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Resources for the Future
1616 P Street, NW
Washington, D.C. 20036
Telephone: 202–328–5000
Fax: 202–939–3460
Internet: http://www.rff.org

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Abstract

Managed forest ecosystems—agroforestry systems in which crops such as coffee and bananas are planted side-by-side with woody perennials—are being touted as a means of safeguarding forests along with the ecological services they provide. Yet we know little about the determinants of land cover in such systems, information needed to design effective forest conservation policies. This paper presents a first-ever spatial regression analysis of land cover in a managed forest ecosystem—a shade coffee region of coastal Mexico. Using high-resolution land cover data derived from aerial photographs, along with data on the institutional, geophysical, socioeconomic, and agronomic characteristics of the study area, we find that plots in close proximity to urban centers are less likely to be cleared, all other things equal. This finding contrasts sharply with the literature on natural forests. In addition, we find that membership in coffee marketing cooperatives, farm size, and certain soil types are associated with forest cover, while common property, proximity to small town centers, and the prevalence of indigenous peoples are associated with forest clearing.

Key Words: deforestation, managed forest ecosystem, agroforestry, shade-grown coffee, Mexico, spatial econometrics, land cover.

JEL Classification Numbers: O13, Q15, Q23

Contents

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1. Introduction

To preserve forests and the ecological services they provide, policymakers in developing countries have traditionally relied on establishing protected areas, a strategy that has significant limitations. For economic and political reasons, only a small percentage of natural forests can be legally protected (Miller 1996). Also, prohibitions on forest clearing are difficult to enforce in countries with weak regulatory institutions (Repetto 1988). Given these drawbacks, alternative forest conservation strategies have begun to receive considerable attention. One such strategy is encouraging private agents to establish or retain "managed forest ecosystems"—agroforestry systems in which crops such as coffee, cocoa, and bananas are planted side-by-side with woody perennials (Szaro and Johnston 1996; Pagiola et al. 2002; Scherr and McNeely 2002). These systems generally provide more environmental services than monocultures. In addition, they can serve as corridors between existing patches of natural forest, and can mitigate adverse "edge effects" that degrade natural forests bordering on cleared areas (Gajaseni et al. 1996).

Although increasingly popular in policy circles, managed forest ecosystems have thus far received limited attention in the economics literature. As a result, we know little about the factors that drive spatial patterns of land clearing in such systems—information needed to design effective forest conservation policies. Does clearing mainly occur in certain geophysical settings—for example, on plots close to urban centers? Or does it mainly occur in certain institutional settings, such as where land is held in common?

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Spatial regression models—that is, models that explicitly account for location within administrative units such as counties and towns—are increasingly being used to explain patterns of land clearing in natural forests (for a review, see Kaimowitz and Angelsen 1998). These analyses almost invariably find that land clearing is associated with proximity to urban centers, proximity to roads, and land deemed more suitable for conventional agriculture because it is flat and has adequate drainage and relatively high soil fertility (Deininger and Minten 2002; Cropper et al. 2001; Nelson and Hellerstein 1997; Mertens and Lambin 1997; Chomitz and Gray 1996). There is less consensus about the impacts of socioeconomic characteristics (such as population density and poverty) which may be confounded by endogeneity and spatial autocorrelation (Deininger and Minten 2002; Rosero-Bixby and Palloni 1998).

Intuition suggests, however, that the findings from spatial regression analyses of natural forests may not apply to managed forest ecosystems. For example, most analysts agree that in natural forests, clearing tends to occur near urban areas mainly because the costs of transporting inputs and outputs associated with conventional agriculture, logging, and ranching are lower in such areas. But in managed forest ecosystems, proximity to urban centers also reduces the costs of transporting inputs and outputs associated with nontimber agroforestry, a factor that would encourage the preservation of forest cover.

This paper presents a first-ever econometric analysis of spatial patterns of land cover in a managed forest ecosystem. We analyze patterns of land clearing in 1993 in a coastal region of southern Mexico dominated by shade coffee—an agroforestry system in which coffee is grown under a forest canopy.[1] From the perspective of forest conservation policy, Mexican shade coffee is a particularly pertinent case study of a managed forest ecosystem for two reasons: it generates important ecological services, and it is increasingly touted as a bulwark against deforestation. Regarding ecological services, shade coffee harbors biodiversity, sequesters carbon, facilitates aquifer recharge, and prevents soil erosion and the siltation of irrigation facilities in low-lying

[1] This system, which generates three-quarters of Mexico's coffee, provides a number of private benefits for coffee farmers: leaf litter and organic matter in the forest provide fertilizer for the coffee plants, tree roots break up the soil, and birds provide pest management (Rice and Ward 1996).

areas (Perfecto et al. 1996; Rice and Ward 1996).[2] As for shade coffee's role as a bulwark, Mexican deforestation rates are among the highest in Latin America, with over 1% of the country's forests disappearing annually (World Bank 2002). Shade coffee growing regions are especially threatened: ranchers and conventional farmers are placing increasing pressure on forests in the coastal mountain ranges where most of Mexico's shade coffee is grown.[3]

To identify the determinants of land cover in a Mexican shade coffee system, we develop a dichotomous choice model of land clearing in coastal Oaxaca, one of Mexico's top shade coffee states (Figure 1). The data that underpin this analysis are notable for two reasons. First, while most land cover maps are derived from satellite images, ours are derived from high-resolution aerial photographs and, therefore, are unusually detailed. As a result, we are able to account for the relatively small patches of cleared land characteristic of our study area. Also, we employ spatially explicit institutional data (on membership in marketing cooperatives and land tenure) along with the geophysical and socioeconomic data commonly used in spatial regression models.

We find that, at altitudes where shade coffee grows, plots closer to large coffee market towns and other sizable urban centers are less likely to be cleared, all other things equal, a pattern of land clearing not observed in natural forests. In addition, we find that membership in coffee marketing cooperatives, farm size, and certain soil types are associated with forest cover, while common property, proximity to small town centers, and the prevalence of indigenous peoples are associated with forest clearing.

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[2] Shade coffee's biodiversity benefits are particularly notable. The crop generally grows at altitudes where tropical and temperate climates overlap—areas that are extremely rich in biodiversity. Indeed, the 14 main coffee growing regions in Mexico have all been designated biodiversity "hotspots" by the country's national commission on biodiversity (Moguel and Toledo 1999).

[3] Although we analyze land cover in the early 1990s, it is noteworthy that beginning in the late 1990s, deforestation in shade coffee regions has been exacerbated by precipitous declines in the international price of coffee. Faced with falling revenues, shade coffee growers themselves are increasingly felling trees on and around their plantations to harvest the timber and grow subsistence crops requiring direct sunlight (Ávalos and Becerra 1999). This recent phenomenon underscores the need to develop an improved understanding of the determinants of land cover in shade coffee systems.

The remainder of the paper is organized as follows. Section 2 provides additional background on shade coffee and our study area. Section 3 presents a model of land cover decisionmaking. Section 4 discusses our data, and Section 5 presents our regression results. Finally, Section 6 discusses policy prescriptions.

2. Study area: definition, coffee production, and land uses

The *Sierra Sur y Costa* region in the state of Oaxaca produces about one-fifth of Mexico's coffee. Three-quarters of its coffee acreage is managed by poor, small-scale farmers using shaded systems (Nestel 1995). Our study area consists of a 634,000 hectare subset of this region (Figures 1 and 2). Within our study area, coffee grows in a 254,000 hectare "coffee range" lying 400–1,600 meters above sea level (m.s.l.). The entire study area comprises 1,155 towns in 43 *municipios* (counties), while the coffee range comprises 427 towns in 33 *municipios*. The entire study area includes nine cities with populations exceeding 2,000, the largest of which are Puerto Escondido, Zicatela, Pochutla, Santa María Huatulco, and La Crucecita—all located on the coast. The 7,214 hectare Parque Nacional Huatulco, located just west of La Crucecita, is the only protected area in the larger study area. It lies well below the coffee range.[4]

Coffee grows on small tropical evergreen trees that produce fruit resembling cherries. In shaded systems, this fruit is picked by hand, typically with the assistance of hired labor. After harvest, the pulp of the coffee fruit is removed and the beans are sorted and dried to produce an intermediate product called *pergamino*. In our study area, growers transport their *pergamino* by donkey or truck to the nearest *cabecera* (*municipio* capital), where they sell it to middlemen or marketing cooperatives. From there, the middlemen and cooperatives ship the *pergamino* by truck to one of two large coffee market towns—Oaxaca City or Pochutla—where they sell it to large-scale buyers and exporters. Roads in our mountainous study are quite poor and, therefore, transportation is costly. Because they have to cover the costs of transporting *pergamino* to Oaxaca City or Pochutla, middlemen and cooperatives pay significantly lower prices for

[4] Although this park was officially established in July 1998, it has been protected from deforestation by government agencies since at least 1990.

pergamino in *cabeceras* that are relatively far from these two cities (Ávalos and Becerra 1999). Hence, coffee growers in such areas earn a lower return on their coffee. None of the shade coffee in our study area is certified as such and, as a result, neither growers nor middlemen receive a premium related to this attribute.

In 1991, the most recent year for which data are available, there were 6,700–8,200 coffee farms in our study area, producing approximately 39,000 tons of coffee cherry annually. These farms—all of which employ shade coffee systems exclusively—covered 37,000–53,000 hectares, about 6–8% of the land in the entire study area, and 15–21% of the land in the coffee range. In the same year, 43,305 hectares of the entire study area was planted in noncoffee agriculture. These farms covered approximately 15% of the entire study area and about 7% of the coffee range. Over two-thirds of this agricultural land was planted in corn, about a sixth in bananas, and a sixth in beans.

Under Mexican law, all persons wishing to clear forested land must obtain a federal permit, and in some cases a local permit, regardless of the scale of the clearing (NACEC 2003). However, persons clearing small plots for agriculture frequently ignore these requirements. Enforcement of forestry laws mainly depends on citizen denunciations of violators and, as a result, is haphazard, especially in remote areas. Within the coffee range, most forest clearing appears to result from shifting agriculture. According to local stakeholders, rural households often clear small plots in order to market the timber and grow subsistence crops. However, the poor soils on these cleared plots—which are typically steeply sloped—are quickly eroded by rainfall. As a result, subsistence farmers typically abandon them and move on to new locations within a few years. Our data support this anecdotal evidence. A comparison of agricultural survey data and our land cover data (discussed below) suggests that, within the coffee range, less than half of the nonurban cleared land was being used for agriculture in the early 1990s. Also, within the coffee range, the majority of the cleared plots are smaller than 1.5 hectares.

3. Model

We model land use decisions using a conventional "land rent" model (Nelson and Hellerstein 1997; Chomitz and Gray 1996). Following von Thunen, the model is premised on the simple idea that any given plot of land may be devoted to a number of competing uses, each of which earns a rent that depends on the characteristics of the plot (e.g., soil quality and proximity to markets). Land owners devote plots to the uses that generate the highest rents. More formally, the rent an agent receives from devoting plot i to land use k is given by

$$R_{ik} = P_{ik}Q_{ik} - C_{ik}X_{ik} \qquad (1)$$

where R is rent, P is price of output, Q is quantity of output, C is price of inputs, X is quantity of inputs, and

$$Q_{ik} = S_{ik}X_{ik}^{\beta} \qquad with \qquad 0 < \beta_k < 1. \qquad (2)$$

Thus, the output from plot i is determined by a Cobb-Douglass production function where S is a plot-specific shifting parameter. This shifting parameter may be expressed as a product of geophysical and agronomic variables, s_i, having to do with, for example, soil type, slope, and plot size. Equations (1) and (2) imply a rent-maximizing demand for X

$$X_{ik} = \left(\frac{C_{ik}}{P_{ik}S_{ik}\beta}\right)^{\left(\frac{1}{\beta-1}\right)}. \qquad (3)$$

Furthermore

$$P_{ik} = \exp(\gamma_{0k} + \gamma_{ik} Z_{ik}) \qquad (4)$$

$$C_{ik} = \exp(\delta_{0k} + \delta_{ik} Z_{ik}) \qquad (5)$$

where Z is a vector of location-specific variables such as distance to markets. Substituting equations (3), (4), and (5) into (1), taking logs, simplifying and adding a stochastic error term yields

$$\ln R_{ik} = \alpha_{ik} + \chi V + u_{ik} \qquad (6)$$

where V is a vector of parameters and χ is a vector of plot-specific variables associated with Z and S.

We assume that each plot is devoted to the land use that generates the highest rent. Empirically, we distinguish between two land uses: those such as shade coffee requiring forest cover (k = 0), and those such as agriculture and logging requiring forest clearing (k = 1). Thus, if we define

$$R_i^* = \ln R_{i1} - \ln R_{i0} \qquad (7)$$

then plot i will be cleared if $R_i^* > 0$ and will remain forested otherwise. Substituting equation (6) into equation (7), we have

$$R_i^* = \gamma_i - \psi W + u_i \tag{8}$$

where W is a vector of parameters and ψ is a vector of plot-specific variables associated with Z and S. Although R^*_i is latent and unobserved, we observe an indicator variable, L_i, such that

$$L_i = 1 \text{ if } R^*_i > 0$$

$$L_i = 0 \text{ if } R^*_i \leq 0.$$

Using this dichotomous dependent variable, equation (8) may be estimated as a probit or logit.

4. Data

Our land cover data are derived from digitized, distortion-corrected, 1993 aerial photographs. We used geographic imaging software (ERDAS Imagine) calibrated by groundtruthing to convert these photographs into digital land cover maps with a two-meter resolution. The maps distinguish among four land uses: forest (including shade coffee), cleared land (including conventional agriculture), urban, and water. They also include locations of paved roads and major unpaved roads, the boundaries of *municipios*, and the locations of town centers.[5]

[5] Data on roads and *municipio* boundaries were supplied by the *Instituto Nacional de Estadística Geografía e Informática* (INEGI). Formal boundaries for the towns in our study area do not exist. Therefore, we constructed artificial boundaries using Thiessian polygons, that is, we assigned each pixel in the data set to the closest town center.

From the (two-billion plus) pixels in our land cover data, we constructed a sample using a 500-meter rectangular grid. Next, we eliminated all pixels classified as either “urban” or “water,” as well as pixels for which data are missing. The resulting sample contains 20,283 pixels, of which 7,156 are in the 400–1,600 m.s.l. coffee range.

Table 1 presents detailed information on the variables used in the econometric analysis, including units, sources, scale, date, and mean values. The variables are grouped into five categories: land cover, institutional, geophysical, socioeconomic, and agronomic. The table presents means for the two samples used in our econometric analysis—one drawn from the entire study area (n = 20,283), and the other drawn from our managed forest ecosystem: the 400–1,600 m.s.l. coffee range (n = 7,156). The remainder of this section describes each of the variables in Table 1, and indicates our *a priori* expectation as to the correlation of each variable with the probability of clearing *inside the coffee range.*

Table 1. Variables in the econometric analysis: description and summary statistics

Variable	Description	Units	Source	Scale	Date	Mean entire study area			Mean coffee range		
						All n=20,283	Forest n=15,344	Cleared n= 5,131	All n=7,156	Forest n=5,635	Cleared n=1,521
Land use											
CLEAR	land cleared?	(0/1)	INEGI[a]/ERDAS	2 m pixels	1993	0.24	0	1	0.21	0	1
Institutional											
COOP	% coffee growers in coops.	%	CECAFE[b]	municipio	1991	n/a	n/a	n/a	55.74	56.18	54.10
EJI_COM	% ejido land in common	%	INEGI[c]	municipio	1991	53.18	54.98	47.31	49.14	49.23	48.82
PARK	plot in protected area?	(0/1)	SEMARNAT[d]	1:1,000,000	1998	0.01	0.01	0	0	0	0
Geophysical											
COF	altitude 400-1,600 m?	(0/1)	NIMA[e]	30 arc seconds[f]	--	0.35	0.37	0.37	1	1	1
N_FACE	plot north-facing?	(0/1)	NIMA	30 arc seconds	--	0.21	0.22	0.17	0.18	0.20	0.14
ALTIT	altitude	m	NIMA	30 arc seconds	--	1,058.11	1,092.09	949.21	936.29	931.23	955.05
SLOPE	slope	degrees	NIMA	30 arc seconds	--	7.11	7.27	6.66	8.52	8.49	8.65
MTNS	terrain mountainous?	(0/1)	CONABIO[g]	1:4,000,000	1992	0.81	0.82	0.80	1	1	1
HILLS	terrain hilly?	(0/1)	CONABIO	1:4,000,000	1992	0.10	0.11	0.04	0	0	0
PLAINS	terrain plains?	(0/1)	CONABIO	1:4,000,000	1992	0.09	0.07	0.16	0	0	0
DIST_CMKT	travel time to n./s. paved road	hours	ARCINFO	10 m pixels	--	2.26	2.38	1.88	2.57	2.56	2.57
DIST_TWN	travel time to nearest town ctr.	hours	ARCINFO	10 m pixels	--	0.50	0.55	0.34	0.45	0.46	0.41
DIST_CITY	travel time to nearest big city	hours	ARCINFO	10 m pixels	--	2.59	2.65	2.43	2.38	2.30	2.67
SOILC_1	soil type: humic acrisol	(0/1)	CONABIO	1:1,000,000	1995	0.35	0.36	0.34	0.33	0.31	0.40
SOILC_2	soil type: eutric cambisol	(0/1)	CONABIO	1:1,000,000	1995	0.21	0.18	0.31	0.18	0.17	0.23
SOILC_3	soil type: rendzina	(0/1)	CONABIO	1:1,000,000	1995	0.01	0.00	0.01	0.00	0.00	0.00
SOILC_4	soil type: haplic phaeozem	(0/1)	CONABIO	1:1,000,000	1995	0.03	0.03	0.01	0.07	0.08	0.02
SOILC_5	soil type: lithosol	(0/1)	CONABIO	1:1,000,000	1995	0.01	0.01	0.01	0.01	0.02	0.00
SOILC_6	soil type: eutric regosol	(0/1)	CONABIO	1:1,000,000	1995	0.39	0.41	0.32	0.41	0.42	0.34
SOILT_1	soil texture: coarse	(0/1)	CONABIO	1:1,000,000	1995	0.26	0.24	0.28	0.02	0.02	0.01
SOILT_2	soil texture: medium	(0/1)	CONABIO	1:1,000,000	1995	0.57	0.60	0.47	0.84	0.85	0.78
SOILT_3	soil texture: fine	(0/1)	CONABIO	1:1,000,000	1995	0.17	0.15	0.24	0.14	0.12	0.22
SOILF_0	soil physical characteristic: none	(0/1)	CONABIO	1:1,000,000	1995	0.57	0.55	0.62	0.50	0.50	0.53
SOILF_5	soil physical characteristic: rock	(0/1)	CONABIO	1:1,000,000	1995	0.40	0.42	0.37	0.43	0.42	0.45
SOILF_6	soil physical characteristic: stony	(0/1)	CONABIO	1:1,000,000	1995	0.03	0.03	0.01	0.07	0.08	0.02
Socioeconomic											
POP	population	n/a	INEGI[h]	town	1995	303.23	309.04	283.50	288.35	288.69	287.10
POVERTY	marginality index	n/a	INEGI	town	1995	0.79	0.76	0.92	0.88	0.85	0.98
INDIG	% population indigenous	%	INEGI	town	1995	4.32	3.78	6.38	7.37	6.49	10.66
Agronomic											
FSIZE	% coffee land on farms > 10 has.	%	CECAFE	municipio	1991	n/a	n/a	n/a	46.66	48.55	39.65

[a]*Instituto Nacional de Estadística Geografía e Informática* (Mexico); [b]*Consejo Estatal del Café de Oaxaca* (Mexico); [c]Ejido census; [d]*Secretaría de Medio Ambiente y Recursos Naturales* (Mexico); [e]National Imagery and Mapping Agency (USA); [f]Approximately 1 kilometer; [g]*Comisión Nacional para el Conocimiento y Uso de la Biodiversidad* (Mexico); [h]Population census

4.1 Land cover variable

The independent variable, CLEAR, is a dummy variable that takes the value of 1 if the plot is cleared and 0 otherwise.

4.2 Institutional variables

COOP is the percentage of the coffee growers in the *municipio* who belong to marketing cooperatives. Cooperative members generally obtain a higher return on coffee than nonmembers for two reasons. First, they receive higher prices for their *pergamino* than nonmembers because cooperatives tend to control quality better than independent growers and have more bargaining power vis-à-vis middlemen than do independent growers—in fact, some sell directly to exporters. Second, cooperative members typically pay lower prices for inputs than nonmembers because cooperatives typically subsidize post-harvest processing, quality control, and agricultural extension. Hence, we expect COOP to be negatively correlated with the probability of clearing within the coffee range, all other things equal.

EJI_COM is the percentage of *ejido* land in the *municipio* that is held in common.[6] Group land holding institutions, *ejidos*, have traditionally controlled most of the forested land in Mexico (Yates 1981). Within *ejidos*, some land is typically parceled out to individual members, and some is held in common. Some economics research has linked communal land tenure to natural resource degradation (Baland and Platteau 1996). The usual explanation is that where institutions governing common property are weak, agents are more likely to degrade it because they do not fully internalize either the benefits of conservation investments or the costs of degradation. Thus, shifting agriculture, logging, and other cleared land uses with short-term payoffs may be more widespread on communal *ejido* land than on parceled *ejido* land or privately held land. In terms

[6] Many, if not most, of the communal land holding institutions in our study area are *comunidades agrarias*, institutions very similar to, but legally distinct from, *ejidos*. For our purposes, the two types of institutions are identical and, therefore, for simplicity's sake, we ignore this distinction and refer to both as "*ejidos*."

of the land rent model in Section 3, one can think of this effect as operating through? the cost of inputs into production—the cost of communal land is relatively low because those using it do not fully internalize the costs. Hence, within the coffee range, we expect EJI_COM to be positively correlated with the probability of clearing, all other things equal.

PARK is a dummy variable that indicates whether or not the plot is located in the one protected area in our study region. As noted above, this park is located on the coastal plain, well outside of the coffee range (Figure 2).

4.3 Geophysical variables

Aspect (directional orientation), altitude, slope, terrain, and soil characteristics can be considered arguments of the production function shift parameter in the land rent model. N_FACE is a dummy that takes the value of 1 if the plot faces north, and 0 otherwise. Because Mexico is north of the equator, north-facing plots receive less direct sunlight and are relatively ill-suited to conventional agriculture. Such plots also tend to be more humid, a characteristic that makes them particularly well-suited to shade coffee. Hence, we expect N_FACE to be negatively correlated with the probability of clearing, all other things equal.

In our study area—as in most coastal mountain ranges—altitude is highly correlated with both temperature and precipitation. Therefore, ALTIT, our altitude variable, is essentially a proxy for weather conditions. The best grades of coffee grow at higher altitudes where lower temperatures cause the beans to mature more slowly. As a result, coffee farmers at higher altitudes in the coffee range earn higher rents on their crop. By contrast, conventional agriculture is generally less productive at higher altitudes. Thus, we expect ALTIT to be negatively correlated with the probability of clearing, all other things equal.

We include four topographical variables: SLOPE, a continuous variable measured in degrees, and three terrain dummy variables—MOUNTAINS, PLAINS, and HILLS. Of these topographical variables, only slope varies within the coffee range: all of the land above 400 meters in our study area—including the entire coffee range and the land north of it—is classified as mountains, while the coastal area is split between plains in the west and hills in the east. We have no strong expectation about the sign of SLOPE inside the coffee range.

We use data on three different soil attributes: type (SOILC_1 through SOILC_6), texture (SOILT_1 through SOILT_3), and physical characteristics (SOILF_0, SOILF_5, and SOILF_6). The meaning of each variable is listed in Table 1. For a more extensive discussion of these variables, see Appendix 1. Because many soils that are well-suited to agriculture are also well-suited to coffee, we do not have a strong expectation as to how the soil variables affect the probability of clearing inside the coffee range.

Finally, we use three impedance-weighted distance variables that are determinants of input and output prices: distance to the nearest town center (DIST_TWN), distance to the nearest city with a population greater than 2,000 (DIST_CITY), and distance from the nearest *cabecera* to the nearest coffee market town (DIST_CMKT). We have parameterized our weighting algorithm so that these distances approximate travel times in hours. For a description of this algorithm, see Appendix 2. The DIST_CMKT variable requires a brief explanation. As noted in Section 2, because middlemen and cooperatives must cover the costs of transporting *pergamino* from *cabeceras* to one of the two coffee market towns in the state—Oaxaca City and Pochutla—the prices they pay to individual growers depend on the distance from the relevant *cabecera* to the relevant coffee market town. *Cabeceras* are not associated with specific coffee market towns. In any given year in any given *cabecera*, middlemen and cooperatives may ship *pergamino* to both of these towns, depending on market conditions and the availability of transportation. Regardless of which market town they use, however, middlemen and cooperatives always first ship *pergamino* from the *cabecera* to the one paved road connecting Oaxaca City in the north with Pochutla in the south (Figure 2). This first leg of the trip over rugged dirt roads typically accounts for the lion's share of the cost of transporting coffee to market. Hence, our plot-specific proxy for distance to coffee markets is the weighted distance from the nearest *cabecera* to the north-south paved road.

Of the three distance variables, we only have an unambiguous expectation about the sign of one. Within the coffee range, we expect DIST_CMKT to be positively correlated with the probability of land clearing because the growers located far from coffee market towns receive relatively low prices for their *pergamino* and, therefore, earn relatively low rents on coffee farming.

By comparison, the expected effect of DIST_CITY on the probability of land clearing is complex. DIST_CITY affects the probability of land clearing through at least two channels: one has to do with transportation costs and the second with the effective cost of cleared land. DIST_CITY has countervailing impacts on the probability of clearing through the first channel. On one hand, proximity to a relatively big city boosts the return to shade coffee because some coffee inputs are purchased there—most notably the labor used to harvest coffee. Indeed, during the off-season, itinerant coffee laborers tend to live in cities where nonfarm job opportunities are relatively plentiful. On the other hand, proximity to the nearest big city also boosts the return to conventional agriculture because cities are markets for both agricultural inputs and outputs. The first effect implies that, all other things equal, shade coffee—and therefore forest—is more likely to be found near big cities. The second effect implies that, all other things equal, agriculture—and therefore cleared land—is more likely to be found near big cities.

DIST_CITY may also affect relative returns to alternative land uses by changing the effective cost of cleared land. Plots cleared without required permits that are closer to big cities are more likely to attract citizen denunciations and, therefore, the attention of regulatory authorities, in part simply because such authorities are located in big cities. Hence, the effective cost of cleared land may be higher near big cities. This implies that, all other things equal, cleared plots are less likely to be found near cities. Thus, DIST_CITY may have varied countervailing effects on the probability of clearing. Its net effect is an empirical question.

The same complex relationship between DIST_CITY and the probability of clearing applies to DIST_TWN, but with one caveat. As noted above, big cities—not smaller towns—are the primary repository for seasonal coffee labor. Hence, proximity to town centers may have less impact on the return to coffee—and on the probability of forest cover—than does proximity to cities.

4.4 Socioeconomic variables.

Each of our socioeconomic variables may be considered a determinant of input and output prices associated with different land uses. Population (POP) affects the supply of and demand for outputs from different land uses, as well as the supply of and demand for agricultural labor, a key input. The effect of population on the probability of land clearing is difficult to predict *a priori* because it depends on the elasticities of supply and demand for various outputs with respect to population, and the elasticities of supply and demand for agricultural labor with respect to population. Note that, as other researchers have argued, causation between population and land use may run in the opposite direction as well: people may settle in locations where coffee is productive and relatively profitable.

Calculated by INEGI, the Mexican statistical agency, and ranging from -1.6 to +2.6 (higher = greater poverty), POVERTY is an index of a number of underlying statistics, including the average number of occupants per room, the percentage of population that is literate, and the percentages of homes with access to various types of infrastructure, including tubed drinking water, drainage, electricity, and nonearthen floors. As with POP, the impact of POVERTY on the probability of land clearing is difficult to predict *a priori*. POVERTY affects the supply of and demand for output as well as the supply of and demand for labor. Also, as with POP, endogeneity may be an issue.

Finally, INDIG is the percentage of population over the age of five speaking an indigenous language but not Spanish. In Mexico, heavily indigenous populations do not have equal access to public sector goods and services, including education, technical extension, agricultural marketing, credit, and infrastructure. Hence, such populations likely pay higher prices for coffee inputs and receive lower prices for their *pergamino*. Therefore, we expect this variable to be positively correlated with the probability of clearing.

4.5 Agronomic variable

FSIZE is the percentage of coffee acreage in the *municipio* found on farms larger than 10 hectares. Anecdotal evidence suggests that the production and (especially) the marketing of shade coffee entail economies of scale. Hence, in terms of our model, FSIZE can be thought to affect the productivity of shade coffee. We expect it to be negatively correlated with the probability of clearing, all other things equal.

5. Results

To identify the determinants of forest clearing in our study area, we employ three different econometric models. Each has a distinct purpose and each corrects for an econometric complication. Models 1 and 2 purport to identify the determinants of forest clearing *inside* the coffee range. Therefore, they use the 7,156 plots in our sample located between 400 and 1,600 meters in altitude. The specification and procedures used for the two models differ. Model 1 uses instrumental variable estimators appropriate for probit for two potentially endogenous regressors: POP and POVERTY (Newey 1987). The standard errors are corrected to account for the use of predicted values as independent variables. Model 2 omits insignificant instrumental variables and corrects for spatial autocorrelation using a Bayesian heteroskedastic spatial autoregressive procedure for logit (LeSage 2000). Model 3 tests whether the determinants of land clearing are the same inside the coffee range versus outside of it. Therefore, it uses the entire sample of all 20,283 plots in the study area. Like Model 2, it omits the instrumental variable estimators and corrects for spatial autocorrelation.

5.1 Determinants of forest clearing inside the coffee range

Table 2 presents our regression results. In Model 1, the instrumental variable estimators for POP and POVERTY are both insignificant.

In Model 2, all but seven of the 18 independent variables are significant at the 1% level. The exceptions are DIST_CITY, which is significant at the 10% level; DIST_CMKT, which is significant at the 5% level; and four of the soil variables—SOILC_2, SOILC_6, SOILT_2, and SOILT_3—which are not significant at all. The signs of most coefficients are as expected. The remainder of this subsection discusses the results from Model 2 in more detail.

Table 2. Regression results
(dependent variable = CLEAR)

		Model 1		Model 2			Model 3	
		n=7,156		n=7,156			n=20,283	
Variable	**Description**	**Coeff.**	**(s.e.)**	**Coeff.**	**(s.e.)**	**E**	**Coeff.**	**(s.e.)**
Constant		-0.3263	(0.2709)	-0.1762	(0.2154)	-0.118	-0.3479**	(0.0943)
COF	400-1,600 m?						-0.8613**	(0.2239)
Institutional								
COOP	growers in coops.	-0.2683**	(0.0843)	-0.2408**	(0.0675)	-0.0877		
EJI_COM	common land	0.2871**	(0.0681)	0.2204**	(0.0674)	0.0708	-0.1298**	(0.0511)
EJI_COM*COF							0.3622**	(0.0806)
PARK	in national park?						-0.2900*	(0.1508)
Geophysical								
N_FACE	north-facing?	-0.2560**	(0.0529)	-0.2352**	(0.0550)	-0.0223	-0.1370**	(0.0324)
N_FACE*COF							-0.1146*	(0.0620)
ALTIT	altitude	-0.0941	(0.0832)	-0.1176*	(0.0709)	-0.0720	-0.1232**	(0.0357)
ALTIT*COF							0.0878	(0.0798)
SLOPE	slope	0.1537**	(0.0500)	0.1232**	(0.0492)	0.0687	0.0251	(0.0377)
SLOPE*COF							0.0816†	(0.0634)
HILLS	hills						-0.4830**	(0.0577)
PLAINS	plains						0.1639**	(0.0475)
DIST_CMKT	time to cof. mkt.	0.0426*	(0.0202)	0.0288*	(0.0141)	0.0483	-0.0222*	(0.0110)
DIST_CMKT*CF							0.0607**	(0.0179)
DIST_TWN	time to twn. ctr.	-0.6569**	(0.0831)	-0.5246**	(0.0739)	-0.1549	-0.5111**	(0.0381)
DIST_TWN*COF							-0.0242	(0.0801)
DIST_CITY	time to big city	0.0277	(0.0280)	0.0310†	(0.0216)	0.0483	0.0915**	(0.0174)
DIST_CITY*CF							-0.0264	(0.0255)
SOILC_2	eutric cambisol	0.1861	(0.1180)	0.1227	(0.1046)	0.0145	0.1920*	(0.0858)
SOILC_2*COF							-0.1411	(0.1354)
SOILC_3	rendzina	1.4729**	(0.3810)	1.1587**	(0.3969)	0.0015	0.8444**	(0.1303)
SOILC_3*COF							-0.2335	(0.4138)
SOILC_4	haplic phaeozem	-0.5182**	(0.1097)	-0.3869**	(0.1010)	-0.0164	-0.0360	(0.1728)
SOILC_4*COF							-0.3156†	(0.2146)
SOILC_5	lithosol	-1.3920**	(0.3877)	-0.7703**	(0.2357)	-0.0058	-0.1583†	(0.1084)
SOILC_5*COF							-0.6883**	(0.2752)
SOILC_6	eutric regosol	-0.0523	(0.0912)	-0.0524	(0.0753)	-0.0139	0.1442*	(0.0841)
SOILC_6*COF							-0.2177*	(0.1115)
SOILT_2	medium texture	0.1581	(0.1837)	0.1147	(0.1732)	0.062	-0.0260	(0.0447)
SOILT_2*COF							0.4320*	(0.1914)
SOILT_3	fine texture	0.3099	(0.1966)	0.2191	(0.1788)	0.0211	0.2040**	(0.0736)
SOILT_3*COF							0.4178*	(0.2107)
SOILF_5	rock	-0.4180**	(0.0980)	-0.3186**	(0.0834)	-0.0885	-0.0266	(0.0416)
SOILF_5*COF							0.0549	(0.0816)
Socioeconomic								
POP[a]	population	-0.1906	(0.3457)					
POVERTY[a]	marginality index	0.0316	(0.0778)					
INDIG	pop. indigenous	0.8623**	(0.2682)	0.6108**	(0.1635)	0.0295	0.5554**	(0.1723)
INDIG*COF							0.0318	(0.2247)
Agronomic								
FSIZE	farms > 10 hs.	-0.8637**	(0.1129)	-0.6531**	(0.0870)	-0.1989		
	Pseudo-R^2	0.0688		0.0697			0.1029	

** significant at 1% level two tailed test
* significant at 5% level two tailed test
† significant at 10% level two tailed test
[a] AGLS estimator

5.1.1 Institutional variables

As expected, COOP is negatively correlated with the probability of clearing, all other things equal, and EJI_COM is positively correlated with the probability of clearing, all other things equal.

5.1.2 Geophysical variables

Of the regression results for the geophysical variables, the most interesting concern distance. As expected, DIST_CMKT is positively correlated with the probability of clearing. In other words, plots closer to coffee market towns are less likely to be cleared, all other things equal. This finding is the opposite of the standard result for natural forests. DIST_CITY is (weakly) positively correlated with the probability of land clearing. As noted in Section 4, this relationship likely stems from the fact that proximity to cities lowers transportation costs for coffee inputs (especially labor) and raises the effective cost of cleared land. DIST_TWN, however, is negatively correlated with the probability of clearing. Here, the conventional relationship between distance to urban areas and clearing holds.

With regard to the remaining geophysical variables, as expected, both N_FACE and ALTIT are negatively correlated with the probability of clearing. SLOPE is positively correlated with the probability of clearing. This last result contrasts with the typical finding for natural forests—in such forests, conventional agriculture is usually found on flat land.[7]

Five of the soil dummies are significant. SOILF_5, the soil physical characteristics dummy for rock, is negatively correlated with the probability of clearing, as is SOILC_5, the soil type dummy for lithosol, a particularly shallow soil. Presumably, neither coffee nor conventional crops are found on these soils. Both SOILC_2, the soil type dummy for eutric cambisol, and

[7] But note that our result jibes with Chomitz and Gray (1996) which finds that in Belize, semisubsistence agriculture is more likely to be found on land that is not flat, all other things equal.

SOILC_3, the soil type dummy for rendzina, are positively correlated with the probability of clearing. This may reflect the fact that although both conventional crops and coffee can be grown on these soils, they are better suited to the former than the latter—eutric cambisol has a high clay content that inhibits coffee root growth, and rendzina is high in calcium carbonate, which can interfere with coffee nutrient uptake. Finally, SOILC_4, the soil type dummy for haplic phaeozem—generally considered the best soil type for both coffee and conventional agriculture—is negatively correlated with the probability of clearing. Presumably, in the coffee range, such soils are typically planted in coffee. Thus, conventional thinking about the types of soils that promote clearing in natural forests do not necessarily hold in our study area. As in natural forests, particularly poor (e.g., rocky soils and shallow) soils are not associated with clearing. However, the "best" soils (e.g., haplic phaeozem) appear to attract coffee rather than conventional agriculture. Therefore, in contrast to natural forests, such soils are associated with forest, not clearing.

5.1.3 Socioeconomic and agronomic variables

As expected, INDIG is positively correlated with the probability of clearing. In other words, clearing is more likely in heavily indigenous towns. Also, as expected, FSIZE is negatively correlated with the probability of clearing.

The elasticities (E) in the third column from the right in Table 2 provide some insight into which of our independent variables are most important economically.[8] In order of absolute

[8] For the continuous variables, this elasticity is the percent change in the probability of clearing due to a one unit increase in the independent variable. For example, the elasticity for SLOPE is the percent change in the probability of clearing due to a one degree increase in slope, all other things equal. For dummy variables, the elasticity is the percent change in the probability of clearing when the dummy is 1 instead of 0. For example, the elasticity for N_FACE is the percent change in the probability of clearing when a plot is north-facing, all other things equal. Because the elasticities for continuous variables are calculated using a marginal change in the independent variable while the elasticities for the dummy variables are calculated using a nonmarginal change, caution must be exercised when comparing the two types of elasticities.

magnitude, the highest elasticities among the continuous variables are for FSIZE, DIST_TWN, and COOP.

5.2 Determinants of forest clearing inside versus outside the coffee range

Model 3 uses a sample of 20,283 plots drawn from the entire study area (including plots located above and below the coffee range) to test whether the determinants of land clearing inside the coffee range are the same as those outside of it. The model includes a dummy variable, COF, that identifies plots located inside the coffee range, as well as COF interaction terms for each regressor. Significance tests for the individual interaction terms indicate the extent to which each regressor has a different effect on the probability of clearing inside the coffee range versus outside this range.

Interaction terms aside, the specification of Model 3 differs slightly from that of Model 2. Model 3 omits COOP and FSIZE, which are not meaningful outside of the coffee range where there are no coffee farms, and includes three new dummy variables—PARK, HILLS, and PLAINS—which describe institutional and geophysical characteristics not found inside the coffee range.[9] Table 2 presents the regression results for Model 3. First, note that COF is negatively correlated with the probability of clearing, all other things equal. Thus, as expected, shade coffee is associated with forest cover.

5.2.1 Institutional variables

EJI_COM is negatively correlated with the probability of clearing. However, EJI_COM*COF is positively correlated with the probability of clearing, and its coefficient is approximately three times that for EJI_COM. Thus, inside the coffee range, common *ejido* land is associated with clearing, while outside of the coffee range it is associated with forest cover.

[9] These differences in specification prevent us from using interaction terms to imbed Models 2 and 3. The omission of COOP and FSIZE in Model 3 may give rise to specification bias. However, if Model 2 is run without COOP and FSIZE, the magnitude and significance of the remaining coefficients change very little, with the exception of several of the soil variables and ALTIT. This finding suggests the omitted variables bias is not severe.

The reason may be that inside the coffee range, *ejido* land parceled out to individual members (versus held in common) tends to be devoted to shade coffee. Therefore, inside the coffee range, nontimber forest products and ecological services generated by forests are relatively plentiful and the opportunity cost of clearing common *ejido* land is relatively low. Outside the coffee range, however, land parceled out to individual *ejido* members is often cleared for conventional agriculture and pasture, so that nontimber forest products and forest ecological services are relatively scarce. As a result, outside the coffee range, the opportunity cost of clearing common *ejido* land is higher.

5.2.2 Geophysical variables

DIST_CMKT is negatively correlated with the probability of clearing. However, DIST_CMKT*COF is positively correlated with the probability of clearing, and its coefficient is almost three times that for DIST_CMKT. Thus, DIST_CMKT has a different effect inside the coffee range than it does outside of it. Inside the coffee range, plots closer to coffee markets tend to be forested, while outside the coffee range, such plots tend to be cleared—the conventional result for natural forests.

Unlike DIST_CMKT, both DIST_TWN and DIST_CITY have the same effect on the probability of clearing inside and outside the coffee range. DIST_TWN is negatively correlated with the probability of clearing, while the coefficient on DIST_TWN*COF is insignificant. DIST_CITY is positively correlated with the probability of clearing, while the coefficient on DIST_CITY*COF is insignificant. Thus, regardless of whether they are located inside the coffee range or outside of it, plots closer to town centers are more likely to be cleared, all other things equal, while plots close to big cities are less likely to be cleared, all other things equal.

DIST_CITY merits a brief discussion. As noted above, DIST_CITY affects the probability of land clearing through transportation costs and through the effective cost of cleared land. Inside the coffee range, proximity to cities boosts the return to shade coffee by lowering the cost of seasonal agricultural labor, and it raises the effective cost of cleared land because restrictions on clearcutting are more likely to be enforced close to big cities. Both of these factors imply that, all other things equal, inside the coffee range one would expect to find forest in close proximity to cities. Outside the coffee range, the transportation costs effect does not come into play, but the enforcement effect does. Presumably, this second effect explains the effect of DIST_CITY outside the coffee range.

Of the remaining geophysical variables, some have different effects on the probability of clearing inside the coffee range, and others do not. The coefficient on N_FACE is negative and significant, as is the coefficient on N_FACE*COF. Thus, the negative correlation between N_FACE and the probability of clearing is stronger inside the coffee range than outside of it, a result that may stem from the relatively high opportunity costs of clearing inside the coffee range.

The coefficient on SLOPE is positive and insignificant. However, the coefficient on SLOPE*COF is positive and (weakly) significant. Thus, while SLOPE has no discernible impact on the probability of clearing outside the coffee range, it has a positive impact inside the coffee range.

ALTIT is negatively correlated with the probability of clearing, all other things equal, while the coefficient on ALTIT*COF is insignificant. Thus, the effect of ALTIT is the same inside and outside the coffee range—plots at higher elevations are less likely to be cleared, all other things equal. Outside the coffee range, this effect likely stems from the fact that low-lying plots are better suited to conventional agriculture and ranching.

Of the eight soil variables, our results suggest that four—SOILC_4, SOILC_5, SOILC_6, and SOILT_2—have different effects on the probability of clearing inside the coffee range than they do outside it. For example, SOILC_6, a dummy indicating the presence of eutric regosol, is positively correlated with the probability of clearing. However, the coefficient on SOILC_6*COF is negative, significant, and larger than the coefficient on SOILC_6. These results suggest that eutric regosol is associated with clearing outside the coffee range, but is associated with forest cover inside this range. Given that many of the soil types and characteristics that promote agriculture also promote shade coffee, explanations for these differential effects are necessarily somewhat speculative. The general result is useful, however—soil characteristics may have different impacts on land cover in a managed forest ecosystem than in a natural forest.

5.2.3 Socioeconomic variables

Finally, INDIG has the same effect on the probability of land clearing inside the coffee range and outside of it. INDIG is positively correlated with the probability of clearing, all other things equal, but the coefficient on INDIG*COF is not significant.

6. Conclusion

We have used a set of spatial regression models to identify the determinants of forest cover in a region dominated by a managed forest ecosystem. Our results suggest that in such systems, the determinants of land cover differ from those in natural forests in a number of ways. In natural forests, proximity to urban centers as well as price and cost advantages for agricultural goods have been repeatedly linked to forest clearing. However, we find that in a managed forest ecosystem, these factors *reduce* the probability of land clearing when the urban centers in question are also key markets for a nontimber agroforestry crop, and when the price and cost advantages in question are associated with that crop. Also, we find that soil types and certain topographical features linked with clearing in natural forests are instead associated with forest cover in a managed forest ecosystem. Several of our other findings jibe with the literature on land cover in natural forests. We find that forest clearing is associated with common property, proximity to small town centers, and the directional orientation of land.

These findings suggest that at least two "conventional" policy prescriptions for preserving forest cover—i.e., policy prescriptions based on studies of natural forests—may not hold in managed forest ecosystems. First, in natural forests, transportation investments that improve access to markets are generally thought to exacerbate deforestation. Our results suggest that in managed forest ecosystems, however, such investments could help to stem deforestation by raising the net return to agroforestry systems that preserve forest cover. The impact on forest cover of road building is likely to be complex, however. More and better roads will inevitably improve access to output and input markets for conventional agricultural goods and timber, as well as to markets for nontimber agroforestry crops. The net effect on forest cover is uncertain. Other means of improving market access such as subsidizing or improving transportation services targeted specifically at producers of nontimber agroforestry crops may have less ambiguous impacts.

Second, in natural forests, “pro-agriculture” policies such as promoting marketing cooperatives and subsidizing inputs are generally thought to promote forest clearing. Our results suggest that in a managed forest ecosystem, however, such policies may help to preserve forest cover when the agricultural good in question is a nontimber agroforestry crop.

Figure 1. Location of Study Area

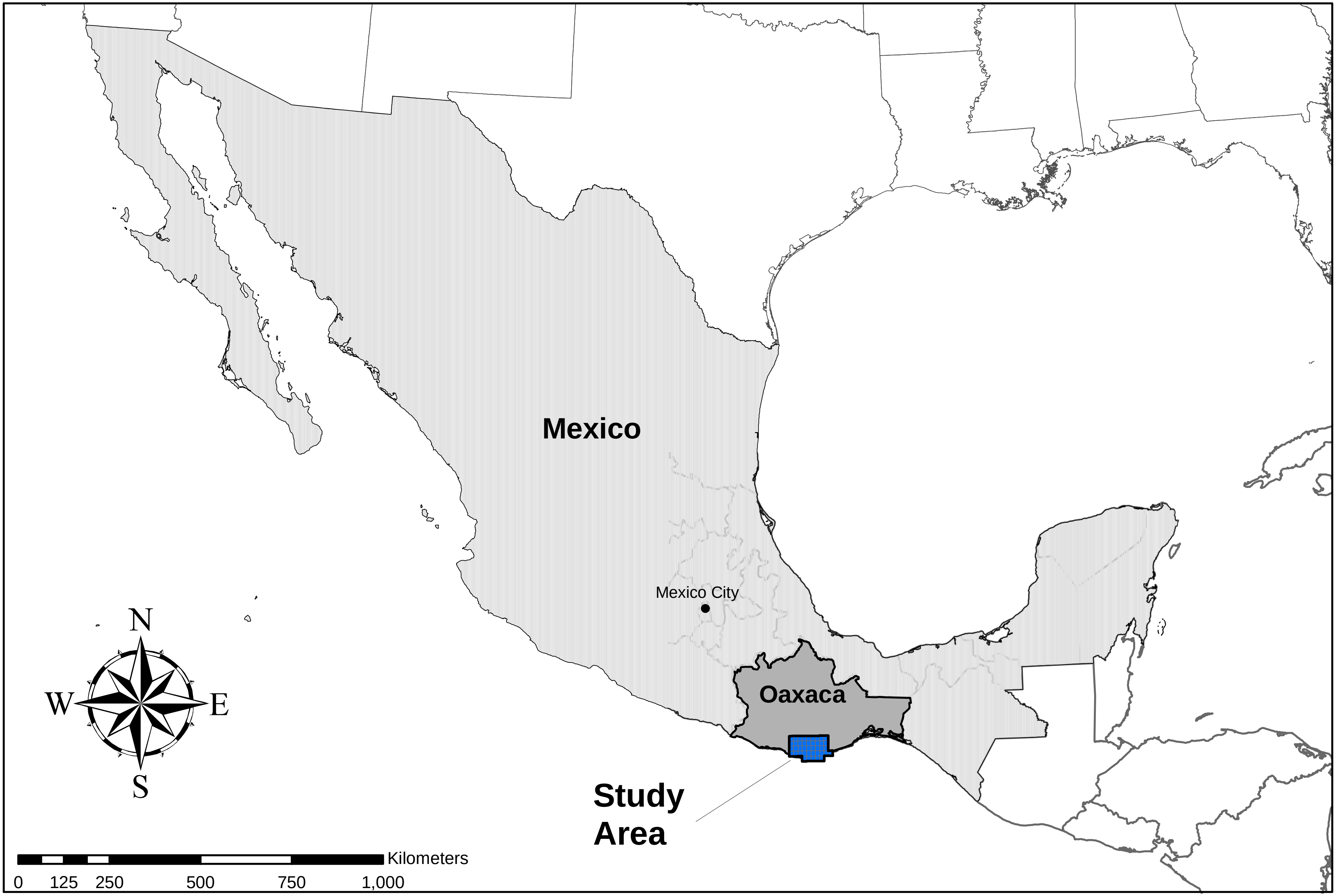
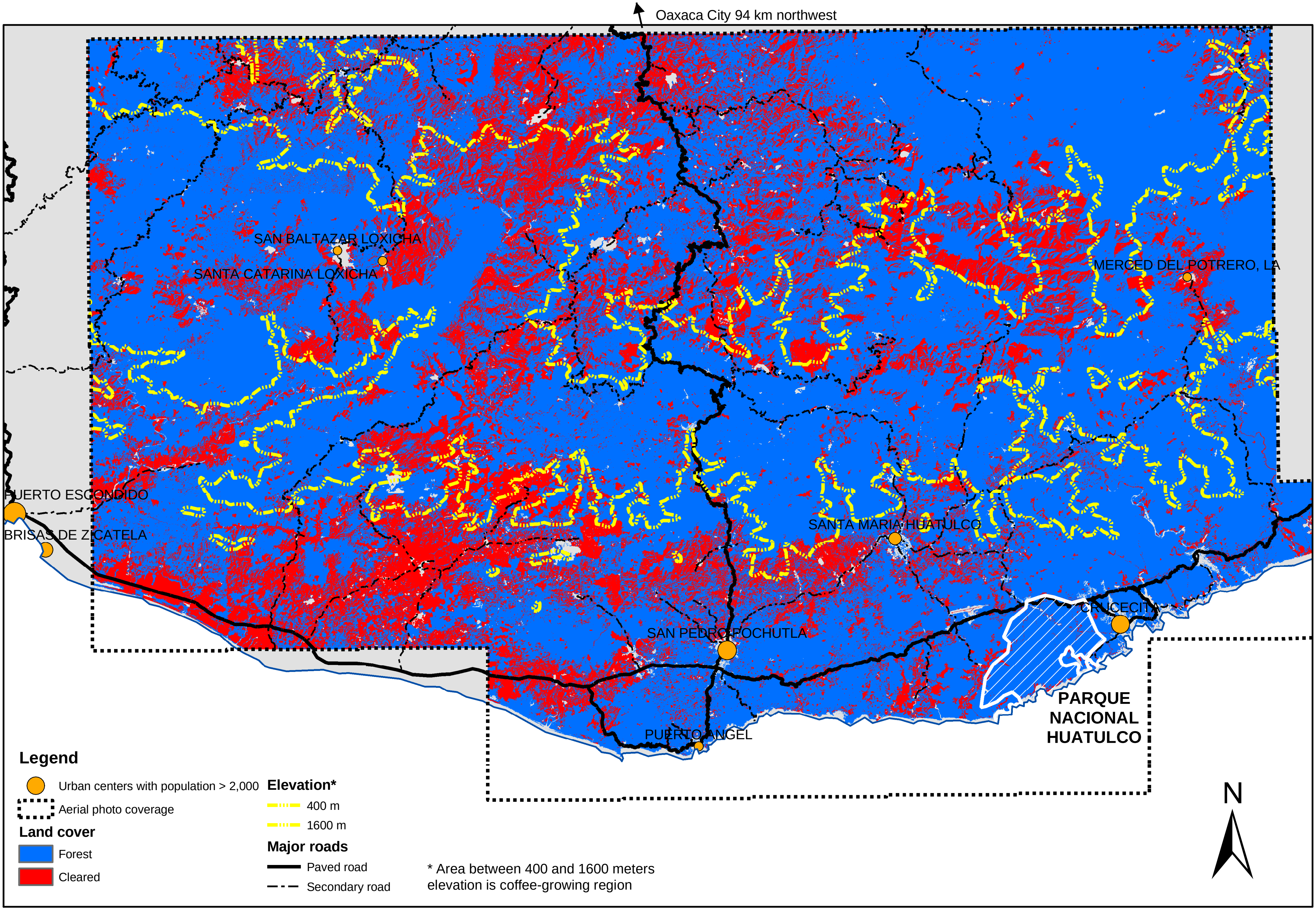


Figure 2.
Land Cover in the Study Area



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Appendix 1. Soil variables

Of the six soil types, haplic phaeozem (SOILC_4) is generally considered the best for all types of agriculture (including coffee) because it is characterized by high organic content, high base saturation, and low levels of calcium carbonate. Lithosol (SOILC_5), on the other hand, is generally considered the worst for all types of agriculture because it is characterized by extremely shallow soils. This feature makes it especially unsuitable for coffee, which has relatively deep roots requiring up to three meters of soil. The remaining four soil types are considered usable—although less than ideal—for both conventional agriculture and coffee. Both humic acrisol (SOILC_1) and eutric cambisol (SOILC_2) are high in clay, which can stunt root growth, a feature that makes them particularly problematic for deep-rooted plants like coffee. Rendzina (SOILC_3) is also viewed as poor soil for coffee because of high levels of calcium carbonate, which inhibits nutrient uptake. Eutric regosol (SOILC_6) is considered poor for coffee due to low levels of organic matter. Of the three soil textures in our study area, fine (SOILT_3) is generally considered best for all types of agriculture. Of the three soil physical characteristics, no characteristics (SOILF_0) is generally considered the best for all types of agriculture, and rock (SOILF_5) the worst (Eswaran 2002, FAO 1998, Wilson 1985 and 1999 and Wellman 1961).

Appendix 2. Impedance-weighted distances

Impedance-weighted distances were calculated in ARCINFO by the following method. First, impedances were assigned to each pixel in our study area to account for slope and whether or not a road was present. More specifically, we used the following formulas: for pixels on paved roads, impedance is equal to 1 plus the square root of slope (in degrees); for pixels on secondary roads, impedance is equal to 3 plus the square root of slope; and for all other pixels, impedance is equal to 10 plus three times the square root of slope. Calculated in this manner, impedance in our study area ranges from 1 to 105, and can be interpreted as the inverse ratio of the rate of travel in hundredths of a kilometer per hour. Thus, the rate of travel on a perfectly flat paved road is 100 kilometers per hour, and the rate of travel on a steep pixel with no road is 0.95 kilometer per hour. Having assigned impedances to each pixel, we used standard iterative techniques to plot the minimum impedance routes from each pixel to the town center, from each pixel to the nearest city with a population greater than 2,000, and from each *cabecera* to the one north-south paved road in our study area. Finally, we divided each of these weighted distances by the constant needed to convert them into travel times in hours. (Our assumptions imply a linear relationship between impedance-weighted distance and the time needed to travel that distance). Thus, the variables DIST_TWN, DIST_CITY, and DIST_MKT may be interpreted as total travel times in hours.