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Central America
Environment for Development Program for Central America
Centro Agronómico Tropical de Investigacíon y Ensenanza (CATIE)
Email: centralamerica@efdinitiative.org

China
Environmental Economics Program in China (EEPC)
Peking University
Email: EEPC@pku.edu.cn

Ethiopia
Environmental Economics Policy Forum for Ethiopia (EEPFE)
Ethiopian Development Research Institute (EDRI/AAU)
Email: ethiopia@efdinitiative.org

Kenya
Environment for Development Kenya
Kenya Institute for Public Policy Research and Analysis (KIPPRA)
Nairobi University
Email: kenya@efdinitiative.org

South Africa
Environmental Policy Research Unit (EPRU)
University of Cape Town
Email: southafrica@efdinitiative.org

Tanzania
Environment for Development Tanzania
University of Dar es Salaam
Email: tanzania@efdinitiative.org

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Abstract

Little is known about land cover change in mixed agroforestry systems, which often supply valuable ecological services. We use a spatial regression model to analyze clearing in El Salvador's shade coffee–growing regions during the 1990s. Our findings buttress previous research suggesting the relationship between proximity to cities and clearing in mixed agroforestry systems is the opposite of that in natural forests. But this result, and several others, depends critically on the characteristics of the growing area, particularly the dominant cleared land use. These findings imply that policies aimed at retaining mixed agroforestry need to be carefully targeted and tailored.

Key Words: agroforestry, shade coffee, land cover, El Salvador, spatial econometrics

JEL Classification Numbers: O13, Q15, Q23

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1. Introduction

To date, conservation policy has concentrated on primary forests. Increasingly, however, the focus is being broadened to include human-dominated landscapes, such as agroforestry systems, managed forests, and hedgerows. There are several reasons. First, human-dominated landscapes can provide many of the same ecological services as primary forest, albeit often at lower levels: they can harbor biodiversity, sequester carbon, prevent soil erosion, and aid in flood control, water purification, and aquifer recharge (Daily et al. 2003; Castro et al. 2003; Vandermeer and Perfecto 1997). Second, managed landscapes can provide corridors between patches of primary forests and may help preserve them by diverting extractive activities, such as hunting and foraging (Gajaseni et al. 1996; Saunders and Hobbs 1991). Finally, large tracts of undisturbed primary forests are becoming scarce. This trend will be difficult to reverse: for economic and political reasons, only a small percentage of primary forests can be legally protected, and protection is often weak in developing countries (Chomitz 2007; FAO 2003; Daily et al. 2003).

Among the different types of human-dominated landscapes that can provide ecological benefits, mixed agroforestry systems—in which crops such as coffee, cocoa, and bananas are planted side by side with woody perennials—have attracted particular attention (Scherr and McNeely 2002; Szaro and Johnston 1996). Most of the economic research on these systems has focused on their adoption, not their retention (e.g., Pattanayak et al. 2003). We know little about the drivers of land use change in established mixed agroforestry systems, information needed to

* Allen Blackman, Senior Fellow, Resources for the Future; blackman@rff.org. Beatriz Ávalos-Sartorio, Director of Academic Development, Polytechnic University of Morelos. Jeffrey Chow, doctoral candidate, Yale School of Forestry and Environmental Studies. Funding for this study was provided by the InterAmerican Development Bank, the Tinker Foundation, and Resources for the Future. We are grateful to Francisco Aguilar, Conrad Coleman, Eili Klein, and Lisa Crooks Murphy for excellent research assistance; Sergio Lombardo Gil, Oscar Gómez, Carlos Pleitez, Oscar Rivas, and Pablo Aguilar at PROCAFE for multifaceted assistance; Sassan Saatchi at NASA's Jet Propulsion Laboratory for providing our land cover data; Diego Arias, Deborah Barry, Jeffrey Jones, and Silvia Oritz for helpful comments and logistical support; and Federico Barillas, Carolina Canales, Luis Arturo Celis, Raphael Guillén, Julio Alberto Olano, Tomás Ovidio Bonilla, Angel Corleto Urey, Wilfredo Fuentes, Ervin Sermeño, and Margarita Villarán for providing data. Any remaining errors are our own.

design effective conservation policies. Does conversion to cleared land uses occur mainly in certain geophysical settings—for example, on plots close to urban centers? Or does it occur mainly in certain institutional settings—for example, where marketing cooperatives for nontimber forest products are absent?

Spatial regression models, which explicitly account for location within counties, towns, and other administrative units, are often used to explain patterns of land clearing in natural forests (for reviews, see Chomitz 2007 and Kaimowitz and Angelsen 1998). These analyses typically find that clearing is associated with proximity to urban centers, proximity to roads, and land deemed more suitable for conventional (nonagroforestry) agriculture because it is flat, fertile, and has adequate drainage (Cropper et al. 2001; Nelson and Hellerstein 1997; Mertens and Lambin 1997; Chomitz and Gray 1996).

Intuition suggests, however, that these findings may not apply to mixed agroforestry systems. For example, in natural forests, clearing tends to occur near urban areas mainly because the costs of transporting inputs and outputs associated with land uses that entail clearing are lower in such areas. But in mixed agroforestry systems, proximity to urban centers also reduces the costs of transporting inputs and outputs associated with nontimber agroforestry products, a factor that would encourage the preservation of tree cover. In essence, in mixed agroforestry systems, land uses that entail clearing compete with agroforestry for land close to urban areas, and it is not clear which will dominate.

To our knowledge, Blackman et al. (2008) is the only spatial regression analysis of land cover in a mixed agroforestry system. The authors examine mid-1990s patterns of accumulated land clearing, mainly for shifting subsistence agriculture, in a Mexican coastal area dominated by shade coffee, a mixed agroforestry system in which coffee is grown alongside trees. They find that clearing tends to occur farther from markets and large cities, all other things equal. This pattern of land cover is the opposite of that generally observed in natural forests. In addition, they find that membership in coffee-marketing cooperatives is associated with tree cover while proximity to small towns, low altitude, and certain soil types is associated with clearing.

In this paper, we examine land cover change in the shade coffee–growing regions of El Salvador during the 1990s. We focus on El Salvador because its shade coffee is particularly important ecologically. El Salvador is the most densely populated country in Latin America and also the most severely deforested. Less than 10 percent of its natural forests survive, and the vast majority of remaining tree cover is associated with shade coffee (FAO 2002). Shade coffee supplies many of the ecological services mentioned above. Of particular note is harboring biodiversity. Shade coffee is grown at altitudes of 500 to 1,600 meters above sea level where tropical and temperate climate zones overlap. These areas are rich in biodiversity (Perfecto et al. 1996). We focus on the 1990s because international coffee prices declined sharply during this decade, a phenomenon known as the coffee crisis.[1] The crisis spurred large scale conversion of coffee farms to more profitable land uses throughout Latin America (Rice 2003). This historical experience serves as a natural experiment that enables us to analyze the drivers of land cover change.

Like Blackman et al. (2008), we use a spatial regression model to analyze remotely sensed land cover data. However, the present analysis embodies two advances. First, instead of examining a single relatively homogeneous shade coffee area dominated by a single cleared land use (shifting subsistence agriculture), we analyze three distinct shade coffee areas with different geophysical and socioeconomic characteristics, including dominant cleared land uses. This enables us to test the extent to which our findings generalize across different settings. Second, instead of using a single cross section of land cover data to examine accumulated patterns of clearing, we use two cross-sections to analyze land cover change during a well-defined time period. This enables us to be certain that plots we designate as having been cleared previously had tree cover, and to know when the clearing occurred. It also allows us to control for potential endogeneity by using explanatory data from the early part of our study period.

Our findings support a key result of Blackman et al. (2008): in mixed agroforestry systems, clearing typically occurs farther from markets, not closer to them, as in natural forests. However, this result, along with several others, depended critically on the characteristics of the area where agroforestry is cultivated, namely on whether it was mainly rural or periurban, and whether urban or other types of cleared land uses dominated. Among the three main coffee-growing regions in El Salvador, we find that in two that were primarily rural, clearing occurred farther from coffee export markets. However, in the one region that was largely periurban, this relationship did not hold. Furthermore, we find that in the one coffee region where nonurban

[1] The extent to which our study period coincides with—or predates—the "coffee crisis" is open to question; a precise definition of this term does not exist. Recent studies frequently use it to refer to the precipitous decline of prices between 1997 and 2001 (e.g., Varangis et al. 2003; World Bank 2005). However, the overall downward trend in coffee prices that culminated in this steep five-year slide began decades earlier, and many researchers use the 1989 collapse of the International Coffee Agreements quota system to mark the start of the coffee crisis (e.g., Ponte 2002; Gresser and Tickell 2002). Hence, using the first definition, our study period overlaps with the last three years of the coffee crisis. Using the second definition, it covers a ten-year period in the middle of the crisis. In both cases, however, our study period misses the trough in prices that occurred in 2001.

cleared land uses like agriculture and pasture dominated, clearing tended to occur on flat land and at low altitudes—that is, on land that favored these activities. But in two coffee regions where urban cleared land uses dominated, these results did not hold. The effect of the coffee regions' socioeconomic characteristics on spatial patterns of clearing also depended on the dominant cleared land use. Our findings imply that policies aimed at retaining mixed agroforestry systems need to be carefully targeted and tailored to specific locations and institutional settings.

The remainder of the paper is organized as follows. The next section provides background on El Salvador's coffee sector. Section 3 discusses the magnitude and characteristics of land use change in El Salvador's coffee areas during the 1990s. Section 4 presents an analytical model of land use. Section 5 describes our data and discusses estimation issues. Section 6 presents our regression results, and the last section summarizes our findings and discusses their policy implications.

2. Background

2.1 Sector statistics and location

In the 2003–04 harvest season, El Salvador produced almost 2 million quintals (46-kg sacks) of green coffee, which represented about 1 percent of the world's total and 11 percent of Central America's total. Ninety percent of the crop was exported, generating more than $120 million in revenue (ICO 2008; PROCAFE 2004).

Coffee in El Salvador grows in three main areas: the west region located in the Apaneca-Ilamatapec mountain range; the center region located in the El Bálsamo and Chichontepec volcano mountain ranges; and the east region located in the Tecapa Chinameca and Cachuatique mountain ranges (Figure 1). In the 2003–04 harvest season, coffee was planted on a total of 161,000 hectares (PROCAFE 2004).

2.2. Grower and processor characteristics

In 1998, 95 percent of El Salvador's coffee was shade grown (GEF 1998). The density of shade cover that farmers use depends partly on the local microclimate. More dense shade cover is used to help retain soil moisture and reduce air temperature in lowland areas, which are generally hotter and drier than upland areas.

El Salvador's roughly 24,000 coffee growers fall into three categories distinguished mainly by land tenure: independent growers who own and manage their farms and sell their crop to private mills; growers affiliated with so-called private cooperatives, who also own and manage their farms but cooperate with each other in processing and marketing their coffee; and growers affiliated with so-called reform cooperatives *(cooperativas de la reforma)* created by the agrarian reforms of the 1980s, in which coffee mills and most land are held communally. Private cooperatives control about 16 percent of El Salvador's total coffee acreage and reform cooperatives control about 8 percent (Barillas 2006; PROCAFE 1998).

In El Salvador, coffee processing is performed almost exclusively by large, centralized mills called *beneficios*, not by the small on-farm operations common in other Latin American countries. Most *beneficios* transform raw coffee cherries into parchment coffee, an intermediate product, and sell it to exporters.

Coffee quality is positively correlated with altitude. The Salvadoran Coffee Council, the country's coffee trade and marketing organization, assigns coffee one of three quality standards depending on the altitude at which it is grown: central standard for coffee grown at 600 to 800 meters above sea level (msl); high grown for coffee grown at 800 to 1,200 msl; and strictly high grown for coffee grown above 1,200 msl. Almost three quarters of Salvadoran coffee exports is either high grown or strictly high grown, the top two quality grades. Although other types of specialty coffees, including certified organic and certified shade grown coffee, have increased market share in the past several years, they still make up less than 3 percent of overall exports (PROCAFE 2004).

2.3. Coffee pricing and crisis

On average, Salvadoran coffee growers receive 55 percent of the international price, with the balance going to *beneficios,* creditors, and state-sponsored technical extension, debt relief, and marketing programs (PROCAFE 2004). The farm-gate prices that growers receive are spatially differentiated because they reflect the cost of transporting coffee from the *beneficio* to ports in the western part of the country (see Appendix 1 for geographic details). Hence, all other things equal, coffee growers in the eastern part of the country typically receive lower prices than those in the west, as do those located relatively far from main east-west roads in all three coffee areas.

Like its counterparts around the globe, the Salvadoran coffee sector was greatly affected by price shocks during the 1990s. After a decade of decline in the 1980s, international coffee prices rebounded for three harvest years in the mid- to late-1990s (in part because of a severe freeze in Brazil that reduced world supply) but then continued a precipitous downward slide in 1998–99. The effects on the coffee sector were dramatic. Production, yields, wages, and permanent employment fell by 23 to 24 percent between 1991–92 and 2000–01.[2] As discussed below, the crisis, among other factors, spurred significant land use change in coffee regions during the 1990s.

3. Tree Cover Loss

We generated land cover change data for El Salvador's three coffee-growing regions by comparing a 1990 digital land cover map derived from LANDSAT satellite images with a compatible digital map for 2000. Both maps were created using the same classification methodology by NASA's Jet Propulsion Laboratory. The land cover change map comprises 57-meter-square pixels, or "plots."

The 1990 and 2000 NASA land cover maps do not distinguish between coffee and other types of land cover. Therefore, to identify areas where coffee is growing (depicted in Figure 1), we used a Salvadoran Ministry of Agriculture (MAG) land use map for 1992–1994. Collectively, these three areas comprise 197,000 hectares. Note that the MAG map identifies only the perimeter of the three main coffee-growing areas; it does not distinguish among land uses within the coffee area. Not all of the land inside the MAG map's coffee perimeters is planted in coffee: some is devoted to cleared land uses, such as housing, pasture, and row crops, and some is natural forest. However, our data suggest that in the early 1990s, more than 80 percent of this total area was devoted to coffee, and that of the portion of this area with tree cover, more than 90 percent was coffee.[3]

Our 1990 and 2000 land cover maps assign each pixel to one of the following five classes: woody vegetation, dense forest, mixed woody vegetation, nonforest, and water. By construction, each of the first three classes requires the presence of trees. As noted above, tree

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[2] The reduction in yields reflects the fact that growers cut back on farm maintenance (e.g., pruning) and inputs (e.g., fertilizer) when price shocks hit.

[3] Our 1990 NASA land cover map indicates that 182,000 hectares (92 percent) of the 197,000-hectare MAG-defined coffee area had tree cover in 1990. Official statistics indicate that in 1990–91, 164,000 hectares in this area were planted in coffee (PROCAFE 2004). These 164,000 hectares constitute 83 percent of all the land in the MAG-defined coffee area and 90 percent of all the land in these areas with tree cover.

density on shade coffee farms varies. In 1990, 63 percent of the coffee area was classified as mixed woody vegetation, 27 percent as dense forest, and 2 percent as woody vegetation.

We define a plot as having been cleared if it was categorized as mixed woody vegetation, dense forest, or woody vegetation in 1990 and as nonforest in 2000. Table 1 presents data on clearing, and Figure 2 represents it graphically. Fully 13 percent of land area in the three coffee regions was cleared during the 1990s. The percentage of land cleared differed dramatically across the three coffee regions. It was far and away the highest in the west region (17 percent) and the lowest in the east region (7 percent). Figure 2 shows that clearing was not confined to large uninterrupted areas. Rather, it was fragmented and patchy. This pattern begs the question of why some plots were cleared and others were not, which is the question addressed by our econometric model.

Table 1. Clearing in Salvadoran coffee regions, 1990–2000

Tree cover	*All coffee regions*		*West region*		*Center region*		*East region*	
	Area (ha.)	*Percentage*	*Area (ha.)*	*Percentage*	*Area (ha.)*	*Percentage*	*Area (ha.)*	*Percentage*
Cleared	24,700	13	14,000	17	7,500	11	3,200	7
Not cleared	172,100	87	70,200	83	60,900	89	41,000	93
Total	196,800	100	84,200	100	68,400	100	44,200	100

(Source: calculated in ArcGIS from NASA JPL land cover maps)

During the 1990s, what specific land uses substituted for shade coffee in each of the three main coffee areas? Unfortunately, to our knowledge, no hard data exist to answer this question. Our land cover maps cannot provide the answer because they lump all land uses that entail clearing into a single nonforest class. Other land cover maps from this period (like the MAG map discussed above) simply designate all land within the perimeter of three coffee regions as "coffee." In-person interviews with a wide range of coffee sector stakeholders suggested that the main land uses substituting for shade coffee between 1990 and 2000 were urban uses, row agriculture, ranching, and clearcutting for lumber and firewood with no land use substituted for coffee.

To get a back-of-the-envelope estimate of the importance of these land uses across the three coffee regions during the 1990s, we interviewed directors of the east, center, and west regional offices of PROCAFE, El Salvador's parastatal coffee extension and research agency, who were responsible for, among other things, estimating coffee acreage in their region and slowing conversion out of shade coffee. They reported that dominant land uses substituting for coffee were different across the three regions during the 1990s. In the center and west regions, more than two-thirds of clearing was due to urbanization. In the east, however, the main land uses replacing coffee were logging for timber and firewood (with no productive land uses replacing coffee), small-scale agriculture, and small-scale ranching (Iglesias 2005; Flores 2005; Tenorio 2005).

That information comports with plentiful evidence of rapid urbanization during the 1990s in El Salvador's southwest highlands, in particular in the greater San Salvador metropolitan area. This phenomenon partly reflects Central American trends during this period (Cerrutti and Bertoncello 2003). But it also was due to civil unrest and chronic poverty in the eastern and northern parts of the country, which spurred a massive internal migration to the southwest.[4] Urbanization in San Salvador and other parts of the southwest was particularly rapid in highland areas historically dominated by coffee, which have a more hospitable climate than lowland areas. In many areas, the price of agricultural land rose well above the net present value of its lifetime productive value, making continued agricultural land uses unprofitable.[5]

4. Analytical Model

We model a land manager's decision to convert shade coffee to cleared land use using the conventional "land rent" formulation (Chomitz and Gray 1996; Nelson and Hellerstein 1997; Munroe et al. 2002). The model is premised on the simple idea that any given plot of land can be devoted to several competing uses, each of which generates a net rent (return) that depends on the characteristics of the plot, such as its elevation and proximity to agricultural markets, and on the fixed cost of converting it from one land use to another. The land manager chooses the land use that generates the highest net rent.

Formally, neglecting for the moment the fixed cost of converting shade coffee to an alternative land use, the rent a manager receives from devoting plot i to land use k at time T is given by

[4] The greater San Salvador metropolitan area had a population of more than 2 million in 2000—roughly a third of the country's population—and had been growing rapidly throughout the 1990s: its population doubled between 1971 and 2000 (Cuéllar et al. 2002).

[5] All manner of farms, including coffee plantations, were carved up into small lots and sold to construction companies or directly to homesteaders, a process known as "lotification." Lotification did not just cater to middle or upper class Salvadorans. Rather, small lots averaging 250 square meters with no preexisting buildings, infrastructure, or services were sold at modest prices to low-income households. In 1995, the typical contract for such land was a 10-year mortgage with monthly payments of only 60–70 colones (World Bank 1997).

$$(1)\ R_{ikT} = \int_{t=0}^{\infty} \left(P_{ikT+t} Q_{ikT+t} - \mathbf{C}_{ikT+t} \mathbf{X}_{ikT+t} \right) e^{-r_i t} dt$$

where R is the present discounted value of a future stream of annual rents, P is the price of output associated with land use k, Q is quantity of this output, **X** is a vector of input quantities indexed by h, **C** is a vector of input prices, and r is the discount rate. Note that the discount rate may vary across plots, a formulation that allows for heterogeneity in effective interest rates and land use rules (e.g., Nelson and Hellerstein 1997). The output from plot i is determined by a Cobb-Douglass production function given by

$$(2)\ Q_{ikt} = S_i \prod_h X_{ihkt}^{\beta_{hk}} \qquad \text{with} \qquad 0 < \beta_{hk} < 1 \qquad \text{and} \qquad 0 < \sum_h \beta_{hk} \leq 1$$

where β and S are parameters. The latter is a shifting parameter that may be expressed as a product of geophysical and agronomic variables, s_i, having to do with, for example, soil type, slope, and elevation. For this analysis, we do not have spatial or temporal data on output prices or input costs. Therefore, following Chomitz and Gray (1996) and others, we construct proxies as follows:

$$(3)\ P_{ik} = \exp(\gamma_{0k} + \gamma_{ik} \mathbf{Z}_{ik})$$

$$(4)\ C_{ik} = \exp(\delta_{0k} + \delta_{ik} \mathbf{Z}_{ik})$$

where **Z** is a vector of observable location-specific variables, such as distance to markets, that determine prices and costs. Substituting equations (2), (3), and (4) into (1), deriving rent-maximizing input demands, taking advantage of the fact that most parameters are not time-dependent, simplifying, and adding a stochastic error term yields

$$(5)\ \ln R^*_{ik} = \mathbf{V}\boldsymbol{\chi} + u_{ik}$$

where R^* is maximized rent, **V** is a vector of plot-specific variables associated with **Z** and S, $\boldsymbol{\chi}$ is a vector of parameters, and μ is an error term.

Following Munroe et al. (2002), we assume that converting shade coffee to another land use entails a fixed cost, w_k, that is orthogonal to all other explanatory variables. For example, converting shade coffee to pasture entails fixed costs associated with clearing tree cover, fencing, and buying and learning how to raise cattle. Given such fixed costs, land managers may choose to retain shade coffee even though alternative land uses generate a higher annual return.

We assume a land manager decides whether to convert shade coffee by calculating and then comparing the *net* returns to different land uses—that is, the present discounted value of a stream of annual returns minus the fixed conversion cost. A land manager will convert when maximum net return to the set of all land uses that involve clearing exceeds the maximum net return to shade coffee—that is, when

$$(6)\ R_i = \pi^*_{iD} - \pi^*_{iC} \geq 0$$

where π^*_{iC} is the maximum net return to shade coffee and π^*_{iD} is the maximum net return to the set of alternative land uses that involve clearing, that is,

$$\pi_{iD} = \max_{k \in D}(R^*_{ik} - w_k)$$

such that D is the set of land uses that involve clearing. Combining equations (5) and (6), we have

$$(7)\ \hat{R}_i = \mathbf{W}\boldsymbol{\psi} + u_i$$

where **W** is a vector of plot-specific variables associated with **Z** and S, and $\boldsymbol{\psi}$ is a vector of parameters. Although $\hat{R}_i$ is latent and unobserved, we observe an indicator variable, L_i, such that

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

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

Using this dichotomous dependent variable, equation (7) may be estimated as a probit.

5. Econometric Model

5.1. Data

Computational constraints make it difficult to explain land cover change on each of the 601,000 57-meter-square plots in our tree cover map. Therefore, we constructed a sample of plots as follows. First, we overlaid a rectangular grid onto the land cover change map, with grid lines spaced 250 meters apart, and selected all of the approximately 30,000 plots where vertical and horizontal grid lines intersected.[6] Next, we eliminated plots classified as "water" and those for which data are missing. The resulting sample contains 29,450 plots. For each, we used ArcGIS to match data on tree cover—our dependent variable—with data on the plot's geophysical, institutional, agronomic, and socioeconomic characteristics—our independent variables. Each sample plot constitutes one record in our econometric analysis.

Table 2 presents detailed information on the variables used in the econometric analysis, including units, sources, scale, and dates. The variables are grouped into four categories: land cover, geophysical, institutional, and socioeconomic. Note that although all 20 of the land cover and geophysical variables are at the plot-level, four of the five institutional and socioeconomic variables are at the canton-level (simply because data at the plot-level do not exist). The three coffee areas comprise 950 cantons, each averaging roughly 200 hectares, so the spatial resolution of the canton-level variables is fairly high. Nevertheless, in interpreting regression results that involve these variables, it is important to keep in mind that they do not reflect the characteristics of the coffee farm on each sample plot. Rather, they reflect the average or median characteristics in the canton in which the plot is located.

[6] Our choice of a 250-meter grid was a compromise between the need for a scale of analysis fine enough to capture the spatial variation in our data set and coarse enough accommodate computational constraints.

Table 2. Variables in econometric analysis

Variable	*Description*	*Units*	*Source*	*Scale*	*Years*
Land cover					
CLEAR	Plot vegetated in 1990, not vegetated in 2000	0/1	NASA JPL[a]	plot	1990–2000
Geophysical					
TT_MK	Travel time from nearest road to major coffee ports by way of nearest *beneficio* (weighted avg.)	minutes	ArcGIS model	plot	n/a
TT_CY	Travel time to nearest city with pop. >19,000	minutes	ArcGIS model	plot	n/a
TT_RD	Travel time from sample point to nearest road	minutes	ArcGIS model	plot	n/a
SLOPE	Slope		Mapmart Inc.	plot	n/a
N_FACE	Aspect is north-facing	0/1	Mapmart Inc.	plot	n/a
AD_0_800	Altitude 0–800 meters	0/1	Mapmart Inc.	plot	n/a
AD_8_1200	Altitude 801–1200 meters	0/1	Mapmart Inc.	plot	n/a
AD_1200_P	Altitude 1200 plus meters	0/1	Mapmart Inc.	plot	n/a
SOIL10	Effusive andesites and basaltics: pyroclastics	0/1	MARN[b]	plot	n/a
SOIL11	Effusive andesites, pyroclastics, volcanic suborded epiclastites	0/1	MARN	plot	n/a
SOIL12	Effusive andesites-basaltics	0/1	MARN	plot	n/a
SOIL13	Effusive basaltics	0/1	MARN	plot	n/a
SOIL16	Effusive basaltics: ashes and lapilli tuffs	0/1	MARN	plot	n/a
SOIL17	Volcanic epiclastites, pyroclastics, streams of intercalated lava	0/1	MARN	plot	n/a
SOIL19	Acidic pyroclastics (white soil)	0/1	MARN	plot	n/a
SOIL21	Acidic pyroclastics, volcanic epiclastites (brown tuffs)	0/1	MARN	plot	n/a
SOIL24	Acidic pyroclastics, volcanic epiclastites, ardient and melted tuffs	0/1	MARN	plot	n/a
CAFE_REGW	Located in west coffee region	0/1	ArcGIS	plot	n/a
CAFE_REGC	Located in center coffee region	0/1	ArcGIS	plot	n/a
CAFE_REGE	Located in east coffee region	0/1	ArcGIS	plot	n/a
Institutional					
F_SIZE	Median area of coffee farms (actually planted in coffee)	ha.	PROCAFE	canton	1998
P_COOP	Percentage total area planted in coffee managed by reform cooperatives	%	PROCAFE[c]	canton	1998
PROT_AREA	Legally protected area	0/1	MARN	plot	1994–1998
Socioeconomic					
POP_DENS	People per square km	n/a	CNR[d]	canton	1992
PERC_WOMEN	Percentage women in population	%	CNR	canton	1992

[a]United States National Aeronautics and Space Administration, Jet Propulsion Laboratory; [b]Ministerio de Medio Ambiente y Recursos Naturales; [c]Fundación Salvadoreña para Investigaciones del Café; [d] Centro Nacional de Registros.

As discussed below, the causes and characteristics of tree cover loss differ in each of El Salvador's three main coffee-growing regions (Figure 2). Therefore, we split the full sample into three regional subsamples. Table 3 presents means for the east subsample (n = 6,627), center subsample (n = 9,519), west subsample (n = 13,304), and full sample (n = 29,450).

Table 3. Sample means

Variable	*East*	*Center*	*West*	*All*
	(n=6,627)	(n=9,519)	(n=13,304)	(n=29,450)
Land cover				
CLEAR	0.075	0.112	0.176	0.133
Geophysical				
TT_MK	420.484	166.675	95.217	191.508
TT_CY	86.203	55.563	49.796	59.853
TT_RD	15.611	15.938	15.997	15.891
SLOPE	12.517	11.960	9.339	10.901
N_FACE	0.429	0.377	0.438	0.417
AD_0_800	0.425	0.481	0.301	0.387
AD_8_1200	0.463	0.427	0.479	0.459
AD_1200_P	0.111	0.092	0.219	0.154
SOIL10	0.422	0.151	0.184	0.227
SOIL11	0.046	0.001	0.052	0.034
SOIL12	0.173	0.249	0.099	0.164
SOIL13	0.007	0.019	0.131	0.066
SOIL16	0.000	0.000	0.028	0.013
SOIL17	0.000	0.282	0.050	0.114
SOIL19	0.000	0.066	0.000	0.021
SOIL21	0.337	0.130	0.409	0.302
SOIL24	0.005	0.092	0.002	0.032
CAFE_REGW	—	—	—	0.452
CAFE_REGC	—	—	—	0.323
CAFE_REGE	—	—	—	0.225
Institutional				
F_SIZE	11.508	17.763	12.771	14.100
P_COOP	4.361	3.893	6.903	5.358
PROT_AREA	0.166	0.009	0.026	0.052
Socioeconomic				
POP_DENS	199.536	331.935	261.001	270.100
PERC_WOMEN	50.692	50.262	50.140	50.304

The remainder of this section describes each independent variable in Table 2 and discusses its possible impacts on the probability of clearing. These impacts amalgamate multiple underlying effects when the independent variable affects the return to more than one land use—a common phenomenon in spatial econometric analyses of land cover based on remote sensing data.[7] In some cases, these multiple effects reinforce each other. For example, available evidence suggests that the altitude of a plot boosts the return to shade coffee and lowers the return to row agriculture. Both effects imply that clearing will be less likely at higher altitudes. In other cases, however, multiple effects are countervailing. For example, available evidence suggests that proximity to a large city boosts the return to both shade coffee and row agriculture. Therefore, the net effect of proximity to a large city is uncertain.

Land use variable

The dependent variable CLEAR equals one if the plot had tree cover in 1990 and none in 2000, and equals zero otherwise.

Geophysical variables

We use three variables, TT_RD, TT_MK, and TT_CY, to analyze the effect of a plot's location—relative to coffee export markets and to the nearest large city—on the probability of clearing. As discussed in Sections 2 and 4, travel times to markets and cities are determinants of farm-gate input and output prices. These two travel times are correlated because each includes the time it takes to travel from the plot to the nearest road. To minimize this correlation and to disentangle the effects of travel time to coffee markets and travel time to the nearest city, we control for travel time to the nearest road. Hence, we include three travel time variables in the regressions: travel time from the plot to the nearest road (TT_RD), travel time from the nearest road to the nearest coffee export port by way of the nearest *beneficio* where coffee cherries are processed (TT_MK), and travel time from the nearest road to the nearest city with a population greater than 19,000 (TT_CY). Appendix 1 describes the ArcGIS model used to estimate travel times.

As noted above, TT_MK varies markedly within coffee regions depending mainly on the plots' proximity to a primary road. We expect TT_MK to be positively correlated with the probability of clearing because the growers located far from coffee market towns receive relatively low prices for their coffee and, therefore, earn relatively low rents on coffee farming.

[7] Such analyses aggregate multiple land uses into a small set of broad land cover categories, often just two ("cleared" and "noncleared") as in our analysis (e.g., Cropper et al. 2001; Munroe et al. 2002). This aggregation implies that the econometric model measures the net effect of plot characteristics on the probability of clearing through the returns to the individual land uses that constitute the land cover categories.

TT_CY has countervailing impacts on the probability of clearing. On one hand, proximity to a relatively large city boosts the return to shade coffee by lowering the transportation and transaction costs involved in acquiring inputs found in cities, notably the labor used to harvest coffee. On the other hand, proximity to a large city also boosts the return to urban and conventional agricultural land uses. The first effect implies that all other things equal, shade coffee—and therefore tree cover—is more likely to be found near big cities. The second effect implies that all other things equal, urban land uses and conventional agriculture—and therefore clearing—are more likely to be found near big cities.

Finally, TT_RD is a significant part of total travel time to both coffee markets and cities and, as a result, has countervailing effects on the probability of clearing, for the reasons just mentioned.

Slope (along with directional orientation, altitude, and soil characteristics) can be considered an argument of the production function shift parameter in the land rent model. A continuous variable measured in degrees, SLOPE measures average incline. We expect SLOPE to be negatively correlated with the probability of clearing in areas where the land uses that compete with shade coffee are best suited to flat land.

To capture directional orientation, we use N_FACE, a dummy variable that takes the value of 1 if the plot faces north, and 0 otherwise. In all three coffee areas, the best grades of coffee grow on south-facing slopes that are exposed to humid ocean breezes (Gómez 2005). As a result, we expect N_FACE to be positively correlated with clearing, all other things equal.

To control for possible discontinuities in the effect of altitude on the probability of clearing, we constructed three dichotomous altitude dummies based on the Salvadoran Coffee Council quality categories (see Section 2.2 above). AD_0_800 identifies plots between 0 and 800 msl; AD_8_1200 identifies plots between 801 and 1,200 msl, and AD_1200_P identifies plots above 1,200 msl. Altitude has countervailing impacts on the probability of clearing. On the one hand, the best grades of coffee grow at higher altitudes, where lower temperatures cause beans to mature more slowly. As a result, coffee farmers at higher altitudes typically receive better prices for their crop. By contrast, conventional agriculture is generally less productive at higher altitudes. These factors suggest that altitude will be negatively correlated with the probability of clearing, all other things equal. But on the other hand, anecdotal evidence indicates that demand for urban land uses is stronger at higher altitudes because temperature and humidity are lower, an effect that suggests altitude will be positively correlated with the probability of clearing, all other things equal. Which effect dominates is an empirical question.

Our model also incorporates nine soil type variables—SOIL10, SOIL11, SOIL12, SOIL13, SOIL16, SOIL17, SOIL19, SOIL21, and SOIL24—as dichotomous dummies. Table 2 includes a description of each variable.[8] Because many soils that are well suited to agriculture are also well suited to coffee, we do not have a strong expectation for how the soil variables affect the probability of clearing.

Finally, CAFE_REGW, CAFE_REGC, and CAFE_RE are dichotomous dummy variables that identify plots located in the west, center, and east coffee regions. In model for the entire country, we use these dummies as regional fixed effects.

Institutional variables

F_SIZE is the median area (in hectares) actually planted in coffee for all farms in the canton.[9] We expect F_SIZE to have countervailing impacts on the probability of clearing. On the one hand, the production and marketing of coffee entail significant economies of scale (PROCAFE 2004). Based on this logic alone, we would expect F_SIZE to be negatively correlated with the probability of clearing. But on the other hand, some cleared land uses that compete with shade coffee also involve economies of scale, making them more profitable on large tracts of land than on small ones. The net effect of these countervailing impacts is an empirical matter. P_COOP is the percentage of the total area planted in coffee in each canton that is managed by reform cooperatives.[10] We do not have a strong expectation about its effect

[8] The nine dummies in our analysis represent a subset of 25 soil classification categories used by the Salvadoran Ministry of the Environment. Of these 25 categories, we omit 16 because they are either completely absent or very rare in our sample.

[9] PROCAFE's 1998 census of coffee farms—to our knowledge, the only relatively complete source of farm-level data on the Salvadoran coffee sector—does not contain geospatial data (latitude and longitude) that could be used to identify the farm size on our sample plots. Therefore, we use these data to generate a single canton-level land tenure variable. We use median farm size instead of mean farm size to control for extremely large farms in some cantons. Although the data used to generate F_SIZE are from the later part of our study period (1998), endogeneity should not be a concern. Because coffee bushes take four to five years to bear fruit for the first time and remain productive for 20 years, farm size responds to changes in expected returns quite slowly. In the short run, farmers react to such changes by varying inputs and harvest effort (Batz et al. 2005).

[10] PROCAFE's 1998 census of coffee farms—again, the only source of complete farm-level data for the coffee sector—differentiates only two categories of land tenure: coffee farms managed by the reform cooperatives, and all other coffee farms. Hence, we are not able to identify farms that belong to private cooperatives. Also, the census does not contain geospatial data that could be used to identify the land tenure on our sample plots. Although the data used to generate P_COOP are from the later part of our study period, endogeneity should not be a concern. Reform cooperatives were created by a series of land reforms that began in 1980 and ended in 1992, and transfers of land into and out of these cooperatives is restricted by law.

on the probability of clearing. On the one hand, interview evidence suggests that reform cooperatives are managed by and consist of the least experienced growers and therefore earn lower profits than nonreform cooperatives (Gómez 2005; Belloso 2005; Barillas 2006). Based on this argument alone, we would expect P_COOP to be positively correlated with the probability of clearing. But on the other hand, farmers who belong to cooperatives—presumably even those that are poorly managed—may obtain a higher return on their coffee because they can typically negotiate more favorable input and output prices than smaller independent growers. Returns to coffee aside, we expect less clearing on reform cooperatives because legal restrictions discourage land sales. Based on this factor, we would expect P_COOP to be negatively correlated with the probability of clearing. The net effect of the two countervailing effects of P_COOP is uncertain.

A dichotomous dummy variable, PROT_AREA indicates whether a plot is in a "protected" area where clearing is prohibited by law. We expect PROT_AREA to be negatively correlated with the probability of clearing.

Socioeconomic variables

POP_DENS is the 1992 population density of each canton. It affects the supply of and demand for outputs from different land uses, as well as the supply of and demand for labor, a key input. The effect of population density 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 (e.g., housing and agricultural produce) with respect to population, as well as the elasticities of supply and demand for various inputs (e.g., coffee farm labor) with respect to population.[11] That said, anecdotal evidence suggests that population density has a very strong impact on the demand for—and therefore the price and profitability of—urban and agricultural land uses. As a result, we expect POP-DENS to be positively correlated with the probability of clearing.

PERC_WOMEN is the percentage of the 1992 population of each canton that is female. It purports to capture outmigration of coffee farmers: presumably, higher values of PERC_WOMEN are correlated with higher rates of outmigration. We expect outmigration to have a variety of countervailing impacts on the probability of deforestation. Outmigration reduces the supply of farm labor and thus dampens profits for the large-scale growers that rely on

[11] 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. However, we expect that such endogeneity is negligible in our model because our 1992 population density data largely predate our 1990–2000 land cover data.

it. But outmigration also generates remittances that can be used for a variety of purposes, including supporting and improving coffee farms.[12] Thus, the net effect of PERC_WOMEN is uncertain.

5.2. Estimation issues

A common problem in spatial econometric models of land cover is spatial autocorrelation—the correlation of land cover on any given plot with that on neighboring plots (Anselin 2002). It may arise from spillovers among the dependent variables or from spillovers among the error terms. In the first case, land cover decisions on any given plot influence decisions on neighboring plots—for example, because land managers learn about cultivation or logging opportunities and techniques from their neighbors. In the second case, unobserved drivers of land cover—for example, the existence of socioeconomic networks among land managers—are correlated across space. Both phenomena may be an issue in our data. Some neighboring plots in our study area are on the same cooperative.

Spatial autocorrelation generates heteroskedastic errors. As a result, standard discrete choice estimators will be inconsistent. In addition, such estimators will be inefficient because they assume independent errors and therefore ignore the information in the off-diagonal terms of the variance-covariance matrix (Fleming 2004). We tested for spatial autocorrelation using Moran's I test modified for probit (Kelejian and Prucha 2001). This test rejected the null hypothesis of no spatial autocorrelation at the 1 percent level in each of the three coffee regions and in the pooled sample.

To correct for spatial autocorrelation, we used the Bayesian heteroskedastic spatial autoregressive procedure for probit detailed in LeSage (2000). A key challenge in generating consistent and efficient estimators in the presence of spatial autocorrelation is the need to evaluate an n-dimensional integral in the course of solving the likelihood function. To overcome this problem, the LeSage procedure uses a Gibbs sampling (Markov chain Monte Carlo) simulation method based on the general concept that a large sample of parameter values in the posterior distribution can be used to estimate a probability density function for the parameters. This procedure generates unbiased estimates of standard errors for all model parameters (see

[12] Unfortunately, spatial data on remittances are not available.

Fleming 2004 for a detailed discussion of the LeSage model and a comparison with competing procedures).

6. Results

We use four models to explain clearing. Model 1 includes observations from the east region only, Model 2 from the center region only, and Model 3 from the west region only. Model 4 pools observations from all three main coffee-growing regions and includes regional fixed effects. The results using probit (Table 4) are quite similar to those using the LeSage spatial autoregressive procedure (Table 5).[13] In the remainder of this section, we focus on the latter.

As discussed below, many of our regression results differ across the three coffee regions. We hypothesize that in most cases, this variation reflects two important underlying differences in the regions' characteristics. First, the center was, and is, dominated by a single megacity: the greater metropolitan area of San Salvador (GMASS), comprising the city of San Salvador and several satellite cities, and as a result, a relatively large portion of the center coffee region is periurban. By contrast, cities in the east and west regions are smaller and geographically distinct and much less land is periurban. Second, as discussed above, cleared land uses competing with shade coffee in the east differ from those in the center and west: logging, ranching, and row agriculture dominate in the east, while urban land uses are most important in the center and west. In the discussion of our results, it is sometimes helpful to refer to the variable R_i, the net return to clearing coffee, defined in equation (6) as the difference between π_D, the discounted expected value of the net return from the most profitable competing land use, and π_C, the discounted expected value of the net return from shade coffee.

[13] In Model 1 (east), three variables that are significant at the 10 percent level using probit are insignificant in the spatial autoregressive procedure (TT_CY, SOIL10, and SOIL21), and one variable that is significant at the 10 percent level using probit is insignificant using the spatial autoregressive procedure (POP_DENS). In Model 2 (center), one variable that is insignificant using probit is significant using the spatial autoregressive procedure (TT_MK). In Model 3 (west), two variables that are insignificant using probit are significant using the spatial autoregressive procedure (TT_MK and SOIL21). Finally, 11 variables that are significant using probit have a higher or lower level of significance using the spatial autoregressive procedure.

Table 4. Probit regression results
(dependent variable is CLEAR = 1 if plot had tree cover in 1990 and none in 2000 and 0 otherwise)

Variable	*Model 1 East*	*Model 2 Center*	*Model 3 West*	*Model 4 All*
	(n=6,627)	(n=9,519)	(n=13,304)	(n=29,450)
Geophysical				
TT_MK	0.0034***	-0.00056	0.00090	0.00055**
	(0.00119)	(0.00037)	(0.00056)	(0.00025)
TT_CY	0.00250*	-0.00176**	-0.00076	-0.00112**
	(0.00151)	(0.00073)	(0.00097)	(0.0005)
TT_RD	0.000003	-0.00407***	0.00394***	0.00154**
	(.0026384)	(0.00164)	(0.00122)	(0.00075)
SLOPE	-0.01069**	0.00026	-0.00162	-0.00415**
	(0.00468)	(0.00308)	(0.00254)	(0.0017)
N_FACE	0.25585***	-0.11429***	0.20948***	0.12937***
	(0.05206)	(0.03838)	(0.02987)	(0.01987)
AD_8_1200	-0.24398***	0.07501*	-0.01209	-0.00552
	(0.05870)	(0.03968)	(0.03258)	(0.02204)
AD_1200_P	-0.32206***	-0.0081	-0.09053*	-0.03881
	(0.10737)	(0.07647)	(0.04751)	(0.0344)
SOIL10	0.35656*	-0.27659	0.20840***	0.06527
	(0.1919)	(0.17434)	(0.07299)	(0.06198)
SOIL11	-0.00524	0.37607	-0.04368	0.11944
	(0.23017)	(0.47267)	(0.09265)	(0.07793)
SOIL12	-0.18817	-0.00850	0.10517	0.12583**
	(0.21377)	(0.16983)	(0.07765)	(0.06362)
SOIL13		-0.56390**	0.05186	-0.08271
	—	(0.23815)	(0.077264)	(0.06828)
SOIL16			-0.29435***	-0.39655***
	—	—	(0.11745)	(0.11225)
SOIL17		0.01842	-0.02018	0.09292
	—	(0.16890)	(0.09128)	(0.06709)
SOIL19		-0.05680		0.03448
	—	(0.17565)	—	(0.09017)
SOIL21	0.32340*	-0.01692	0.10779	0.06265
	(0.18915)	(0.16966)	(0.06829)	(0.05974)
SOIL24		0.11629	-0.13709	0.18228**
	—	(0.17207)	(0.33810)	(0.07982)
CAFE_REGW				0.62321***
	—	—	—	(0.08139)
CAFE_REGC				0.26120***
	—	—	—	(0.0701)
Institutional				
F_SIZE	0.00021	0.00051*	-0.00043	0.00024
	(0.00119)	(0.00030)	(0.00038)	(0.00022)
P_COOP	0.00998***	-0.00101	-0.00445***	-0.00226***
	(0.00279)	(0.0017)	(0.00117)	(0.00087)
PROT_AREA	-0.65178***	0.63384***	-0.23901***	-0.35550***
	(0.11104)	(0.16495)	(0.09499)	(0.05782)
Socioeconomic				
POP_DENS	0.00015*	0.00003*	0.00013***	0.00008***
	(0.00009)	(0.00002)	(0.00002)	(0.00001)
PERC_WOMEN	-0.02244***	0.00680	-0.02578***	-0.01891***
	(0.0086)	(0.00870)	(0.00735)	(0.00451)
CONSTANT	-2.0494***	-1.28279***	0.10316	-0.68228***
	(0.70677)	(0.44591)	(0.38258)	(0.2524434)
L. Likelihood	-1677.7353	-3311.5073	-6080.5419	-11211.004
Pseudo R^2	0.0496	0.0170	0.0188	0.0301

Table 5. Spatial autorgressive probit regression results
(dependent variable is CLEAR = 1 if plot had tree cover in 1990 and none in 2000 and 0 otherwise)

Variable	*Model 1 East*	*Model 2 Center*	*Model 3 West*	*Model 4 All*
	(n=6,627)	(n=9,519)	(n=13,304)	(n=29,450)
Geophysical				
TT_MK	0.00263*	-0.00063*	0.00080*	0.00055**
	(0.00165)	(0.00041)	(0.00060)	(0.00030)
TT_CY	0.00212	-0.00197**	-0.00019	-0.00118***
	(0.00212)	(0.00110)	(0.00107)	(0.00058)
TT_RD	0.00033	-0.00407**	0.00301***	0.00173**
	(0.00373)	(0.00228)	(0.00134)	(0.00096)
SLOPE	-0.00943*	0.00008	-0.00135	-0.00365*
	(0.00626)	(0.00413)	(0.00315)	(0.00230)
N_FACE	0.22950***	-0.11778***	0.20955***	0.13380***
	(0.06488)	(0.05330)	(0.03858)	(0.02506)
AD_8_1200	-0.19255***	0.07437*	-0.02008	-0.00115
	(0.07837)	(0.05491)	(0.03651)	(0.02592)
AD_1200_P	-0.28106***	-0.00335	-0.08980**	-0.03024
	(0.14359)	(0.10364)	(0.05199)	(0.04242)
SOIL10	0.27274	-0.24813	0.19984*	0.07337
	(0.24736)	(0.24529)	(0.08868)	(0.07646)
SOIL11	0.03571	0.34781	-0.04896	0.10760
	(0.29424)	(0.72711)	(0.11158)	(0.09556)
SOIL12	-0.17093	0.03132	0.10327	0.13258**
	(0.27519)	(0.22989)	(0.08914)	(0.07611)
SOIL13		-0.47676*	0.05635	-0.06705
	—	(0.31193)	(0.09159)	(0.08353)
SOIL16			-0.20922**	-0.37018***
	—	—	(0.13579)	(0.13935)
SOIL17		0.05742	-0.01073	0.09896
	—	(0.23275)	(0.10690)	(0.08465)
SOIL19		-0.02828		0.04546
	—	(0.24348)	—	(0.11636)
SOIL21	0.24569	0.01053	0.10543*	0.07164
	(0.23643)	(0.23837)	(0.08310)	(0.07473)
SOIL24		0.174431	-0.15349	0.188456**
	—	(0.23796)	(0.38170)	(0.10322)
CAFE_REGW				0.58298***
	—	—	—	(0.094787)
CAFE_REGC				0.22700***
	—	—	—	(0.08195)
Institutional				
F_SIZE	-0.000143	0.00063*	-0.00026	0.00024
	(0.001511)	(0.00042)	(0.00039)	(0.00027)
P_COOP	0.00872***	-0.00141	-0.00342***	-0.00237***
	(0.00370)	(0.00263)	(0.00127)	(0.00106)
PROT_AREA	-0.41924***	0.69967***	-0.22873***	-0.29320***
	(0.14090)	(0.23561)	(0.10681)	(0.06543)
Socioeconomic				
POP_DENS	0.00014	0.00003*	0.00013***	0.00008***
	(0.00012)	(0.00003)	(0.00003)	(0.00002)
PERC_WOMEN	-0.01771**	0.009564	-0.02298***	-0.01970***
	(0.01094)	(0.01229)	(0.00845)	(0.00551)
CONSTANT	-2.08764***	-1.67434***	0.02899	-0.67009***
	(0.93551)	(0.62162)	(0.44040)	(0.30899)
RHO	0.07007***	0.03851*	0.28090***	0.16864***
	(0.03002)	(0.02537)	(0.01968)	(0.01417)
Pseudo R^2	0.1916	0.0712	0.0746	0.1295

6.1. Geophysical variables

TT_MK is positive and significant in Model 1 (east) and Model 3 (west) but is negative and significant in Model 2 (center). In Model 4 (all regions), TT_MK's net effect is positive and significant. Hence, for the east and west regions and for the entire country, we obtain the expected result: plots farther from coffee export markets were more likely to have been cleared, all other things equal, presumably because the growers managing these plots were paid lower farm-gate prices for their coffee and earned lower profits. In the center region, however, plots closer to coffee markets were more likely to have been cleared.

We propose two complementary hypotheses for TT_MK's unexpected sign in the center region. First, in this region, high returns to urban land uses swamped spatial variation in the return to coffee due to proximity to markets. As noted above, a significant portion of the center coffee region is periurban San Salvador, which saw sharp increases in urban development and property values during the 1990s. Consequently, it is reasonable to assume that returns to urban land uses in the center region were particularly high, and that coffee growers' land use decisions were little affected by relatively minor variations in returns to coffee due to proximity to market. Using the notation from equation (6), in the center region, π_D was so much larger than π_C that variation in π_C due to proximity to markets did not affect the sign of R.

Second, in the center region, TT_MK is likely negatively correlated with an omitted variable, the return to urban land uses, which in turn is positively correlated with clearing. The main east-west highway used to transport coffee to export markets runs through the heart of greater San Salvador, where returns to urban land uses were likely to have been highest. As a result, for plots close to this highway, TT_MK was relatively small (because travel times on secondary roads are much greater than those on highways) and returns to urban uses were relatively high. Unfortunately, spatial data from the 1990s needed to control for returns to urban land uses (e.g., land values) are not available.

TT_CY is negative and significant in Model 2 (center) and insignificant in Model 1 (east) and Model 3 (west). The net effect in Model 4 (all regions) is negative and significant. Hence, in the center and in the country as a whole, plots closer to major urban areas were more likely to be cleared, all other things equal, while in the east and west, proximity to major cities does not help explain clearing. As discussed above, we expected TT_CY could be either positively or negatively correlated with the clearing because proximity to large cities has two countervailing effects: it boosts the return to cleared land uses and it boosts the return to coffee. Our results suggest that in the center coffee region during the 1990s, the first effect dominated—an explanation that comports with our hypothesis that in area around GMASS, returns to urban uses swamped those from coffee. In the east and west, however, neither effect dominated the other.

TT_RD is positive and significant in Model 3 (west), negative and significant in Model 2 (center), and insignificant in Model 1 (east). The net effect in Model 4 (all regions) is positive and significant. As noted above, TT_RD, like TT_CY, has countervailing impacts on the probability of clearing.

SLOPE is negative and significant in Model 1 (east) but is insignificant in Model 2 (center) and Model 3 (west). The net effect in Model 4 (all regions) is negative and significant. Hence, in the east, relatively flat land was more likely to have been cleared, all other things equal. Differences in competing land uses across the three regions help explain our results. These results suggest that flat land boosted returns to the principal cleared land uses in the east (logging, ranching, and row agriculture) but did not have a significant impact on the returns to the principal cleared land use in the center and west (urbanization).

As expected, N_FACE is positive and significant in Model 1 (east) and Model 3 (west). However, it is negative and significant in Model 2 (center). The net effect in Model 4 (all regions) is positive and significant. Thus, in the east and west regions, north-facing plots were more likely to have been cleared, all other things equal, because as discussed above, returns to coffee are highest on south-facing slopes. We suspect that the opposite result for the center region stems from the pattern of expansion in greater San Salvador during the 1990s. For idiosyncratic reasons, urban and agricultural development has been more intense on the south-facing slopes of the El Balsamo mountain range and the Quezaltepec (San Salvador) volcano.

At least one of our two altitude dummies is significant in each of the regional models. In Model 1 (east), both AD_8_1200 and AD_1200_P are negative and significant; in Model 2 (center) AD_8_1200 is positive and significant; and in Model 3 (west), AD_1200_P is negative and significant. Our reference group comprises plots located in the low-altitude range (below 800 msl). Therefore, these results suggest that, all other things equal, in the east, all plots at higher altitudes were less likely to be cleared than low-altitude plots; in the center, plots in the middle altitude range (800 and 1200 msl) were more likely to be cleared; and in the west, plots in the highest altitude range (above 1200 msl) were less likely to be cleared. Here, too, differences in competing land uses across the three regions help explain these results. In the east, higher altitudes favored coffee more than the principal competing land uses (logging, agriculture, and ranching). In the west and center, however, altitude favored the principal land use competing with coffee (urbanization) because developers preferred high-altitude land for its moderate climate. In other words, in the east, increases in altitude raised π_C but either lowered π_D or increased it by less than π_C, such that *R* was often negative at higher altitudes. In the center and west, although increases in altitude raised π_C, they raised π_D by more, such that *R* was often positive at higher altitudes.

Several of the soil dummies are significant. SOIL13 is significant in Model 2 (center). SOIL10, SOIL16, and SOIL21 are significant in Model 3 (west). And SOIL12, SOIL16, and SOIL24 are significant in Model 4 (all regions).

In Model 4 (all regions), both CAFE_REGW and CAFE_REGC are positive and significant. This result suggests that, all other things equal, clearing was more likely to have occurred in the center and west regions than in the east region.

6.2. Institutional variables

F_SIZE is positive and significant in Model 2 (center) and insignificant in Model 1 (east), Model 3 (west), and Model 4 (all regions). Hence, plots in cantons with large average farm sizes were more likely to be cleared in the center. As discussed above, farm size has countervailing impacts on the probability of clearing because it likely boosts the returns to both shade coffee and cleared land uses. Anecdotal evidence suggests that in the center, the second effect dominated because developers prefer buying large properties to take advantage of economies of scale in clearing and building.

P_COOP is positive and significant in Model 1 (east), insignificant in Model 2 (center), and negative and significant in Model 3 (west). The net effect in Model 4 (all regions) is negative and significant. Hence, in the east region, plots that were more likely to have been managed by reform cooperatives were also more likely to have been cleared, a result that comports with the conventional wisdom. In the west, however, the opposite is true. Again, we hypothesize that differences in competing land uses across the two regions explain these results. Legal restrictions limit reform cooperatives' ability to transact property. Presumably, then, coffee farms in these cooperatives are less attractive to developers than privately held land. Hence, in the west region, coffee land in reform cooperatives is less likely to be cleared, all other things equal. Legal restrictions on land sales do not prevent members of cooperatives from converting their farms to other uses, however. Hence, in the east region, if the conventional wisdom that reform cooperatives perform poorly holds, we would expect that plots in such cooperatives were more likely to be cleared.

As expected, PROT_AREA is negative and significant in Model 1 (east) and in Model 3 (west). However, it is positive and significant Model 2 (center). In Model 4 (all regions), the net effect is negative. Thus, El Salvador's protected areas appear to have been an effective means of stemming deforestation in some, but not all, of El Salvador's coffee growing regions.

6.3. Socioeconomic variables

As expected, POP_DENS is positive and significant in Model 3 (west) and Model 2 (center). It is not significant in Model 1 (east). The net effect in Model 4 (all regions) is positive. Hence, clearing tended to occur in more densely populated areas in the west and center. Here, too, differences in competing land uses across the three regions help explain these results. Population density is more closely associated with the principal competing land use in the west and center (urbanization) than with competing uses in the east (logging, ranching, and row agriculture).

Finally, PERC_WOMEN is negative and significant in Model 1 (east) and Model 3 (west) and is insignificant in Model 2 (center). The net effect in Model 4 (all regions) is negative. Thus, areas in the east and west regions with more women per capita experienced less clearing, all other things equal. To the extent that PERC_WOMEN proxies for remittances, these results suggest that remittances stemmed deforestation.

7. Conclusion

We have used a spatial regression model to identify the drivers and characteristics of land cover change in a mixed agroforestry system—shade coffee. The analysis encompasses three separate areas with diverse geophysical and socioeconomic characteristics. Our results buttress previous research on land cover in shade coffee areas suggesting that in some areas, plots farther from markets are more likely to be cleared—the opposite of the typical pattern of land cover in natural forests. However, we also find that this result, along with several others, does not necessarily generalize to all settings. Rather, it depends critically on the characteristics of the area where coffee was cultivated: plots farther from export markets were more likely to be cleared only if they were in primarily rural instead of periurban areas; flat, low-altitude plots were more likely to be cleared only if nonurban cleared land uses dominated the area; and plots in areas with high population density were more likely to be cleared only if urban land uses dominated. Other studies have shown that the impact of various drivers of land cover change in natural forests can vary significantly across locations (Mertens et al. 2004). Our findings suggest that this is equally true in mixed agroforestry systems.

Our results suggest that one-size-fits-all conservation policies and programs aimed at expanding or retaining agroforestry systems are almost certain to be inefficient when applied on a broad geographical scale. Such initiatives need to be carefully targeted and tailored to specific locations and institutional settings. As for geographical targeting in El Salvador, a policy that, for example, only targeted coffee farms in lowland areas would not address the bulk of tree cover loss, which is occurring in the center and west highland areas. Similarly, a policy that only targeted coffee farms close to big cities would miss clearing in rural areas in the east region. As for tailoring policies in El Salvador, a policy that, for example, relied solely on market-based forest conservation approaches, such as payments for environmental services and coffee certification programs, would likely be far less effective in the west and center regions than in the east region. In areas where high land prices associated with urbanization are driving land use changes, it is hard to imagine programs that could provide financial incentives on par with the land market. However, such policies might well be effective in the east, where less profitable land uses compete with coffee.

Appendix. ARCGIS Travel Time Model

Impedance-weighted distances were calculated in ArcGIS by the following method. First, impedances were assigned to each plot to account for slope and the presence of a road. More specifically, we used the following formulas: for plots on paved roads, impedance is equal to one plus the square root of slope (in degrees); for plots on secondary roads, impedance is equal to three plus the square root of slope; and for all other plots 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 190 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 plot on a paved road is 100 kilometers per hour, and the rate of travel on a steep plot with no road is 0.95 kilometers per hour. Having assigned impedances to each pixel, we used standard iterative techniques to find three minimum impedance routes: (i) from each plot to the nearest road; (ii) from the nearest road to the nearest *beneficio* and then on to each of two coffee market export centers—either Acahutla in coastal western El Salvador or the Guatemalan border town of San Cristobal; and (iii) from the nearest road to the nearest city with a population greater than 19,000. The cities with population greater than 19,000 are Acajutla, Aguilares, Ahuachapan Apopa, Chalchuapa, Cojutepeque, Ilopongo, Izalco, La Union, Los Planes, Nueva San Salvador, Puerto El Triumpho, Quezaltepeque, San Martin, San Miguel, San Rafael Oriente, San Salvador, San Vicente, Santa Ana, Sonsonate, Usulutan, Zacatolecoluca. We assume that primary rivers can be crossed only on an existing bridge and ignore other rivers and waterways. Finally, we convert these weighted distances into travel times in hours. Because our assumptions imply a linear relationship between impedance-weighted distance and the time needed to travel that distance, this conversion simply involves dividing by a constant. Thus, the variables TT_RD, TT_MK, and TT_CY may be interpreted as total travel times in minutes.

As discussed in Section 2, virtually all Salvadoran coffee is processed in a *beneficio* and then exported. Therefore, travel time from a plot to coffee markets is equal to the sum of travel times from (i) the plot to the nearest road; (ii) the nearest road to the nearest *beneficio*; and (iii) the nearest *beneficio* to an export center. Virtually all exports are shipped from one of two export centers: Acahutla in coastal western El Salvador or Guatemala ports (La Hachadura, St. Tomas, and Puerto Barrios) reached via the Salvadoran border town of San Cristobal. According to PROCAFE, a *beneficio*'s choice between these two export centers depends on market conditions, not on proximity. Furthermore, since 1990, the average annual percentage of Salvadoran coffee shipped from Acahutla has declined dramatically because of disruptions caused by the civil war and significant improvements in the Guatemalan port's infrastructure. In the early 1990s, 70 percent of Salvadoran exported coffee was shipped from Acahutla and 30 percent was shipped from Guatemala. Today, however, 25 percent of the Salvadoran export is shipped from Acahutla and 75 percent is shipped from Guatemala. We assume that TT_MK is a weighted average of travel times from the nearest road to Acahutla (25 percent) and San Cristobal (75 percent). We ignore travel times inside Guatemala, since they are invariant to the location of plots within El Salvador and therefore would not help explain variations in the probability of clearing across plots.

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Figures (see following page).

Figure 1. Major coffee-growing areas in El Salvador in 1993 (West, Center, East)

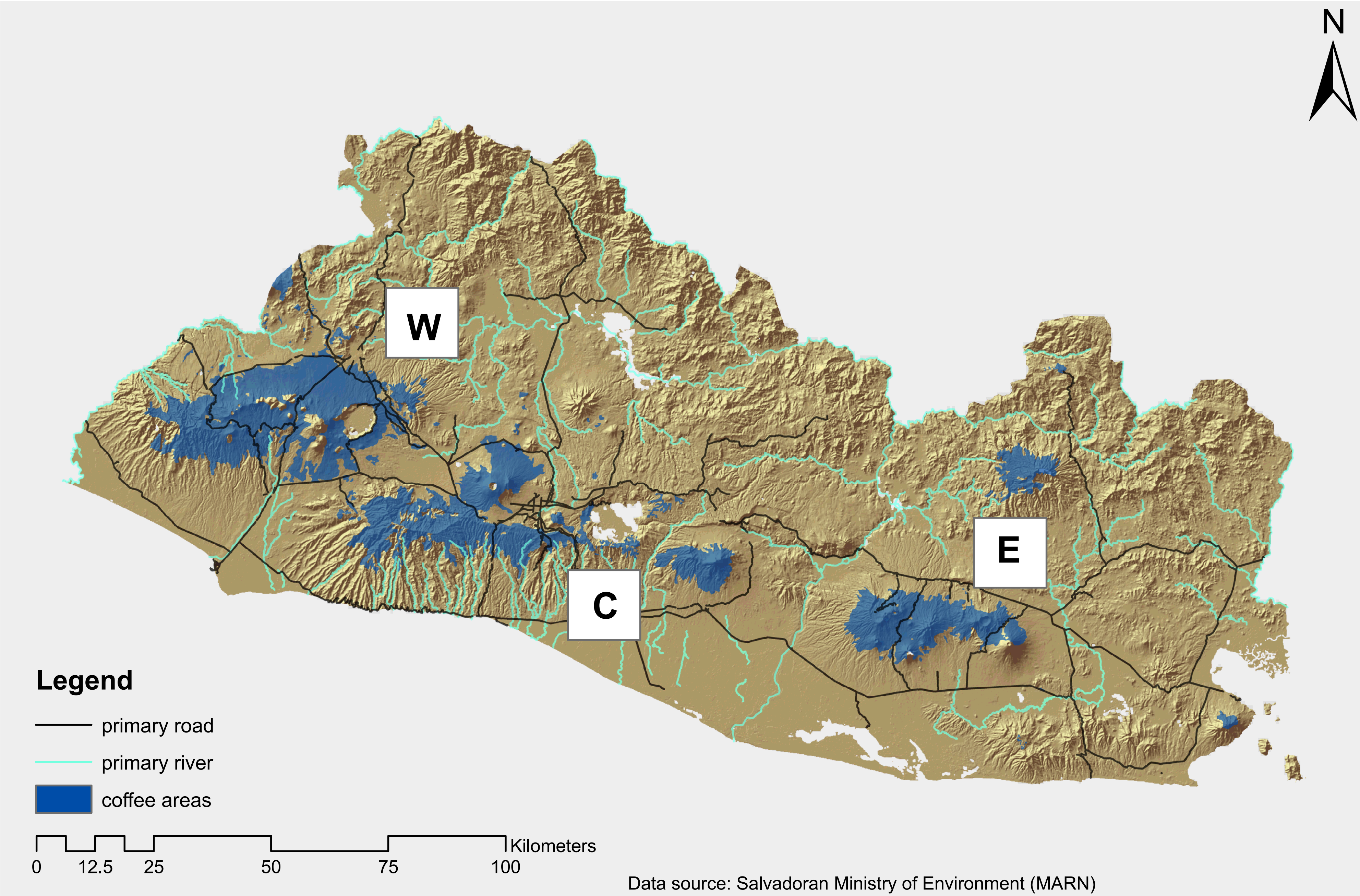
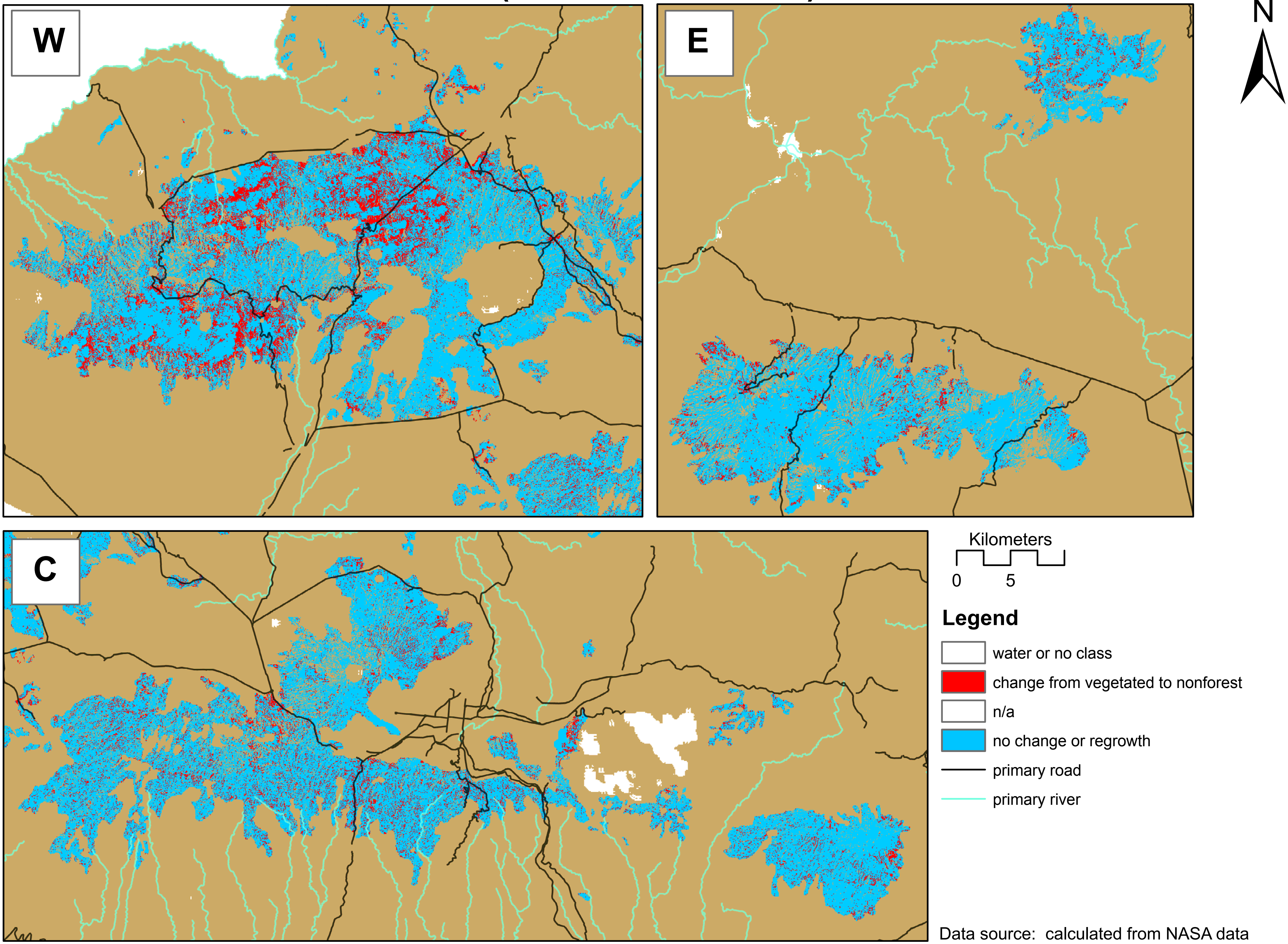


Figure 2. Clearing between 1990 and 2000 in major coffee growing areas (West, Center, East)



Data source: calculated from NASA data