export, and Conservation Unit Implementation. Simulations 1 and 2 show the effects of policies aimed at enhancing regional economic development. Improvements in infrastructure and access to external markets, while likely to provide economic benefits, may also result in negative environmental consequences such as increased deforestation and accidental fire. In light of these environmental externalities, the federal government is proposing an ambitious plan to vastly expand conservation areas in the Amazon by an estimated 500,000 km^2 of new national forests (Verissimo et al., 2002).

To account for additional land under conservation, we combine the original protected areas map used in the initial probit regression with a map of potential

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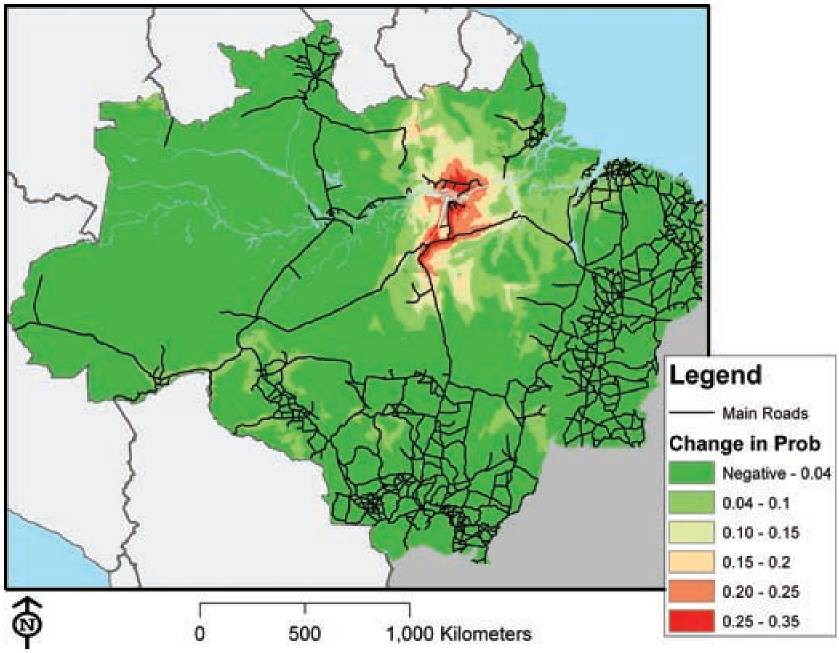

FIGURE 7: Estimated Change in Probability of Fire in Amazonia from Base Scenario According to Scenario 2—Paved Roads and Cattle Exports.

conservation areas produced by Veríssimo et al. (2002), creating a new coverage (call it Pt^f) to simulate the potential effects of this expanded area upon fire vulnerability. The third simulation integrated this new combined protected areas data, along with transport cost reductions stemming from road-paving (simulation 1) and price increases for beef derived from market expansion (simulation 2), to determine the potential impact of environmental policy in mitigating fire vulnerability. The model becomes:

$$pr\hat{o}b_i = \Phi(\hat{\beta}_1 Pb_i^e + \hat{\beta}_2 Ps_i^* + \hat{\beta}_1 Pt_i^f + \mathbf{v}_i\hat{\beta})$$

The results from the simulation indicate that the creation of the new conservation units may significantly reduce the number of cells expected to experience fire on the order of 12 percent in comparison to scenario 2 (Figure 8). The total number of cells predicted to experience fire is slightly (0.3 percent) less than the base, no-change, scenario. Therefore, in gross terms, establishment of the conservation units may offset the effects of paving and beef exportation, although the spatial distribution of fires may be considerably different. In particular, the states with the largest reductions in fire are predicted to be those wherein substantial forest reserves remain. Since Maranhão, Tocantins, and Mato Grosso do not have substantial areas for the creation of new conservation areas, they are not expected to experience any reduction in fire occurrence. On

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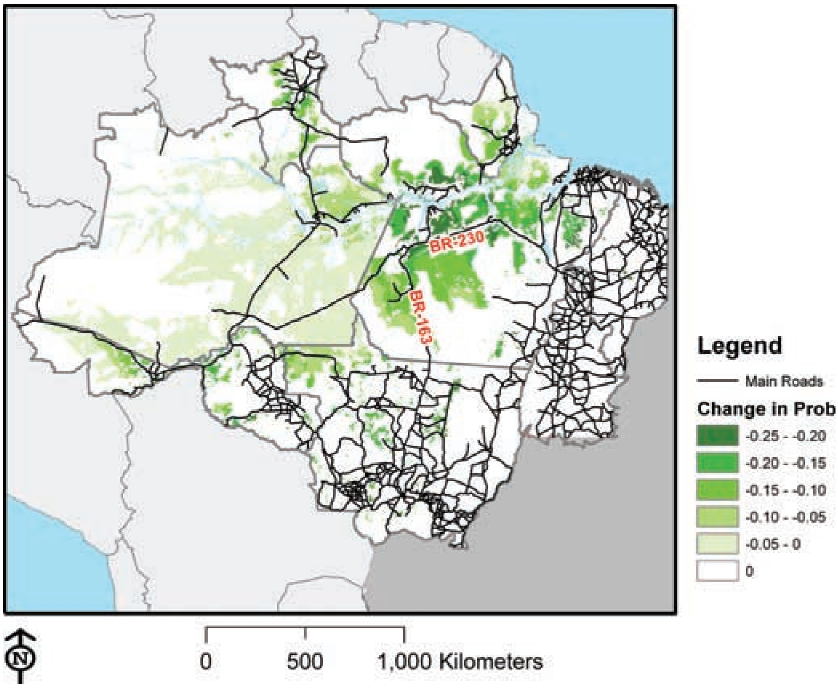

FIGURE 8: Estimated Change in Probability of Fire in Amazonia from Scenario 2 to Scenario 3—Paved Roads, Cattle Exports, and Conservation Units Implemented.

the other hand, Roraima is expected to see a 32 percent reduction in comparison to scenario 2, while Pará, Rondonia, and Acre will experience a 25 percent reduction. In Amazonas, the predicted change is small in absolute terms with a reduction to 139 cells, representing a 39 percent reduction from scenario 2.

7. CONCLUSIONS AND IMPLICATIONS FOR PUBLIC POLICY

In our opinion, the model results and simulations presented above are relevant for public policy implementation. First and foremost, the results from the probit regression show that the occurrence of fire is highly correlated with the economic variables, farmgate prices of cattle and soybean. In terms of beef prices, the results support our hypothesis that increases of beef prices due to reduced transportation costs create greater incentive for land clearing for pasture, which leads to increasing fire vulnerability. The findings, however, do not support our proposition that land-use intensification, represented by soybean production, reduces fire occurrence. In fact, the results show a reverse causal link with fire probability increasing as farmgate prices for soybean increase. This increase in fire could be explained, in part, by the greater demand for land clearing, which uses fire, stimulated by rising soybean prices.

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As expected, the control variables, distance to deforested areas, annual precipitation, and protected areas, were statistically significant and served to lessen fire vulnerability. In particular, the results showed that as distance to deforestation increased, fire vulnerability decreased. In a similar vein, fire occurrence shows a strong negative relationship to increasing rainfall and areas with protected legal status. The last result, that fire probability is less in protected areas, has important implications for public policy. For instance, it indicates that the establishment of protected areas, whether they are production forests, reserves or parks, has a mitigating effect on the number of fires. The reduction of fire in protected forests may simply be attributed to the low population density or the prohibition against fire use. Furthermore, protected areas serve to inhibit loggers from entering these forests and making them more susceptible to subsequent fires (Holdsworth and Uhl, 1997).

Finally, the simulations conducted using the estimators from the regression reveal interesting prospects for future fire vulnerability in the Amazon. Simulations 1 and 2 showed that paving the BR-163 and BR-230 highways, which will lead to increases in farmgates prices for beef due to a reduction in transport cost, and the possibility of opening the Amazonian beef market to exportation as hoof-and-mouth disease is brought under control, could increase the likelihood of fire in diverse areas across the Amazon. However, the simulations also show that the expansion of forest under conservation may counterbalance the negative environmental impacts of these development policies, reducing the overall probability of fire, particularly if created along the major highways to be asphalted (Figure 8).

The combined effect of economic and environmental policy initiatives in the Brazilian Amazon may produce the best of both worlds, resulting in increases in economic development in tandem with environmental conservation. The increased economic production, tax revenue generation, and job creation accompanying the increased competitiveness of Brazilian products in international markets are sorely needed in a country faced with so many social problems. At the same time, the Brazilian government does not want to repeat the mistakes of the past, which have generated so many environmental problems. Today the Government, through its programs *Avança Brasil*, *Programa Nacional de Florestas* and *Programa de Áreas Protegidas* has to choose which investments to make in the Amazon in terms of infrastructure and conservation. These decisions will determine whether the investments will bring economic returns associated with environmental costs or whether the region will benefit from a more balanced development program.

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