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Forest Fallow Ecosystem Services: Evidence from the Eastern Amazon

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Abstract

With tropical deforestation a major contributor to greenhouse gas emissions and biodiversity loss, the land-use decisions of small-scale farmers at the forest margins have important implications for the global environment. Farmers' incentives for maintaining forest fallow in a shifting cultivation agricultural system depend upon the market and non-market services it provides to them. This study estimates the value of those services, including hydrological externalities that may affect other farms downstream.

The analysis uses cross-sectional farm-level survey data from the Zona Bragantina in the Eastern Brazilian Amazon to assess the value of forest fallow to farmers and test whether it provides local externalities. I estimate production functions for crops and forest products to determine the contributions of on-farm and off-farm forest fallow to income from these two activities. Instrumental variables and spatial econometric approaches help address issues of endogeneity and variation in unobservable factors over space. I use geographic information on the location of farms to obtain data on external forest fallow and to model the hydrological externality as an upstream-to-downstream process.

The results indicate that fallow does contribute significantly to productivity both on-farm and downstream, boosting income from both crops and forest products. In addition, most farms appear to allocate sufficient land to fallow, accounting for both the value of hydrological spillovers and the opportunity cost of land left out of cultivation. These results suggest that farming communities may have some self-interest in preserving forest cover locally—a finding that may bolster policy efforts aimed at conserving tropical forests.

Introduction

With tropical deforestation a major contributor to greenhouse gas emissions and biodiversity loss, the land-use decisions of small-scale farmers at the forest margins have important implications for the global environment. In some tropical forested areas, such as the Zona Bragantina in the Eastern Brazilian Amazon, farmers practice a shifting cultivation, or slash-and-burn, system that maintains large amounts of land under forest fallow. Farmers' incentives for maintaining forest fallow depend upon the market and non-market services it provides to them. This study estimates the value of fallow ecosystem services in shifting cultivation, including hydrological externalities that may affect other farms downstream.

Where land is abundant and other inputs are scarce, long fallow periods can be a cost-effective way to restore land for future agricultural uses. Secondary forest fallow provides on-site benefits to farmers, such as soil regeneration, erosion prevention, weed control, and harvestable products. It also provides off-site services, supplying some of the same public goods as mature forests. These services are not only global in scale but may also be local, such as hydrological regulation that moderates the flow of water in the soil. Understanding the magnitude of secondary forests' contribution to agricultural productivity will be increasingly important as population and economic pressures spur many of the estimated 300 million[1] shifting cultivators world-wide to shorten fallow periods, adopt new technologies, and intensify cultivation. Valuing the net benefits of forest cover to local populations could help justify conservation efforts with global importance (Chomitz and Kumari 1998).

[1] Current estimates of the number of shifting cultivators are hard to come by. The 300-million figure was given by Sanchez (1996) and Brady (1996).

Economic studies accurately estimating the value of forest ecosystem services are sparse, and results from hydrologic studies have been ambiguous as to the effects of reforestation on water yields (Bruijnzeel 2004). The Millennium Ecosystem Assessment (2005) has identified lack of information about the value of non-market ecosystem services—particularly regulating services such as hydrological functions—as a major knowledge gap hampering informed decision-making on ecosystem management.

This paper takes up this challenge by quantifying the returns to fallowing in agricultural production. The analysis uses cross-sectional farm survey data from the Zona Bragantina to assess the value of forest fallow to farmers and test whether it provides economically significant local externalities that may justify forest conservation from a local perspective. Private land tenure in the study region allows me to disentangle the on-farm and externality effects. I estimate production functions for crops and forest products to determine the contributions of on-farm and off-farm forest fallow to income from these two activities. Instrumental variables and spatial econometric approaches help address issues of endogeneity and variation in unobservable factors over space. I use geographic information on the location of farms to obtain farm-level data on external forest fallow and to model the hydrological externality as an upstream-to-downstream process, allowing for identification in the presence of spatial correlation.

Fallow as a production input in shifting cultivation

In many contexts world-wide, fallow is a common property resource prone to overexploitation in the absence of community controls (López 1993, 1997). Even under private land tenure, inefficiencies could arise if fallow biomass provides local positive externalities in addition to on-site ecosystem services. Correcting these inefficiencies can boost downstream farm income while providing incidental carbon sequestration services. Thus, whether fallow biomass provides economically significant local externalities is an empirical question with important implications for tropical forest policy.

Fallowing restores plots for future cultivation by drawing soil nutrients and water to the surface, raising soil pH, minimizing surface erosion, and suppressing weeds (Nepstad et al. 2001; Holscher et al. 1997; Altieri 1995; Sanchez et al. 1982; de Rouw 1995; Staver 1991).[2] Root systems remain intact after manual land clearing, fostering rapid vegetative regeneration during initial fallow years. Forest cover also plays an important role in the hydrological cycle. Tree cover lessens peak flows and surface runoff due to increased soil infiltration capacity and evapotranspiration of soil water (Hamilton and King 1983, Bruijnzeel 2004), which may benefit agricultural activities by reducing floods and waterlogging.

While few studies have estimated the value of fallow biomass and forest cover in agricultural production, some have found that it provides economically important services. López (1993, 1997) showed that village-level fallow biomass (capturing both on-farm soil quality and external hydrological benefits) contributed significantly to agricultural profitability in Ghana and Côte d'Ivoire. Research in Ruteng National Park, Indonesia, found that off-farm forest cover provided beneficial hydrological services (in this case, drought mitigation) to small-scale agricultural production (Pattanayak and Kramer 2001; Pattanayak and Butry 2005).

[2] Secondary forest root systems also provide below-ground carbon storage comparable to that of mature forests (Sommer et al. 2000), although converting land to shifting cultivation entails a loss of above-ground carbon stocks. In addition, forest stands can affect nearby farms' productivity through crop pollination (Ricketts et al. 2004, Kremen et al. 2004) and tree seed availability (Tucker et al. 1998). I do not concentrate on these services here.

Study region and data

The Zona Bragantina offers a compelling case study as a region with over one hundred years of agricultural settlement where shifting cultivation persists as the principal means of livelihood. Despite integration into regional markets through railways and roads, perennial cash-crop agro-processing, and government programs to encourage agricultural intensification, shifting cultivation dominates other land-use practices in the region. Figure 1 presents a map of the region.

Most households in Bragantina are considered smallholders by Brazilian standards, with landholdings under 100 hectares. Family labor and manual land clearing predominate, though hired labor and mechanized equipment are also used for labor-intensive tasks like land preparation, weeding, and harvesting. A typical one to two year cropping sequence includes maize, upland rice, and cowpea, with cassava grown as the final crop while fallow vegetation reestablishes (Holscher et al. 1997). These annual crops are used for home consumption and sale to regional markets. Since the mid twentieth century, smallholders have also branched into perennials like black pepper, passion fruit, oranges, and coconut, as well as ranching.

While virtually all virgin forest in Bragantina has been cleared over the decades, roughly 75% of the land area remains under secondary forest (Kato et al. 1999). Soil is relatively homogenous in the region, though rainfall does decrease along a gradient from west to east (Borner 2005). The climate is humid, receiving an average rainfall of 2400-2700 mm annually. The region faces major challenges in improving agricultural productivity due to poor quality Oxisol, Spodosol, and Ultisol soils vulnerable to acidity and aluminum toxicity (Tucker et al. 1998; Holscher et al. 1997). Experiments varying fertilizer treatments in the Zona Bragantina identified phosphorus and nitrogen as major limiting factors in crop production and fallow biomass growth (Gehring et al. 1999).

Data for the study were collected as part of the SHIFT (Studies on Human Impact on Forests and Floodplains in the Tropics) project, an initiative to study tropical livelihoods and ecosystem dynamics in Brazil. Three municipios out of the 14 that comprise the Bragantina were chosen for study to capture regional variation in distance to commercial centers, agricultural intensification, and rainfall (Mendoza 2004). In late 2002, 271 households in 22 villages were randomly selected and surveyed. The survey gathered farm production, land use, and demographic data for the 2001-2002 growing season. Table 1 presents the mean values for selected household-level characteristics.

Comprehensive farm-level data on forest fallow for the entire Zona Bragantina would be ideal to estimate the off-site flow of benefits and their spatial scale, but are unavailable. I make use of the household survey data on land use among the sampled farms as one solution. As an additional approach to address this gap, I turn to GIS (geographic information systems) data on forest cover, using the MODIS Vegetation Continuous Fields (VCF) to construct an alternative measure of external fallow. The VCF data consist of 25 hectare resolution pixels created using 40 day composite satellite images from March 2001-March 2002 (Hansen et al. 2006).[3] Each pixel represents percent canopy cover, defined as the amount of sunlight blocked by tree canopies over five meters high. Figure 2 shows 2001-02 tree canopy cover for the Zona Bragantina.

[3] The 2001-02 VCF data provide the closest available estimates of forest cover during the 2001-2002 cropping season. Twenty-five hectare pixels are a sufficiently fine measure of tree cover relative to the size of landholdings among the surveyed farmers, as the median farm size is also 25 hectares. The percent canopy cover approximates both the area and density of forest cover, since the share of land with five-meter tree cover is likely to be highly correlated with vegetation density.

I also use GIS flow direction data from the US Geological Survey to determine where farms lie along a gradient from upstream to downstream in relation to one another. According to a flow direction map for the region (Figure 3), farms cluster into 11 groups defined by a common drainage area and flow direction. Each cluster includes at least one sampled community. Within each group, I assume each observation affects farms downstream and is affected by farms upstream. The US Geological Survey also provides slope data for the region at 1-km resolution.

Crop production function estimation

My approach to valuing the services provided by on-farm and off-site forest fallow involves estimating production functions for two primary activities in the Zona Bragantina: crop production and forest product harvesting.[4] The surveyed farmers produced a total of 50 annual and perennial crops, with cassava, maize, beans, and black pepper among the most common. Collecting forest products made a modest contribution to income relative to cropping but was practiced by over two-thirds of the surveyed farms. The production function estimations allow me to measure the contribution of on- and off-farm fallow to these activities and test for positive fallow externalities in each. I also calculate the contribution of fallow resources to total farm income by aggregating the respective contributions of fallow to crops and forest products.

The dependent variable in the crop production function is the log of crop output value, with different commodities aggregated using average output prices in the region. Although farms reserved some crops for home consumption, market prices provide appropriate values for these commodities since 97% of sampled farmers sold at least

[4] Ranching and livestock products make up the remainder of agricultural activities, though they are less common in the Zona Bragantina than either cropping or forest product collection.

some of their produce. I employ a Cobb-Douglas specification for cropping technology. Output is modeled as a function of cultivated land area, family and hired labor, fertilizer, on-farm fallow area, and off-farm (upstream) fallow area.[5]

The crop value equation can be represented as follows

$$\ln y_i = \beta_o + \beta_1 \ln f_i + \beta_2 W_1 \ln F + \beta_3 \ln X_i + \beta_4 H_i + \varepsilon_i$$
$$\varepsilon_i = \lambda W_2 \varepsilon + u_i$$

where y_i represents the i^{th} farm's crop value. The farm's fallow area is represented by f_i, while F is a vector of all farms' fallow area. Cultivated land area, family and hired labor, and fertilizer are represented by X_i, a vector of conventional inputs.

The error term is given by ε_i, which includes a component that varies over space and a white noise term, u_i. A spatial error model accounts for the fact that unobserved factors may influence farmers' and their neighbors' land use decisions in similar ways, allowing for efficient estimation of the parameters. The strength of the spatial correlation among the disturbances is represented by λ.

Spatial weighting matrices for off-farm fallow and the error term are represented by W_1 and W_2, respectively. W_1 is a row-normalized matrix that gives equal weight to neighbors upstream of each farm to capture the hydrological externalities of local forest fallow.[6] $W_1 \ln F$ thus represents a weighted average of off-farm fallow area upstream of each observation.[7] I also refer to this term as a spatial lag of the fallow variable.[8]

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[5] Because farm products are marketed goods, valuation of the fallow ecological services using a production function approach is straightforward and does not depend on detailed knowledge of the ecological mechanisms at work (Maler 1991).
[6] Estimation results do not qualitatively differ when upstream neighbors are weighted by inverse distance.
[7] Although row normalization is not appropriate in all spatial analyses, normalizing by the number of sampled farms in each farm's neighborhood is important in this case to avoid inferring that farms with more sampled neighbors have higher levels of nearby forest cover.
[8] Following the convention used by Anselin (1988) and others, I use the term spatial lag to mean a weighted sum of neighboring or contiguous values of the variable of interest, somewhat analogous to the concept of temporally-lagged variables in time-series analysis.

W_2 is a matrix of inverse distances between all sampled farms, reflecting correlation in unobserved factors expected to decline with distance, such as weather shocks. W_2 is not row normalized, as row normalization would imply that more isolated farms are affected by their neighbors' disturbances as much as farms with many neighbors in close proximity. The uniqueness of the two spatial weighting matrices is thus justified conceptually, and it allows for identification of the spatial autoregressive parameters.[9] However, if spatial correlation among the disturbances or other non-stochastic factors follows the same pattern as the hypothesized hydrological externality, then these effects cannot be disentangled without further parameter restrictions.

I include household and farm characteristics in the vector H_i to control for observable aspects of management ability and land quality. The household head's schooling years, use of extension services, and land ownership help control for farmer management skills. A binary variable for perennial crop production controls for the higher prices perennial crops command in regional markets relative to annual crops.[10] Land quality indicators include farmer-reported dummy variables for black clay and charcoal-enriched soil ("*massape*" and "*preta*," both favorable types) and poor soil ("*arisca*") and GIS data on slope, which indicates the farm's vulnerability to erosion. While soil is fairly homogenous throughout the region and land is not steeply sloped, these variables help account for micro-level agroecological variation. The equation also

[9] As shown by Anselin 1988 (pp. 84-85), spatial lag and spatial error parameters are generally not identified without nonlinear restrictions when the two weighting matrices are the same.

[10] In a preliminary attempt to control for the potential endogeneity of producing perennial crops, I estimated a treatment effects model. I could not reject they hypothesis that the crop output and perennial production equations are independent (p = 0.86-0.88, depending on the measure of off-farm fallow used), so I treat perennial production as exogenous in the regressions that follow. Perennial crops can be grown in soil conditions found throughout the Zona Bragantina. However, farmers with facing higher rainfall, better access to extension services, and those less averse to price risks are more likely to produce perennials.

includes municipality dummies. Table 2 reports the mean values for the variables used in the production function estimation.

The primary parameters of interest are the coefficients of on-farm fallow and external fallow. These coefficients give the output elasticities of on-farm and external fallow, indicating the contribution of these fixed environmental factors to crop production. I tackle the hypothesis that local forest cover provides positive externalities to downstream farms by testing whether the coefficient of the spatially-weighted upstream forest fallow variable is significantly greater than zero.

Fallow variable definitions

I use area under fallow during the cropping season as a proxy for fallow biomass. While fallow area does not directly measure biomass or capture the dynamic aspects of fallowing, larger fallow relative to cultivated area allows for more forest recovery time and higher peak biomass density.[11] The two alternative measures of off-farm fallow are 1) the average area under forest fallow upstream of each farm, indicated by the household survey data and using the spatial weighting matrix W_1 to define which farms are considered neighbors,[12] and 2) percent canopy cover upstream of each farm, given by the VCF data.[13] Both approaches define the externality at the farm level, allowing for more

[11] When fallow management is in steady state equilibrium, fallow area has a direct relationship with biomass volume, though the relationship is still positive when the system is out of equilibrium (López 1993). The steady state assumption is plausible in the conditions of the Zona Bragantina, where agronomic practices have been in place and minimal migration has occurred for the past several decades, unlike much of the Brazilian Amazon. López (1997) also found similar output elasticities of fallow using biomass volume and fallow area as alternative measures in Ghana.

[12] Those farms furthest upstream within a locality are assumed to affect all downstream farms; however, they have no neighbors among the sampled farms and so are excluded from the final crop value equation testing for externalities.

[13] The GIS data give upstream forest cover for all farms for which I have GIS coordinates. GIS coordinates are missing for 10 farms in the sample, which are excluded from the analysis. I cannot extract upstream forest cover within each drainage area individually for each farm using the GIS data, so I instead extract a wedge-shaped neighborhood upstream of each farm with a radius of 3 km. As expected, the survey- and GIS-derived variables are positively and significantly correlated (rho = 0.36).

variation in the off-farm upstream forest cover variable compared to other studies that define the forest externality at the village or sub-watershed level (e.g., López 1993, 1997; Pattanayak and Kramer 2001; Pattanayak and Butry 2005).

Figure 4 illustrates the geographic structure of the relationship. Land use on farm 1 affects all farms downstream, but I have no information on land use upstream of farm 1. Meanwhile, farm 8 is affected by land use on farms 1-7 in its position as the farthest observation downstream. Table 3 summarizes the fallow variables and indicates the proportion of farms without on-farm or upstream fallow.

Endogeneity and identification strategy

Potential endogeneity of the fallow variables is a concern in obtaining consistent parameter estimates, particularly if poor soil quality spurs farmers to allocate more land to fallow while depressing yields. This effect could bias the on-farm fallow coefficient downward. Measurement error of the fallow variables, which proxy for but do not exactly measure fallow biomass, may cause attenuation bias, further lowering the elasticity estimates (Greene 2000). In addition, differing measurement error between the on-farm fallow area and off-farm GIS canopy cover variable may also be a source of bias due to the different data sources used to construct them. The GIS canopy cover data indicates fallow biomass density as well as area, while the on-farm fallow variable only incorporates fallow area. Thus, the coefficient of on-farm fallow may be biased downward and the coefficient of GIS canopy cover upward if external canopy cover is correlated with on-farm biomass density. However, the survey-reported data on off-farm fallow area avoids this source of bias. The error term in the production equation thus encompasses not only white noise, but also measurement error, agroecological conditions, farmer intentions, and other factors unaccounted for in the data.[14]

With these drawbacks in mind, I employ several strategies in an effort to consistently estimate the parameters of interest. As discussed above, I include several observed indicators of land quality and management ability. Modeling spatial correlation in the error terms based on distance between farms helps control for unobserved patterns in agroclimatic factors and farmer knowledge over space.[15] I also use an instrumental variables (IV) estimator to address potential omitted variables and measurement error issues. Finally, the likely downward bias on the on-farm fallow coefficient suggests that a least-squares estimate can be interpreted as a lower bound of the elasticity.

I use the log of farm size, forest product prices, and binary variables indicating ownership of firewood and gas stoves to instrument for on-farm fallow. Farm size affects the amount of land available for fallowing and so is likely to be a strong predictor of fallow area. In addition, farm size has no direct effect on crop output because cultivated land area, clearly a crucial factor of production, is included directly in the production function, making total farm area unrelated to crop value and hence a valid instrument. I expect forest product prices and firewood stove ownership to be positively correlated with on-farm fallow since fallow land typically serves as a source of forest products for sale or home consumption, with firewood the most common product. Conversely, gas

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[14] In addition, the coefficients of cultivated area, labor, fertilizer, and on-farm fallow may be biased upward if the farmer chooses input and output levels simultaneously. Off-farm fallow is less vulnerable to simultaneity problems since the farmer does not determine fallow levels on neighboring farms, though it may still be affected by climatic shocks experienced by all farms within a neighborhood.

[15] Mardia and Marshall (1984) show that the maximum likelihood estimator of the spatial error model is consistent if the domain or observation area of the data increases as the sample size increases (domain asymptotics). The consistency of the maximum likelihood estimator has not been shown when the sample size increases under a fixed domain, causing an increase in the density of observations within the given region (infill asymptotics) (Cressie 1993). Therefore, consistency of the spatial errors estimators discussed in this paper applies only under increasing domain asymptotics.

stove ownership could negatively affect on-farm fallow by decreasing the household's dependence on firewood fuel. Forest product price is a good instrument because it is unlikely to be correlated with unobservable factors affecting crop output mix and yields despite its impact on the marginal returns to fallow area. Firewood and gas stove ownership have similar advantages as instruments unless farmers invest in stoves based on their planned allocation of land to fallow.

To instrument for off-farm fallow, I use the spatially-lagged values of the on-farm fallow instruments and of other household-level variables included in the crop production equation. Thus, the instruments include the spatial lags of the log of farm size, forest product prices, firewood and gas stove ownership, and other household and agroecological characteristics expected to affect crop production. The spatially-lagged values of farm and household characteristics affect neighbors' land allocation decisions and hence off-farm fallow but are uncorrelated with the residual of own-farm output because own-farm characteristics are controlled for directly in the production function.[16] I do not use the spatially-lagged values of conventional inputs or the perennial production indicator due to concerns about the potential endogeneity of these variables. I use the same spatial weighting matrix to construct the instrumental variables as that used to construct the lagged fallow variables to ensure that neighbors' fallow area is regressed on the characteristics of these same neighbors.

First-stage regressions for the on- and off-farm fallow variables are presented in the appendix (table A1). The instruments are strong predictors of on- and off-farm

[16] I also tested the exogeneity of all inputs jointly, including cultivated area, labor, and fertilizer. I added the log of family size and the share of males age 16-65 as instruments in this regression. I could not reject exogeneity of all inputs jointly (p = 0.76-0.96, depending on the off-farm fallow variable). Thus, I focus on controlling for endogeneity of the fallow variables only.

fallow, as indicated by R-squared statistics of 0.68-0.91.[17] While the IV estimates are consistent, a Hausman test could not reject exogeneity of the on- and off-farm fallow variables, whether using the survey or GIS measures of off-farm fallow (p= 0.40-0.88). Thus, the least squares estimates of the elasticities of on- and off-farm fallow are both consistent and more efficient than the IV estimates.

Treatment of non-essential inputs

Use of the Cobb-Douglas specification implies that all inputs are used in positive quantities. However, some farmers in the sample use no fertilizer, hired labor, or fallow land, and a few have no survey-reported upstream fallow area (tables 2 and 3). I do not employ the widely-used strategy of adding a small shifter to the inputs before taking logs because parameter estimates tend to be highly sensitive to the value of the shifter (Soloaga 2000). Instead, I deal with non-essential inputs according to the approach outlined by Battese (1997), adding dummy variables to indicate non-use of each input.[18] These dummy variables function as different intercepts for the farmers who do not use each of the inputs (including the on- and off-farm fallow variables). While non-use of fallow or conventional inputs, or location downstream of land with no fallow cover, might be indicative of a different production system than that used by most farmers, data

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[17]The Sargan test for overidentification indicates that the instrumental variables as a group are uncorrelated with the residuals of the output equations (p = 0.89-0.95, depending on the upstream fallow variable). In addition, none of the instruments were significant at conventional levels when included one-by-one in the IV estimation of crop value. Although these IV validity tests have low power, they support the assertion that the instruments are uncorrelated with crop value.

[18] Battese represents a two-input Cobb-Douglas production technology using two equations, assuming that one input, x1, is used by all firms, and a second input, x2, is used by only some firms:

$$\ln y = b0 + b1*\ln x1 + b2*\ln x2 + u, \text{ for all farms with } x2>0$$

$$\ln y = a0 + b1*\ln x1 + u, \text{ for all farms with } x2=0$$

The two equations can be pooled to write

$$\ln y = b0 + (a0-b0)*D + b1*\ln x1 + b2*\ln z + u$$

where D is a dummy variable indicating non-use of x2 and z = max(D,x2). This strategy assumes a constant parameter b1 and error u across both equations.

are insufficient to estimate separate production functions for these individuals. In addition, ten farms produce no outputs during the season and are excluded from the crop production regression.

Results

Table 4 presents four sets of estimates of the crop production function. The first two columns report estimates from the spatial error model (SEM) (1) and from the spatial error model with instrumental variables (SEM-IV) (2) using survey-reported off-farm fallow area to represent upstream fallow. The last two columns show SEM (3) and SEM-IV (4) estimates with the GIS canopy cover variable as an alternative measure of upstream fallow. As stated above, the fallow variables can be considered exogenous, so all four sets of elasticity estimates are consistent. All models have a satisfactory fit, as indicated by R-squared statistics of 0.56-0.60, and the coefficients largely have the expected signs across the different models. The spatial error correlation coefficient is not significantly different from zero in any of the specifications, indicating that unobserved variables varying with distance between farms have no systematic effect on crop output once inputs and observed farmer and soil characteristics are controlled for.

Comparisons among the four models reveal that on-farm and upstream fallow are both important factors of crop production in the Zona Bragantina. The elasticity of on-farm fallow is positive across all models and significantly different from zero in two of the four models, varying from 0.09-0.18. These estimates suggest that own-fallow land makes a substantial contribution to crop output, close to that of hired labor or fertilizer. In addition, the non-IV coefficient estimates (0.09-0.10) from models (1) and (3) represent a lower bound on elasticity due to the potential for downward bias caused by omitted soil quality variables and measurement error, though formal tests could not reject exogeneity of on-farm fallow.

The elasticity estimates are similar in magnitude to those from other econometric and agronomic studies. For instance, López (1993, 1997) finds the village-level fallow biomass factor share to vary between 0.15 and 0.2 in Ghana and Cote d'Ivoire. Mendoza (2004) uses the same data set as this study to estimate the contribution of fallow length to cassava profits, finding an output elasticity of 0.22. An Altamira, Pará, field study finds the elasticity of maize yields with respect to fallow age to be 0.33 (Silva-Forsberg et al. 1997). An agronomic study from Bragantina showed rice yields to improve by 10-44% as fallow age increased from four to ten years, corresponding to a fallow elasticity of 0.07-0.29, with the lower elasticities found on fields to which fertilizer was applied (Kato et al. 1999). The wide use of fertilizer by sampled farms may help explain why the elasticities estimated here fall in the lower range of previous studies.

The estimated elasticity of off-farm fallow in crop production is positive across three of the four estimates, providing evidence that upstream forest fallow improves productivity for downstream farms. The actual elasticity estimate varies considerably based on the estimator used. Models (1) and (2), which use survey-reported fallow area as the measure of upstream fallow, show a significant and positive elasticity of 0.37-0.38. In model (3), which employs the GIS canopy cover variable to measure off-site fallow, the elasticity jumps to 0.66. This high coefficient could result from off-farm canopy cover proxying for on-farm biomass density, which is not completely reflected by the on-farm fallow area variable. The SEM-IV estimate of upstream canopy cover in model (4) drops to 0.23, which is closer in magnitude to the elasticities from models (1) and (2), though not significantly different from zero.

The large magnitude of the upstream fallow elasticity estimate, which surpasses the on-farm fallow elasticity, is surprising. Potential explanations include downward bias of the on-farm fallow coefficient, discussed above, and the possibility that non-stochastic factors correlated with forest cover other than hydrological externalities affect downstream crop production. While the hydrological externality effect cannot be isolated if other factors lead to a correlation between off-farm land use and on-farm output, the positive and significant coefficient provides support for the hypothesis that farms benefit from forest cover upstream. In addition, the magnitude of the upstream fallow effect estimated in models (1), (2), and (4) is similar to the results from the Ruteng National Park, Indonesia, study, where a 10% increase in soil moisture due to afforestation was associated with a 2-3% boost in farm profits (Pattanayak and Butry 2005).

As an additional verification that forest cover provides hydrological externalities, I also estimate all four specifications of the crop production function including downstream forest cover as an additional regressor. If forest cover provides positive hydrological externalities, then upstream forest cover will affect crop production but downstream forest cover will not. The appendix (table A2) presents the results of these regressions. Across all four models, downstream forest cover has no significant effect on crop value, in contrast to the elasticity of upstream forest cover. In fact, the coefficient on downstream forest cover is negative. These findings support the contention that forest cover improves crop output by regulating floods and soil moisture, and that other potential non-hydrological services such as crop pollination do not drive the results.

Elasticity estimates for the conventional inputs are largely positive and significantly different from zero across all four specifications (table 4). Cultivated area makes the most substantial contribution to crop output, with an elasticity of 0.41-0.44. Hired labor and fertilizer are also important, supplying 17-19% and 15-17% of crop output, respectively. Production of perennial crops raises output value considerably. Agroecological variables are also important—black clay and charcoal-enriched soils boost output, while poor soils and steeper slopes dampen it, though only the effect of charcoal-enriched soil is statistically significant. The household head's schooling, use of extension services, and ownership of the farm have no significant effect on output value, which could result if differences in management ability are reflected in input quantities rather than farmer characteristics. Models (3) and (4) indicate that farms in Castanhal municipality garner higher crop revenues than those from Igarapé Açu or Bragança. Farms with no family labor, on-farm fallow, or upstream fallow area produce higher crop values, as indicated by the coefficients of the dummy variables for non-use of each input.

Resampling and robustness analysis

I carry out a number of robustness checks to ensure that the estimated elasticities of on- and off-farm fallow are stable across different sub-samples of farmers. When farms in the lowest and highest tenth percentiles of on-farm and upstream fallow area are excluded from the regression, the coefficient for on-farm fallow varies between 0.08-0.11. Upstream fallow area is less robust, though still high in magnitude, ranging from 0.20-0.51. The elasticity of GIS canopy cover varies from 0.55-0.67 and is significantly different from zero in both sub-groups, indicating that the estimates are stable.

Coefficient estimates are similar when each observation is dropped one-by-one in a leave-one-out cross-validation procedure (LOOCV; see, e.g., Stone 1974, Geisser 1975). The elasticity estimates fall within a similar range as those estimated when dropping the top and bottom tenth percentiles: 0.07-0.12 for on-farm fallow, 0.30-0.43 for upstream survey-reported fallow area, and 0.60-0.70 for upstream GIS canopy cover. Averaging the results of the LOOCV gives elasticities of 0.10, 0.37, and 0.66 for on-farm fallow, upstream fallow area, and upstream canopy cover, all very close to the SEM estimates reported in table 4. Finally, the bootstrap bias estimates of on- and off-farm fallow elasiticities from the four models calculated using 500 replications indicate that the finite sample biases are small relative to the sizes of the parameter estimates (table 5).

Forest product harvesting function

I now turn to forest product harvesting, an important use of fallow land beyond the ecosystem services it provides in crop production. Sixty-nine percent of farmers in the sample collect products from their fallow land. The most common products are wood and charcoal, used primarily for cooking fuel, though farmers also gather honey and forest fruits. Most of the produce is reserved for home consumption, with only one farmer selling the entire harvest. Twenty-six percent of harvesters both consume and sell some of their products. Forest products tend to be overshadowed by cropping, comprising 14% of the income from farm activities on average among sampled farmers. Some studies argue that forest product harvesting represents an important risk mitigation or “natural insurance” strategy for small-scale farmers (Pattanayak and Sills 2001, Hedden-Dunkhorst et al. 2003). Research from the Amazon indicates that forest product harvesting can contribute substantially to shifting cultivators' incomes, though virgin forest may yield more lucrative products than secondary forest (Smith et al. 1999).

I estimate an equation to measure the value of fallow in harvested forest products. The dependent variable is the log of forest product value. Although most products are reserved for home consumption, I aggregate over different commodities using farmer-reported market prices in the absence of alternative weights.

The logs of on-farm and upstream fallow land are the primary regressors of interest. On-farm fallow land proxies for fallow biomass, which is the source of the harvested commodities. Upstream forest fallow may facilitate easier harvesting and more abundant products by moderating floods and soil moisture. I again use the two alternative measures of off-farm fallow biomass derived from survey and GIS data. The equation can be written as

$$\ln q_i = \alpha_o + \alpha_1 \ln f_i + \alpha_2 W_1 \ln F + \alpha_3 \ln H_i + \varepsilon_i$$
$$\varepsilon_i = \lambda W_2 \varepsilon + u_i$$

Here, q_i represents the value of forest product harvests. On- and off-farm fallow are again given by f_i and F, respectively, while W_1 represents the same row-normalized spatial weighting matrix as that used in the crop production function, giving all upstream neighbors equal importance. Use of the same weighting matrix is appropriate if the externalities provided to forest products are similar to those relevant in crop production. Household characteristics expected to affect output value are included in the vector H_i. The disturbance, ε_i, is again comprised of a component that varies systematically over space with inverse distance, $\lambda W_2 \varepsilon$, and white noise, u_i. I also use Battese's (1997) approach, discussed above, adding dummy variables to indicate observations with no fallow on their own farms and no fallow upstream.

I cannot estimate a structural production function due to missing input data, namely harvesting labor. To proxy for collecting labor availability, I include the log of household size and the agricultural wage rate. I also include black clay, charcoal-enriched, and poor soil type indicators and slope to control for land quality. I add variables indicating ownership of firewood and gas stoves, as cooking fuel is an important commodity for home consumption. I also include three indicators of household wealth—car ownership, television ownership, and electricity use—to examine whether low-income households are more likely to collect forest products. Other control variables include forest product prices,[19] the household head's education level, ownership of the farm, and municipality dummies.

Treatment of censoring in forest product harvests

Because only 69% of farms harvest forest products, the econometric model must account for censoring to consistently estimate the parameters of interest. Factors affecting demand for forest products, such as market prices, opportunity cost of labor, and land quality, may have different impacts on the decision to harvest and the amount of output conditional on participation. The two-part hurdle model allows for different effects across the two processes.[20] Because the same set of variables affects both the binary

[19] In the absence of data on market prices for the harvested commodities, I use village medians of farmer-reported forest product prices as regressors to avoid bias due to common measurement error and quality effects by including farmer-reported prices directly on both sides of the equation. Use of unit value cluster means outperforms other proxies for market prices in estimating price elasticities in a study using Vietnamese data (Niimi 2005). I use village medians to minimize the influence of outliers.

[20] I test the Tobit restriction against the two-part Cragg hurdle model, which nests the Tobit, to determine whether the coefficients vary across the two processes (Fin and Schmidt 1984). The explanatory variables do differ in magnitude, and in some cases even sign, across the probit and non-limit regression models. Indeed, a likelihood ratio test rejects equality of the coefficients across the two equations for all four model specifications ($p = 0.00$). Results of these regressions are available upon request I use the hurdle model estimates in the remainder of my analysis. I employ the two-part probit-least squares model rather than the Cragg approach to facilitate estimation using spatially-correlated errors and instrumental variables. However, the significance and magnitudes of the coefficients are very similar across the Cragg and probit-least squares models, indicating that the hurdle model is robust across the two specifications.

choice and conditional outcome, the lack of valid exclusion restrictions makes the Heckman selection model infeasible to implement. A hurdle model of forest product harvesting with spatially correlated error terms in both equations can be written as

$$
\begin{aligned}
&D_i = \gamma_0 + \gamma_1 \ln f_i + \gamma_2 W_1 \ln F + \gamma_3 H_i + \xi_i, \qquad D = \{0,1\} \\
&\ln q_i = \beta_0 + \beta_1 \ln f_i + \beta_2 W_1 \ln F + \beta_3 H_i + \varepsilon_i \quad \text{if } D_i = 1 \\
&\xi_i = \lambda_1 W_2 \xi + u_i \\
&\varepsilon_i = \lambda_2 W_2 \varepsilon + v_i
\end{aligned}
$$

where D denotes a dummy variable indicating participation in harvesting forest products. The selection equation is estimated using a probit model, while the conditional outcome equation can be estimated by ordinary least squares regression on the non-limit observations (Wooldridge 2001, p. 536).

Identification and instrumental variables

Similar to the omitted variable problem raised in the crop production function, poor land quality could lead farmers to allocate more land to fallow but reap lower yields of forest products, biasing the on-farm fallow coefficient downward. Measurement error may also lead to attenuation bias on the fallow coefficients since fallow biomass is proxied by fallow area or canopy cover. The elasticity of GIS off-farm canopy cover may also be overestimated and the elasticity of on-farm fallow area underestimated if canopy cover is correlated with on-farm fallow biomass density. Simultaneity between fallow area and forest product output may bias the coefficient of on-farm fallow upwards as well, though it is less likely to affect the coefficient of off-farm fallow.

I employ similar approaches as those used in the crop production estimation to address concerns about endogeneity. Control variables on land quality and farmer characteristics are included directly in both the probit and non-limit regressions models.

Spatially correlated errors are included in both to reflect unobserved factors that vary between farms with distance.

I again use the log of farm size as an instrument for on-farm fallow. Total farm size determines the land available for allocation to fallow. However, beyond its effect on the size of fallow land, farm area should have no direct effect on forest product harvests. Forest product prices and firewood and gas stove ownership, used as instruments for fallow in the crop production function, are not valid exclusion restrictions and are included in the forest products equation. I employ spatially-lagged values of farm size and several other household-level exogenous variables from the forest products equation as instruments for off-farm fallow.

The instruments explain much of the variation in on-farm fallow area, upstream fallow area, and canopy cover, as seen in first-stage equations with R-squared statistics of 0.74, 0.90, and 0.65, respectively (table A3 of the appendix). Overidentification tests confirm that the instruments are uncorrelated with forest product harvesting decisions and output value.[21] Smith-Blundell tests indicate that on- and off-farm fallow can be considered exogenous to the forest product harvesting decision in model (1) but not in model (3). In addition, the fallow variables are not exogeneous to the value of forest products conditional on harvesting, according to Hausman test results ($p = 0.04\text{-}0.09$). Therefore, the SEM-IV estimates of the probit and non-limit regressions are consistent, while the regular SEM-probit and non-limit regression estimates are not.

[21] The instruments are also uncorrelated with the outcome variables individually, as shown by including each in the outcome equations. Certain lagged household characteristics, including education, farm ownership, electricity use, and slope were not used as instruments because they were found to be correlated with the forest product harvesting decision or conditional value.

Results

Tables 6 and 7 show the results of the forest product harvesting participation and outcome equations, respectively. Columns (1) and (2) of table 6 report SEM probit and SEM-IV probit coefficient estimates using survey-derived off-farm fallow area. Columns (3) and (4) instead use GIS canopy cover. Table 7 follows the same pattern, with columns (1) and (2) giving non-limit SEM and SEM-IV estimates using survey-reported upstream fallow area, and columns (3) and (4) using GIS canopy cover. The spatial correlation coefficient of the probit equation error term is positive and significant across all four models, indicating that unobservable factors do have similar effects on neighbors' harvesting decisions. The error terms are not significantly spatially correlated in the non-limit regressions, however.

While I use separate probit and non-limit regression models to estimate the parameters of the hurdle model, the combined effect or unconditional elasticity of the fallow variables are the main parameters of interest from the model of forest product harvesting.[22] The non-limit regression equations estimate the conditional elasticity directly, since product value and fallow are expressed in log form. I calculate the probability elasticities using the coefficients from the probit models, using

$$\frac{d \ln \Pr(q > 0)}{d \ln f} = \gamma_1 \frac{\varphi(\gamma z)}{\Phi(\gamma z)}$$

where γ_1 is the coefficient of the log of on-farm fallow from the probit equation, and γz is the linear prediction.

[22] McDonald and Moffitt (1980) derive the decomposition of the effects of the participation decision and the value of the outcome conditional on participation in the Tobit context, showing that $E(y \mid x) = \Pr(y > 0 \mid x) \cdot E(y \mid y > 0, x)$. Log differentiating this expression reveals that the unconditional elasticity is simply the sum of the probability elasticity and the conditional elasticity.

Table 8 reports the probability, conditional, and unconditional elasticities of on- and off-farm fallow in forest product harvesting. The unconditional output elasticity of on-farm fallow is positive across all four models, varying from 0.22 to 0.49. However, it is higher in magnitude and significantly different from zero only in models (2) and (4), when the IV approach addresses the endogeneity of on- and off-farm fallow. This finding indicates that omitted variables and measurement error bias the estimates of the probability and conditional elasticities downward. These results confirm that on-farm fallow makes an important contribution to the value of forest products, as expected. In fact, the elasticities derived from the SEM-IV estimates suggest that on-farm fallow contributes close to 50% of the value of forest products.

The estimates of the unconditional elasticity of off-farm fallow are also all positive, spanning 0.76-0.89. Similar to the results from the crop production function, the elasticity of upstream fallow area is significantly greater than zero in models (1), (2), and (3). The SEM-IV estimate (model (4)) is not significantly different from zero. These results suggest that farms located downstream of neighbors with higher levels of forest fallow garner higher incomes from forest products, even accounting for positive spatial correlation in omitted variables affecting neighbors' harvesting decisions.[23] The net effect is positive and statistically significant for three out of four estimates. Thus, these findings provide some support the hypothesis that upstream forest fallow provides

[23] I also investigate whether fallow externalities only arise from upstream forest cover by estimating the probit and non-limit regressions including downstream fallow. I find that downstream fallow has no significant effect on the probability of harvesting forest products, and the coefficient is actually negative across all four models. The results from the conditional outcome equation are less conclusive—Models (2) and (3) show downstream fallow to have a positive, though not significant, effect on harvest value. Thus, I cannot confirm whether the positive effects of off-farm fallow on forest product harvests are strictly hydrological, flowing from upstream to downstream, or whether insect pollinators, tree seed availability, or other potential forest ecosystem services may play a role. These results are available upon request.

positive externalities not only in crop production but also in forest product harvests, thought the results are less conclusive than those from the crop production function.

Turning to the other explanatory variables in the hurdle model of forest product harvesting, labor availability is important in the decision to collect forest products, as indicated by the positive and significant coefficient of the log of household size and the negative and significant coefficient of the wage rate in the probit equation. Ownership of a gas stove is negatively associated with harvesting forest products, as expected given these farms' decreased reliance on firewood as a cooking fuel. Farms that do not own a car or use electricity are more likely to collect forest products, implying that low-income farmers rely more heavily on forest products than do better-off households. However, car and television ownership have the opposite effect on the conditional value of forest products, suggesting that wealthier households reap greater value from this activity when they choose to participate. Families with a more educated household head also earn higher revenues from harvesting. Land quality affects harvests as well: favorable black clay soils and less steeply-sloped land increase the conditional value of harvested products. Farmers located in Castanhal and Igarapé Açu are more likely to collect forest products than those in Bragança. In addition, households' whose upstream neighbors maintain no fallow area are significantly less likely to harvest any forest products Village median forest product prices, firewood stove ownership, and farm ownership do not have significant effects on the probability of harvesting or on conditional harvest value.

Resampling and robustness analysis

I carry out similar tests of robustness to those used in the crop production section to investigate whether the results hold across different sub-groups of farmers. Excluding farms from the top and bottom tenth percentiles of on-farm fallow from the probit and non-limit regressions, I find that the results are largely stable. On-farm fallow has a positive and significant effect on the probability of harvesting across the different sub-samples, though it has no significant effect on the conditional value of the harvest. The effect of upstream fallow area is somewhat less robust across different groups—farms with more fallow upstream experience a much larger impact on the probability of harvesting, but find less of an effect on the conditional harvest value. Upstream canopy cover has a consistent effect on the probability of harvesting across different sub-samples, but farms with less upstream canopy cover reap greater benefits in terms of harvest value.

Using the leave-one-out cross-validation procedure, the total elasticity estimates do vary quite a bit, ranging from 0.09-0.20 for on-farm fallow, 0.52-0.78 for upstream fallow area, and 0.64-0.89 for upstream canopy cover, with means of 0.13-0.16, 0.70, and 0.77, respectively. Thus, while total elasticity estimates for forest product harvests with respect to on-farm and upstream fallow are positive across different sub-samples of farmers, they are more variable than those from the crop production function.

Total on- and off-farm fallow elasticities

To better understand the economic significance of forest fallow services in farm activities, I calculate the total farm output elasticity of on- and off-farm fallow using the results from all four models of the crop and forest product estimations. The total output elasticities of on- and off-farm fallow account for their respective contributions to both crop and forest product income, which vary by farm with the share of income from each activity.

The mean elasticity of on-farm fallow ranges from 0.11-0.22, depending on the estimates used, but is significantly different from zero in all four specifications (table 9). This positive mean elasticity underscores the importance of forest fallow to farms in the Zona Bragantina in providing both consumable products and ecological support services.

In addition, the mean output elasticity of upstream fallow is significantly different from zero in three of the four sets of estimates, spanning 0.29-0.68. The effect of off-farm fallow on farm revenue appears to be important both statistically and in magnitude. As in the results from the crop production function alone, I cannot rule out whether the high magnitude of the off-farm effect is in part driven by other factors that lead upstream land use to be correlated with downstream farm income. However, the positive and significant effect of upstream but not downstream forest cover on crop value does provide support for the hypothesis that hydrological externalities contribute to agricultural income.

These findings support the hypothesis that upstream forest fallow provides flows of economically significant ecological services to farms in the Zona Bragantina. They suggest that off-site hydrological regulation may be important even in low and moderately sloped regions with porous soils. These hydrological support services may justify continued allocation of significant amounts of land to forest fallow in the future, even if farms increasingly substitute chemical fertilizer for fallow-based soil nutrients.

Land allocation efficiency

While fallow provides important ecological services in shifting cultivation, it can be a costly investment when the opportunity costs of land and labor are considered. Land must remain out of cultivation for years at a time to ensure sustainability, and land clearing requires large investments of labor. The total returns to fallowing thus depend on the relative contributions of fallow and cultivated land to farm income once all costs are considered.

The estimated income elasticities of cultivated area, on-farm fallow, and upstream fallow can be used to determine whether farmers allocate land between cultivation and fallow efficiently. Farmers manage land efficiently from a social perspective if they balance the marginal contribution of cultivated area to crop income with the marginal value of the lost fallow services to on-farm and downstream crop production and forest product harvesting. Klemick (2008) derived the expression for efficient land allocation from an optimal control model of shifting cultivation. This measure, termed the social income elasticity of cultivated land, represents the impact of a 1% increase in cultivated area on agricultural profits earned on the farm itself and on farms affected downstream.[24] Using this expression, Klemick calculated whether each farmer allocated the optimal amount of land to fallow using the estimated parameters from the crop and forest product equations presented in model (1).

Efficient allocation of land between cultivation and fallow implies that the social income elasticity of cultivated land is equal to zero. If the elasticity is significantly greater (less) than zero at the 1% level, the farm is considered to be over-(under-)

[24] The social income elasticity of cultivated land is written as

$$\varepsilon_{soc}^{i} = \frac{r_{crop}^{i}}{\pi^{i}}\left(\varepsilon_{x} - \frac{x^{i}}{r_{crop}^{i}}c\right) - \frac{x^{i}}{\pi^{i}}\left(\frac{1+r}{r + x^{i}/\overline{X}^{i}}\right)\left(\varepsilon_{\theta}\frac{r_{crop}^{i}}{\overline{X}^{i} - x^{i}} + \xi_{\theta}\frac{r_{for}^{i}}{\overline{X}^{i} - x^{i}} + \sum_{j}^{N}\frac{1}{(\overline{X}^{j} - x^{j})}\left(\varepsilon_{\Sigma\theta}r_{crop}^{j} + \xi_{\Sigma\theta}r_{for}^{j}\right)\right)$$

and depends on the amount of land under cultivation (x) and fallow ($\overline{X} - x$), crop and forest product income (r_{crop}, r_{for}), total farm profits (π),and marginal land-clearing costs (c), factors that vary across all farms in the sample. It also depends on the elasticities of crop output with respect to cultivated area (ε_x), on-farm fallow (ε_θ), and upstream fallow ($\varepsilon_{\Sigma\theta}$), and on the elasticity of forest product harvests with respect to on-farm fallow (ξ_θ) and upstream fallow ($\xi_{\Sigma\theta}$), which can be approximated by the parameters from the equations estimated in this article. The rate of interest is given by r. The variance of this expression can be estimated using the variance-covariance matrices from the crop and forest product equations.

fallowing. I follow the same procedure here to test whether sampled farmers managed land efficiently, allocated too much land to fallow, or allocated too little according to each of the four sets of parameter estimates.

Table 10 presents the results on land allocation efficiency, assuming that farmers face a 10% interest rate.[25] The results suggest that most sampled farmers did indeed allocate land between cultivation and fallow efficiently—74-88% of them, depending on the elasticity estimates used. While some farmers devoted too much (1-17%) or too little (2-12%) land to fallow, by and large, most farmers managed land optimally. These results contrast those of López (1993, 1997), who found that farmers in Ghana and Cote d'Ivoire holding fallow in common property cleared excessive amounts of fallow for cultivation relative to the social optimum, indicating that private property ownership may improve the efficiency of land management.

Summary and conclusions

This study adds to the growing body of literature quantifying the value of forest resources for human livelihoods, specifically agriculture. Such knowledge is essential for policy-makers involved in land-use planning and economic development in forested areas where poverty remains widespread.

Fallow makes an important contribution to farm income in semi-commercial, smallholder agriculture in the Zona Bragantina, a region with similar agroecological conditions and a somewhat more developed infrastructure than other frontier regions in Brazil. Fallowing provides ecological services to farmers by improving land quality and

[25] As discussed in Klemick (2008) and López (1997), the interest rate is a key parameter because it determines how heavily farmers discount the future value of the fallow biomass stock. In the absence of data on interest rates facing sampled farmers, I assume a 10% interest rate to capture a balance between the subsidized credit programs and market interest rates available to farmers in the region.

serving as a source of harvestable products. The econometric analysis indicates that fallow provides valuable hydrological services to downstream farmers as well. The results also suggest that farmers allocated land between cultivation and fallow efficiently, even accounting for the value of these downstream services.

These findings imply that farming communities may have some self-interest in preserving forest cover locally, even if transition to permanent cultivation becomes more attractive in the future. Knowledge of the local benefits of forest fallow may bolster efforts aimed at conserving tropical forests as a strategy to mitigate greenhouse gas emissions and biodiversity loss. Conversely, policies encouraging farmers to transition from slash-and-burn to permanent cultivation may have unintended consequences due to the loss of local hydrological services.

References

Anselin, Luc, 1988. *Spatial Econometrics: Methods and Models*. Dordecht, The Netherlands: Kluwer Academic Publishers.

Altieri, Miguel. 1995. *Agroecology: the Science of Sustainable Agriculture*. Boulder, CO: Westview Press.

Battese, George. 1997. "A note on the estimation of Cobb-Douglas production functions when some explanatory variables have zero values." *Journal of Agricultural Economics* 48: 250-252.

Brady, N.C. 1996. "Alternatives to slash and burn: a global imperative." *Agriculture, Ecosystems and Environment* 58: 3-11.

Bruijnzeel, L.A. 2004. "Hydrological functions of tropical forests: not seeing the soil for the trees?" *Agriculture, Ecosystems and Environment* 104: 185-228.

Chomitz, Kenneth M. and Kanta Kumari. 1998. "The domestic benefits of tropical forests: a critical review." *World Bank Research Observer* 13 (1): 13-35.

Cragg, J. "Some statistical models for limited dependent variables with application to the demand for durable goods." *Econometrica* 39: 829-844.

Cressie, Noel. 1993. *Statistics for spatial data*. New York: J. Wiley.

de Rouw, Anneke. 1995. "The fallow period as a week-break in shifting cultivation (tropical wet forests)." *Agriculture, Ecosystems and Environment* 54: 31-43.

Fin, T. and P. Schmidt. 1984. "A test of the tobit specification against and alternative suggested by Cragg." *Review of Economics and Statistics* 66: 174-177.

Gehring, Christoph, Manfred Denich, Milton Kanashiro, and Paul Vlek. 1999. "Response of secondary vegetation in Eastern Amazonia to relaxed nutrient availability constraints." *Biogeochemistry* 45: 223-241.

Geisser, Seymour. 1975. "The predictive sample reuse method with applications." *Journal of the American Statistical Association* 70(350): 320-328.

Greene, William. 2000. *Econometric analysis*, fourth edition. Upper Saddle River, NJ: Prentice-Hall, Inc.

Hamilton, Lawrence S. and Peter N. King. 1983. *Tropical Forested Watersheds*. Boulder, CO: Westview Press.

Hansen, M., R. DeFries, J.R. Townshend, M. Carroll, C. Dimiceli, and R. Sohlberg, 2006. Vegetation Continuous Fields MOD44B, 2001 Percent Tree Cover, Collection 4, University of Maryland, College Park, Maryland, 2001.

Hedden-Dunkhorst, B., M. Denich, K. Vielhauer, F. Romualdo de Sousa Filho, T. D. de Abreau Sa, T. Hurtienne, F. de Assis Costa, A. Mendoza-Escalante, and J. Borner. 2003. "Forest-based fallow systems as a safety net for smallholders in the Eastern Amazon." Paper presented at the International Conference on Rural Livelihoods, Forests and Biodiversity, Bonn, Germany, 19-23 May 2003.

Holscher, D., B. Ludwig, R.F. Moller, and H. Folster. 1997. "Dynamic of soil chemical parameters in shifting cultivation agriculture in the Eastern Amazon." *Agriculture, Ecosystems and Environment* 66: 153-163.

Kato, M.S.A., O.R. Kato, M. Denich, and P.L.G. Vlek. 1999. "Fire-free alternatives to slash-and-burn for shifting cultivation in the eastern Amazon region: the role of fertilizers." *Field Crops Research* 62: 225-237.

Klemick, H. 2008. "Do Liquidity Constraints Help Preserve Tropical Forests? Evidence from the Eastern Amazon." Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Orlando, FL, July 27-29, 2008.

Kremen, Claire, Neal Williams, Robert Bugg, John Fay and Robin Thorp. 2004. "The area requirements of an ecosystem service: crop pollination by native bee communities in California." *Ecology Letters* 7: 1109-1119.

LeSage, James. 1998. "Spatial Econometrics." [Available at www.spatial-econometrics.com]

López, R. 1993. "Resource Degradation, Community Controls and Agricultural Productivity in Tropical Areas." Working Paper No. 93-08, AREC, University of Maryland.

López, R. 1997. "Environmental Externalities in Traditional Agriculture and the Impact of Trace Liberalization: the Case of Ghana." *Journal of Development Economics* 53: 17-39.

Maler, Karl-Goran. 1991. "Measuring environmental damage: the production function approach." Valuing environmental benefits in developing countries, proceedings of a seminar, Feb. 1990, Michigan State University.

Mardia, K.V. and R.J. Marshall. 1984. "Maximum Likelihood Estimation of Models for Residual Covariance in Spatial Regression." *Biometrika* 71(1): 135-146.

McDonald, John and Robert Moffitt. 1980. "The uses of Tobit analysis." *Review of Economics and Statistics* 62: 318-321.

Mendoza-Escalante, Arisbe. 2004. “Analysis of smallholder agricultural production in the Eastern Amazon: empirical evidence and policy perspectives for the Bragantina region.” PhD diss., ZEF, University of Bonn.

Millennium Ecosystem Assessment. 2005. *Ecosystems and Human Well-being: Synthesis*. Washington, DC: Island Press.

Nepstad, Daniel, Paulo Moutinho, and Daniel Markewitz. 2001. “The recovery of biomass, nutrient stocks, and deep soil functions in secondary forests.” In *The Biogeochemistry of the Amazon Basin*. Micheal McClain et al., eds. New York: Oxford University Press.

Niimi, Yoko. 2005. “An analysis of household responses to price shocks in Vietnam: can unit values substitute for market prices?” PRUS Working Paper no. 30.

Pattanayak, Subhrendu and David Butry. 2005. “Spatial complementary of forests and farms: accounting for ecosystem services.” *American Journal of Agricultural Economics* 87(4): 995-1008.

Pattanayak, Subhrendu and Randall A. Kramer. 2001. “Worth of watersheds: a producer surplus approach for valuing drought mitigation in Eastern Indonesia.” *Environment and Development Economics* 6: 123-146.

Pattanayak, Subhrendu and Erin O. Sills. 2001. “Do tropical forests provide natural insurance? The microeconomics of non-timber forest product collection in the Brazilian Amazon.” 77(4): 595-612.

Ricketts, Taylor, Gretchen Daily, Paul Erlich, and Charles Michener. 2004. “Economic value of tropical forests to coffee production.”

Sanchez, Pedro, Dale Brandy, J. Hugo Villachica, and John Nicholaides. 1982. “Amazon basin soils: management for continuous crop production.” *Science* 216: 821-827.

Sanchez, Pedro. 1996. “Introduction.” *Agriculture, Ecosystems and Environment* 58: 1-2.

Silva-Forsberg, Maria Clara and Philip M. Fearnside. 1997. “Brazilian Amazonian *caboclo* agriculture: effect of fallow period on maize yield.” *Forest ecology and management* 97:283-291.

Smith, Joyotee, Petra van de Kop, Keneth Reategui, Ignacio Lmbardi, Cesar Sabogal, and Armando Diaz. 1999. Dynamics of secondary forests in slash-and-burn farming: interactions among land use types in the Peruvian Amazon. *Agriculture, Ecosystems and Environment* 76: 85-98.

Soloaga, Isidro. 2000. Production and factors allocation in farm households." PhD diss., Agricultural and Resource Economics Department, University of Maryland.

Sommer, Rolf, Manfred Denich, and Paul L.G. Vlek. 2000. "Carbon storage and root penetration in deep soils under small-farmer land-use systems in the Eastern Amazon region, Brazil." *Plant and Soil* 219: 231-241.

Staver, C. 1991. "The role of weeds in the productivity of Amazonian bush fallow agriculture." *Experimental Agriculture* 27: 287-304.

Stone, M. 1974. "Cross-validatory choice and assessment of statistical predictions." *Journal of the Royal Statistical Society. Series B (Methodological)* 36(2): 111-147.

Tucker, Joanna M., Eduardo S. Brondizio and Emilio Moran. 1998. "Rates of forest regrowth in Eastern Amazonia: a comparison of Altamira and Bragantina Regions, Para State, Brazil." *Interciencia* 23 (2): 64-73.

U.S. Geological Survey, National Center for Earth Resources Observation & Science (EROS). HYDRO1k South America. [Accesed Nov. 16, 2005 http://edc.usgs.gov/products/elevation/gtopo30/hydro/sa_fd.html]

Wooldridge, Jeffrey. 2001. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: The MIT Press.

Figure 1 Municipios in the Zona Bragantina

Source: http://pt-uf.pt-dlr.de/Shift/english/map/env101.htm, Accessed Nov. 28, 2005

Figure 2 Tree canopy cover in the Zona Bragantina, March 2001-March 2002

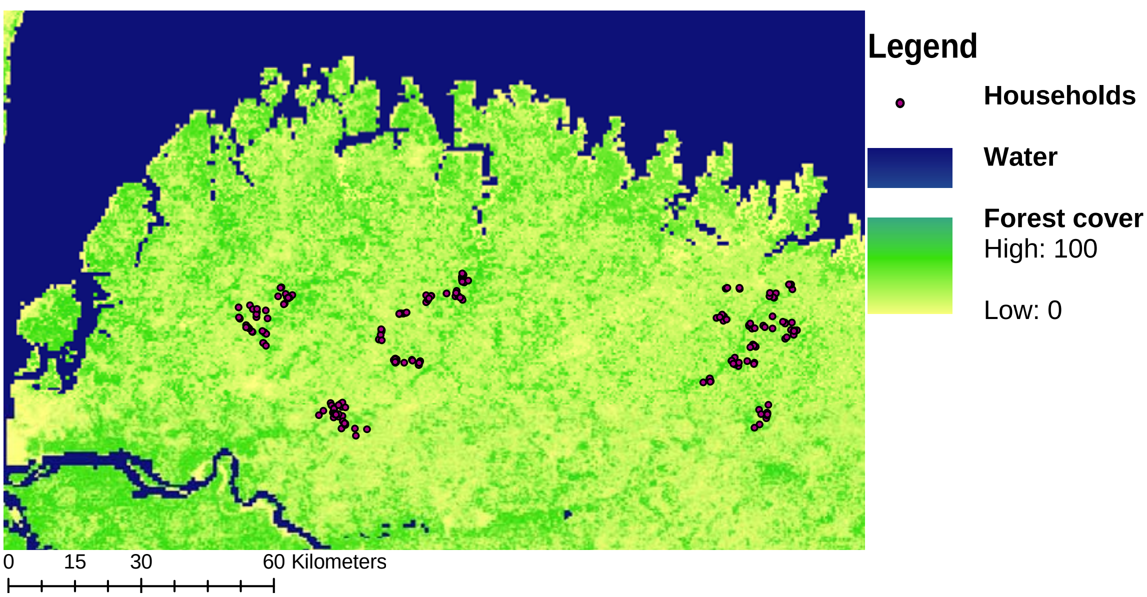

Figure 3 Flow direction in the Zona Bragantina

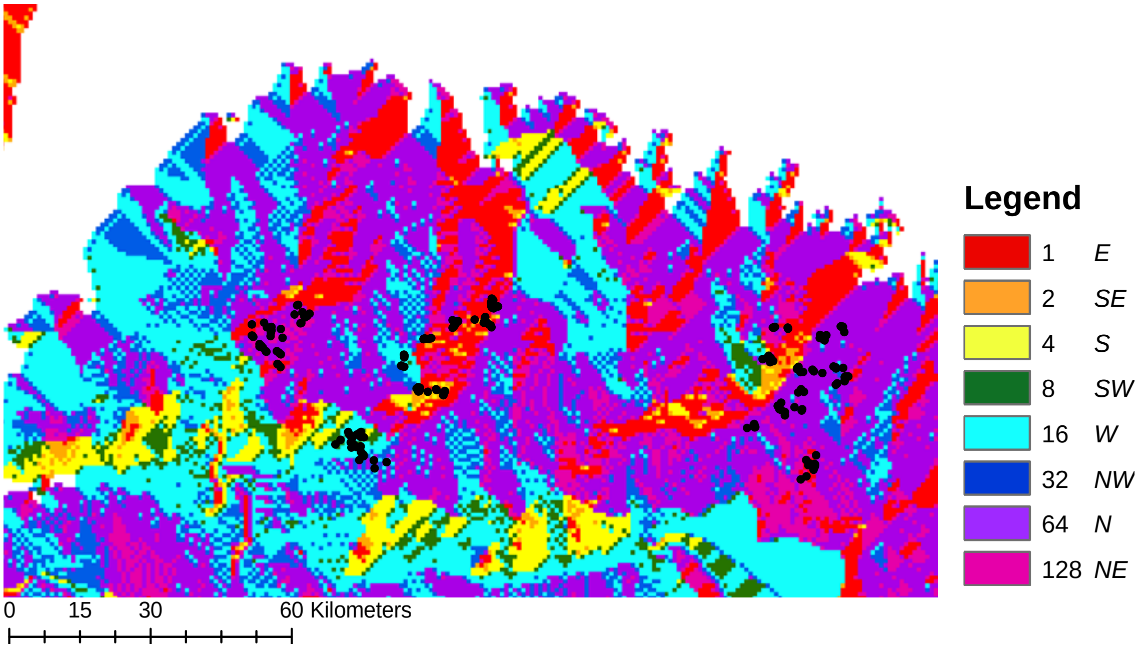

Figure 4 Flow direction of hypothesized hydrological externalities

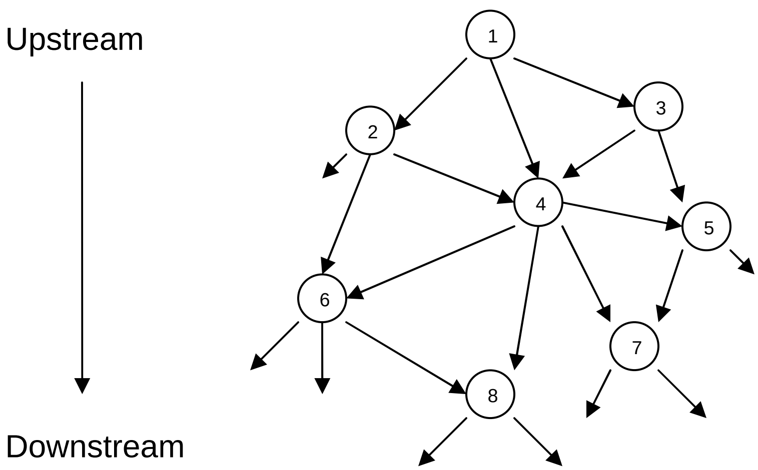

Table 1 Household characteristics

	Mean (Standard deviation)	Observations
Farm size (ha)	40.73 (47.97)	271
Household size (members)	6.18 (2.78)	271
Own farmland (legal title) 1 = yes, 0 = no	0.65 (0.48)	271
Household head education (years)	3.77 (2.91)	271
Use extension services 1 = yes, 0 = no	0.24 (0.43)	271
Own car 1 = yes, 0 = no	0.09 (0.28)	271
Own television 1 = yes, 0 = no	0.60 (0.49)	271
Use electricity 1 = yes, 0 = no	0.62 (0.49)	271
Own firewood stove 1 = yes, 0 = no	0.85 (0.36)	271
Own gas stove 1 = yes, 0 = no	0.84 (0.37)	271
Village-level annual price index ($B/kg)	0.81 (0.23)	271
Village-level perennial price index ($B/kg)	3.26 (1.81)	271
Forest product price ($B/kg)[26]	6.57 (14.76)	187
Agricultural wage rate ($B/day)	8.26 (1.38)	271

[26] I impute forest product prices for households that do not collect forest products using village averages.

Table 2 Production function variables

	Mean (Standard deviation)	Observations
Crop output value ($B)	5118.27 (11972.62)	261
Cultivated area (ha)	3.75 (4.64)	270
Family labor (person-days)	112.47 (97.42)	271
No family labor used 1 = yes, 0 = no	0.02 (0.15)	271
Hired labor (person-days)	52.94 (75.36)	271
No hired labor used 1 = yes, 0 = no	0.17 (0.37)	271
Fertilizer (kg NPK)	389.90 (1525.69)	271
No fertilizer used 1 = yes, 0 = no	0.29 (0.46)	271
Slope (degrees)	2.65 (2.54)	261
Black clay (*massape*) soil 1 = yes, 0 = no	0.10 (0.30)	271
Charcoal enriched (preta) soil 1 = yes, 0 = no	0.10 (0.31)	271
Poor (*arisca*) soil 1 = yes, 0 = no	0.06 (0.24)	271

Table 3 Fallow variables

	Mean (Standard deviation)	Observations
On-farm fallow area (ha)	22.60 (28.97)	271
No on-farm fallow land 1 = yes, 0 = no	0.14 (0.35)	271
Off-farm (upstream) average fallow area – survey data (ha/upstream neighbor)	24.54 (19.62)	236
No upstream fallow area 1 = yes, 0 = no	0.03 (0.16)	236
Off-farm (upstream) canopy cover – GIS data, 3km radius (% area)	24.61 (9.08)	261
No upstream canopy cover 1 = yes, 0 = no	0 (0.00)	261

Table 4 Crop production function estimation

	SEM[27] (1)	SEM-IV (2)	SEM (3)	SEM-IV (4)
Log on-farm fallow area	0.098*	0.125	0.093	0.177**
	[0.058]	[0.078]	[0.058]	[0.090]
Log off-farm fallow – upstream	0.366**	0.378**		
survey fallow area	[0.158]	[0.184]		
Log off-farm fallow – 3 km			0.655***	0.231
upstream GIS canopy cover			[0.231]	[0.403]
Log cultivated area	0.414***	0.405***	0.438***	0.434***
	[0.099]	[0.101]	[0.094]	[0.096]
Log family labor	0.128	0.126	0.062	0.074
	[0.093]	[0.094]	[0.088]	[0.090]
Log hired labor	0.175***	0.172***	0.194***	0.171***
	[0.065]	[0.066]	[0.061]	[0.063]
Log chemical fertilizer	0.146***	0.146***	0.174***	0.159***
	[0.055]	[0.056]	[0.056]	[0.058]
Perennial producer (binary)	0.911***	0.914***	0.826***	0.830***
	[0.177]	[0.178]	[0.165]	[0.167]
Use extension services (binary)	0.262	0.27	0.205	0.206
	[0.177]	[0.178]	[0.164]	[0.166]
Household head schooling years	-0.018	-0.018	-0.02	-0.02
	[0.025]	[0.025]	[0.024]	[0.024]
Farm owner (binary)	0.07	0.07	-0.045	-0.018
	[0.157]	[0.158]	[0.148]	[0.151]
Black clay soil (binary)	0.221	0.227	0.193	0.179
	[0.236]	[0.238]	[0.233]	[0.236]
Charcoal-enriched soil (binary)	0.373*	0.381*	0.363*	0.414*
	[0.215]	[0.216]	[0.215]	[0.221]
Poor soil (binary)	-0.122	-0.125	0.213	0.106
	[0.309]	[0.310]	[0.283]	[0.298]
Slope	-0.011	-0.013	-0.021	-0.012
	[0.027]	[0.027]	[0.027]	[0.028]
Castanhal municipality (binary)	0.25	0.251	0.634***	0.456*
	[0.228]	[0.229]	[0.234]	[0.273]
Igarapé Açu municipality (binary)	0.281	0.277	0.304	0.244
	[0.229]	[0.233]	[0.214]	[0.220]
No on-farm fallow (binary)	0.429	0.495	0.515**	0.676**
	[0.285]	[0.323]	[0.261]	[0.312]
No upstream fallow area (binary)	1.102*	1.131*		
	[0.602]	[0.657]		
No family labor (binary)	1.260*	1.243*	0.898	0.901
	[0.651]	[0.653]	[0.641]	[0.649]
No hired labor (binary)	0.018	0.013	0.173	0.066

[27] All regressions estimated in Stata 8 unless otherwise noted

	[0.284]	[0.285]	[0.269]	[0.278]
No fertilizer (binary)	0.174	0.157	0.325	0.275
	[0.308]	[0.312]	[0.299]	[0.305]
Constant	3.343***	3.202***	2.500***	3.720***
	[0.732]	[0.758]	[0.952]	[1.419]
Spatial error correlation coefficient (λ)	-0.033 [0.138]	-0.055 [0.142]	-0.016 [0.156]	-0.021 [0.30]
Observations	228	228	251	251
R-squared	0.60	0.60	0.57	0.56
Log likelihood	-313.83	-314.36	-347.77	-350.80

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5 Bootstrap bias estimates for crop production function parameters, 500 replications

	Model (1)	Model (2)	Model (3)	Model (4)
On-farm fallow	-0.004	-0.005	-0.004	-0.008
Upstream fallow area	0.003	0.003		
Upstream canopy cover (3km radius)			-0.005	-0.041

Table 6 Forest product harvesting: participation equation

	SEM [28] Probit (1)	SEM-IV probit (2)	SEM Probit (3)	SEM-IV probit (4)
Log on-farm fallow area	0.281***	0.370***	0.395***	0.473***
	[0.110]	[0.146]	[0.117]	[0.198]
Log off-farm fallow – upstream survey fallow area	0.430	0.425		
	[0.278]	[0.302]		
Log off-farm fallow – 3 km upstream GIS canopy cover			0.591	1.754**
			[0.491]	[0.980]
Forest product price (village median)	-0.224790	-0.181	0.164	0.185*
	0.182062	[0.168]	[0.143]	[0.138]
Log household size	0.965***	0.962***	0.834***	0.896***
	[0.300]	[0.260]	[0.310]	[0.313]
Agricultural wage rate	-0.245***	-0.234***	-0.230**	-0.237**
	[0.010]	[0.095]	[0.100]	[0.104]
Household head schooling years	0.051	0.061*	0.034	0.041
	[0.047]	[0.043]	[0.051]	[0.052]
Farm owner (binary)	0.303	0.274	-0.066	-0.080
	[0.294]	[0.275]	[0.315]	[0.320]
Own car (binary)	-0.975***	-0.936***	-0.946**	-0.852**
	[0.403]	[0.397]	[0.473]	[0.480]
Own television (binary)	0.047	-0.015	-0.064	0.022
	[0.314]	[0.320]	[0.362]	[0.365]
Use electricity (binary)	-0.841***	-0.744***	-0.723**	-0.755**
	[0.335]	[0.316]	[0.390]	[0.377]
Own firewood stove (binary)	0.293	0.326	0.474*	0.332
	[0.329]	[0.319]	[0.384]	[0.428]
Own gas stove (binary)	-1.498***	-1.478***	-1.075**	-0.994***
	[0.552]	[0.553]	[0.508]	[0.563]
Black clay soil (binary)	0.851*	0.858*	0.799*	0.654*
	[0.534]	[0.550]	[0.599]	[0.549]
Charcoal-enriched soil (binary)	0.197	0.185	0.101	0.073
	[0.396]	[0.394]	[0.447]	[0.482]
Poor soil (binary)	-0.381	-0.311	-0.343	-0.075
	[0.602]	[0.609]	[0.692]	[0.064]
Slope	-0.008	-0.020	-0.047	-0.075
	[0.054]	[0.053]	[0.057]	[0.0064]
Castanhal municipality (binary)	0.742**	0.685**	0.821**	1.330**
	[0.404]	[0.423]	[0.503]	[0.690]
Igarapé Açu municipality (binary)	1.497***	1.401***	0.918**	1.023**
	[0.479]	[0.509]	[0.501]	[0.564]
No on-farm fallow area (binary)	0.248	0.581	0.149	0.635
	[0.483]	[0.592]	[0.548]	[0.711]
No upstream fallow area (binary)	-2.858**	-3.018**		

[28] Spatial errors probit model estimated using Gibbs sampler algorithm in Matlab (LeSage 1998).

	[1.441]	[1.384]		
Constant	0.936	0.364	-1.674	-5.860**
	[1.568]	[1.667]	[1.911]	[3.043]
Spatial error correlation	0.535***	0.545***	0.345***	0.341***
coefficient (λ)	[0.245]	[0.234]	[0.239]	[0.250]
Observations	236	236	261	261
McFadden R-squared	0.30	0.29	0.66	0.26

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 Forest product harvesting: conditional outcome equation

	SEM (1)	SEM-IV (2)	SEM (3)	SEM-IV (4)
Log on-farm fallow area	0.065	0.283**	0.025	0.269*
	[0.107]	[0.139]	[0.111]	[0.163]
Log off-farm fallow – upstream	0.549**	0.548*		
survey fallow area	[0.278]	[0.322]		
Log off-farm fallow – 3 km			0.598	-0.002
upstream GIS canopy cover			[0.411]	[0.781]
Forest product price (village	0.037	0.116	0.158	0.202
median)	[0.187]	[0.191]	[0.175]	[0.178]
Log household size	0.087	0.113	0.209	0.234
	[0.265]	[0.264]	[0.260]	[0.259]
Agricultural wage rate	0.027	0.01	-0.02	-0.031
	[0.100]	[0.098]	[0.088]	[0.088]
Household head schooling years	0.03	0.041	0.07	0.082*
	[0.047]	[0.047]	[0.046]	[0.046]
Farm owner (binary)	-0.191	-0.201	-0.334	-0.264
	[0.267]	[0.264]	[0.270]	[0.270]
Own car (binary)	1.215**	1.217**	1.130**	1.109**
	[0.525]	[0.517]	[0.512]	[0.511]
Own television (binary)	0.631**	0.652**	0.666**	0.664**
	[0.274]	[0.271]	[0.271]	[0.271]
Use electricity (binary)	-1.078***	-1.102***	-1.021***	-1.090***
	[0.270]	[0.268]	[0.270]	[0.275]
Own firewood stove (binary)	0.406	0.386	0.284	0.412
	[0.378]	[0.373]	[0.392]	[0.402]
Own gas stove (binary)	-0.017	-0.088	0.119	0.023
	[0.308]	[0.305]	[0.304]	[0.310]
Black clay soil (binary)	0.963**	0.968**	0.753*	0.783*
	[0.413]	[0.408]	[0.401]	[0.400]
Charcoal-enriched soil (binary)	-0.124	-0.079	-0.444	-0.355
	[0.386]	[0.382]	[0.393]	[0.398]
Poor soil (binary)	0.44	0.522	0.671	0.581
	[0.537]	[0.534]	[0.525]	[0.540]
Slope	-0.064	-0.084*	-0.076	-0.074

	[0.048]	[0.049]	[0.047]	[0.051]
Castanhal municipality (binary)	0.647	0.625	0.672	0.408
	[0.442]	[0.446]	[0.467]	[0.542]
Igarapé Açu municipality (binary)	0.235	0.136	-0.072	-0.23
	[0.462]	[0.481]	[0.404]	[0.418]
No on-farm fallow area (binary)	-0.178	0.352	-0.112	0.57
	[0.563]	[0.604]	[0.557]	[0.616]
No upstream fallow area (binary)	0.401	0.007		
	[1.633]	[1.655]		
Constant	2.942	2.116	2.177	3.388
	[1.908]	[2.003]	[1.976]	[2.824]
Spatial error correlation coefficient (λ)	0.153	0.176	0.075	0.087
	[0.186]	[0.197]	[0.198]	[0.175]
Observations	167	167	184	184
R-squared	0.19	0.20	0.17	0.18
Log likelihood	-293.23	-291.62	-330.65	-330.17

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8 Forest product harvesting elasticities

		SEM (1)	SEM-IV (2)	SEM (3)	SEM-IV (4)
Log on-farm fallow area	Probability elasticity	0.14** (0.06)	0.19*** (0.07)	0.19*** (0.06)	0.23** (0.09)
	Conditional elasticity	0.06 (0.11)	0.28** (0.14)	0.03 (0.11)	0.27* (0.16)
	Unconditional elasticity	0.21 (0.13)	0.47*** (0.17)	0.22 (0.13)	0.49** (0.20)
Log upstream fallow – survey fallow area	Probability elasticity	0.22 (0.14)	0.22 (0.16)		
	Conditional elasticity	0.55* (0.28)	0.55* (0.32)		
	Unconditional elasticity	0.77** (0.34)	0.76* (0.38)		
Log upstream off-farm fallow – GIS canopy cover (3 km radius)	Probability elasticity			0.29 (0.24)	0.84* (0.47)
	Conditional elasticity			0.60 (0.41)	-0.002 (0.78)
	Unconditional elasticity			0.89* (0.51)	0.84 (0.99)

Standard errors of the probability elasticities were calculated using the delta method.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9 Total output elasticities of on- and off-farm fallow

	SEM (1)	SEM-IV (2)	SEM (3)	SEM-IV (4)
Total output elasticity of on-farm fallow (sample mean)	0.11* (0.06)	0.17** (0.08)	0.11* (0.06)	0.22** (0.10)
Total output elasticity of upstream fallow area (sample mean)	0.42** (0.16)	0.43** (0.19)		
Total output elasticity of upstream canopy cover (sample mean)			0.68*** (0.24)	0.29 (0.44)

Note: sample means of standard errors given in parentheses were calculated using the estimated standard errors from the previous analyses.

Table 10 Land allocation efficiency of sampled farms, assuming 10% interest rate

	Model (1)	Model (2)	Model (3)	Model (4)
Optimal fallow	85%	88%	74%	88%
Over-fallow	4%	1%	17%	10%
Under-fallow	12%	10%	9%	2%

Appendix

Table A1. First stage OLS regressions for on- and off-farm fallow used in crop production equations

	Model 2		Model 4	
	Log of fallow area	Log of upstream fallow area – survey data	Log of fallow area	Log of upstream canopy cover – GIS data, 3km radius
Log cultivated area	-0.038	-0.012	-0.006	-0.005
	[0.087]	[0.025]	[0.080]	[0.023]
Log family labor	-0.175**	0.02	-0.086	-0.007
	[0.083]	[0.023]	[0.075]	[0.022]
Log hired labor	0.002	-0.027*	0	-0.001
	[0.056]	[0.016]	[0.051]	[0.014]
Log chemical fertilizer	0.023	-0.021	0.027	-0.022
	[0.052]	[0.015]	[0.046]	[0.014]
Perennial producer (binary)	-0.053	-0.117***	-0.09	-0.024
	[0.154]	[0.043]	[0.143]	[0.041]
Use extension services (binary)	-0.031	0.035	-0.038	0.033
	[0.156]	[0.044]	[0.141]	[0.040]
Household head's schooling years	-0.006	0.001	-0.004	0.006
	[0.023]	[0.006]	[0.021]	[0.006]
Farm owner (binary)	0.133	-0.032	0.147	0.049
	[0.134]	[0.038]	[0.123]	[0.035]
Black clay soil (binary)	-0.246	-0.122**	-0.186	0.019
	[0.217]	[0.061]	[0.203]	[0.062]
Charcoal-enriched soil (binary)	-0.022	-0.034	-0.053	0.019
	[0.183]	[0.052]	[0.181]	[0.053]
Poor soil (binary)	0.061	-0.069	-0.017	-0.04
	[0.283]	[0.080]	[0.255]	[0.073]
Slope	0.074**	0.025**	0.039	0.006
	[0.036]	[0.010]	[0.035]	[0.010]
No on-farm fallow (binary)	-1.884***	0.021	-1.840***	-0.014
	[0.213]	[0.060]	[0.187]	[0.053]
No family labor (binary)	-0.808	0.215	-0.177	0.03
	[0.571]	[0.161]	[0.539]	[0.155]
No hired labor (binary)	-0.016	-0.152**	0.041	-0.058
	[0.242]	[0.068]	[0.219]	[0.063]
No fertilizer (binary)	0.106	-0.069	0.141	-0.047
	[0.280]	[0.079]	[0.242]	[0.072]
No upstream fallow (binary)	1.177**	-1.423***		
	[0.491]	[0.139]		
Log of farm size	0.856***	-0.032*	0.743***	0.019
	[0.063]	[0.018]	[0.058]	[0.017]
	0.005	0	0.008**	-0.001

Forest product prices (farm-level)	0.005	0	0.008**	-0.001
	[0.004]	[0.001]	[0.004]	[0.002]
Own firewood stove (binary)	-0.133	-0.005	-0.067	0.132***
	[0.169]	[0.048]	[0.160]	[0.046]
Own gas stove (binary)	-0.048	-0.016	0.002	-0.041
	[0.170]	[0.048]	[0.160]	[0.046]
Log of farm size – upstream weighted ave.	-0.058	0.512***	-0.102	0.058***
	[0.143]	[0.040]	[0.078]	[0.022]
Forest product price – upstream weighted ave.	-0.016	0.016**	-0.010***	0.001
	[0.025]	[0.007]	[0.004]	[0.002]
Own firewood stove – upstream weighted ave.	0.422	0.432***	0.325	0.452***
	[0.538]	[0.152]	[0.343]	[0.097]
Own gas stove – upstream weighted ave.	-0.035	-0.483***	-0.097	0.151*
	[0.568]	[0.160]	[0.276]	[0.078]
Use extension service – upstream weighted ave.	-0.495	0.085	-0.244	-0.295***
	[0.381]	[0.108]	[0.269]	[0.077]
Household head schooling – upstream weighted ave.	-0.04	-0.012	-0.165	0.024
	[0.079]	[0.022]	[0.151]	[0.044]
Farm owner – upstream weighted average	0.2	-0.119	0.036	0.149**
	[0.408]	[0.115]	[0.242]	[0.071]
Black clay soil – upstream weighted ave.	-0.536	-1.161***	-0.167	-0.111
	[0.658]	[0.186]	[0.314]	[0.089]
Charcoal-enriched soil – upstream weighted ave.	-0.326	-0.159	-0.336	-0.185**
	[0.602]	[0.170]	[0.278]	[0.081]
Poor soil – upstream weighted ave.	0.132	-0.026	-0.166	-0.316***
	[0.540]	[0.153]	[0.401]	[0.115]
Slope – upstream weighted ave.	-0.041	-0.012	-0.032	0.017
	[0.043]	[0.012]	[0.040]	[0.011]
Castanhal municipality	0.243	-0.175*	0.096	-0.311***
	[0.328]	[0.093]	[0.228]	[0.065]
Igarapé Açu municipality	0.044	-0.253**	0.222	-0.145**
	[0.365]	[0.103]	[0.217]	[0.062]
Constant	0.602	1.934***	0.909	2.468***
	[0.810]	[0.229]	[0.657]	[0.188]
Observations	235	235	270	260
R-squared	0.75	0.91	0.74	0.68

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A2. Crop production function estimation including downstream forest fallow

	SEM (1)	SEM-IV (2)	SEM (3)	SEM-IV (4)
Log on-farm fallow area	0.107*	0.174**	0.091	0.164*
	[0.058]	[0.079]	[0.059]	[0.089]
Log off-farm fallow – upstream survey fallow area	0.373**	0.403**		
	[0.157]	[0.178]		
Log off-farm fallow – 3 km upstream GIS canopy cover			0.740***	0.435
			[0.285]	[0.605]
Log off-farm fallow – downstream survey fallow area	-0.15	-0.302**		
	[0.098]	[0.140]		
Log off-farm fallow – 3 km downstream GIS canopy cover			-0.297	-0.172
			[0.592]	[1.085]
Log cultivated area	0.423***	0.395***	0.446***	0.435***
	[0.099]	[0.099]	[0.096]	[0.101]
Log family labor	0.132	0.136	0.06	0.069
	[0.093]	[0.093]	[0.088]	[0.090]
Log hired labor	0.166**	0.168***	0.194***	0.180***
	[0.065]	[0.065]	[0.061]	[0.063]
Log chemical fertilizer	0.145***	0.147***	0.168***	0.161***
	[0.055]	[0.055]	[0.057]	[0.059]
Perennial producer (binary)	0.896***	0.907***	0.835***	0.834***
	[0.176]	[0.176]	[0.166]	[0.169]
Use extension services (binary)	0.236	0.242	0.21	0.212
	[0.177]	[0.177]	[0.164]	[0.168]
Household head schooling years	-0.018	-0.019	-0.018	-0.019
	[0.025]	[0.025]	[0.024]	[0.025]
Farm owner (binary)	0.092	0.112	-0.048	-0.028
	[0.157]	[0.157]	[0.148]	[0.152]
Black clay soil (binary)	0.201	0.146	0.168	0.183
	[0.236]	[0.237]	[0.238]	[0.251]
Charcoal-enriched soil (binary)	0.342	0.316	0.35	0.393*
	[0.215]	[0.216]	[0.216]	[0.227]
Poor soil (binary)	-0.184	-0.198	0.201	0.139
	[0.310]	[0.309]	[0.284]	[0.294]
Slope	-0.013	-0.019	-0.022	-0.017
	[0.027]	[0.027]	[0.027]	[0.029]
Castanhal municipality (binary)	0.238	0.152	0.613***	0.516**
	[0.228]	[0.231]	[0.237]	[0.263]
Igarapé Açu municipality (binary)	0.234	0.13	0.3	0.261
	[0.230]	[0.238]	[0.214]	[0.219]
No on-farm fallow (binary)	0.451	0.632*	0.507*	0.668**
	[0.284]	[0.323]	[0.261]	[0.312]
No upstream fallow area (binary)	1.247**	1.387**		
	[0.606]	[0.654]		
No family labor (binary)	1.269**	1.259*	0.894	0.89

	[0.648]	[0.645]	[0.640]	[0.648]
No hired labor (binary)	-0.033	-0.001	0.174	0.115
	[0.284]	[0.282]	[0.269]	[0.279]
No fertilizer (binary)	0.195	0.183	0.318	0.284
	[0.307]	[0.308]	[0.299]	[0.303]
Constant	3.787***	3.968***	3.285*	3.671
	[0.805]	[0.851]	[1.849]	[2.630]
Spatial error correlation coefficient	-0.026	-0.045	-0.014	-0.018
(λ)	[0.129]	[0.125]	[0.138]	[0.131]
Observations	228	228	251	251
R-squared	0.60	0.60	0.57	0.56
Log likelihood	-312.65	-311.87	-347.64	-350.48

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A3. First stage OLS regressions for on- and off-farm fallow used in forest product equations

	Model 2		Model 4	
	Log of fallow area	Log of off-farm upstream fallow area – survey data	Log of fallow area	Log of off-farm upstream canopy cover – GIS data, 3km radius
Forest product price (village median)	-0.083	0.042*	-0.171***	0.011
	[0.082]	[0.023]	[0.054]	[0.016]
Log of household size	-0.099	0.043	-0.092	-0.013
	[0.122]	[0.035]	[0.110]	[0.034]
Wage rate	-0.031	-0.021	-0.012	0.005
	[0.046]	[0.013]	[0.040]	[0.012]
Household head's schooling years	-0.003	0.007	-0.007	0.003
	[0.021]	[0.006]	[0.020]	[0.006]
Farm owner (binary)	0.116	-0.059	0.094	0.045
	[0.130]	[0.037]	[0.117]	[0.035]
Car owner (binary)	-0.22	-0.114*	-0.241	-0.113*
	[0.223]	[0.063]	[0.202]	[0.060]
Television owner (binary)	0.098	0.016	0.108	-0.005
	[0.145]	[0.041]	[0.132]	[0.040]
Use electricity (binary)	-0.092	-0.022	-0.053	0.005
	[0.145]	[0.041]	[0.135]	[0.041]
Own firewood stove (binary)	-0.218	-0.01	-0.151	0.129***
	[0.166]	[0.047]	[0.155]	[0.046]
Own gas stove (binary)	-0.08	-0.013	-0.068	-0.012
	[0.169]	[0.048]	[0.160]	[0.049]
Black clay soil (binary)	-0.27	-0.075	-0.289	0.002
	[0.217]	[0.061]	[0.198]	[0.060]
	0.025	-0.056	0.046	0.054

Charcoal-enriched soil (binary)	0.025	-0.056	0.046	0.054
	[0.189]	[0.053]	[0.180]	[0.054]
Poor soil (binary)	0.082	0.006	-0.045	-0.084
	[0.276]	[0.078]	[0.245]	[0.073]
Slope	0.047*	0.014**	0.038*	0.013*
	[0.025]	[0.007]	[0.023]	[0.007]
No on-farm fallow (binary)	-1.995***	-0.004	-2.046***	-0.035
	[0.202]	[0.057]	[0.182]	[0.054]
No upstream fallow (binary)	0.748	-1.280***		
	[0.601]	[0.170]		
Log of farm size	0.818***	-0.033**	0.745***	0.032**
	[0.058]	[0.016]	[0.052]	[0.016]
Log of farm size – upstream weighted ave.	-0.091	0.550***	-0.042	0.088***
	[0.141]	[0.040]	[0.079]	[0.024]
Log of household size – upstream weighted ave.	0.129	0.027	-0.058	-0.049*
	[0.422]	[0.119]	[0.087]	[0.026]
Wage rate – upstream weighted ave.	0.051	0.033	0.11	-0.049
	[0.141]	[0.040]	[0.240]	[0.072]
Car owner (binary) – upstream weighted ave.	-0.069	-0.548**	-0.29	-0.299**
	[0.872]	[0.246]	[0.414]	[0.123]
Television owner (binary) – upstream weighted aver.	0.159	-0.205*	0.13	-0.003
	[0.386]	[0.109]	[0.230]	[0.069]
Own firewood stove – upstream weighted ave.	0.663	0.05	0.457	0.450***
	[0.613]	[0.173]	[0.314]	[0.094]
Own gas stove – upstream weighted ave.	-0.531	-0.339*	-0.353	0.157**
	[0.612]	[0.173]	[0.252]	[0.075]
Black clay soil – upstream weighted ave.	-0.284	-1.127***	-0.085	-0.155
	[0.624]	[0.176]	[0.316]	[0.094]
Charcoal-enriched soil – upstream weighted ave.	-0.368	-0.223	-0.264	-0.07
	[0.592]	[0.167]	[0.283]	[0.084]
Poor soil – upstream weighted average	0.197	0.003	0.297	-0.443***
	[0.459]	[0.129]	[0.379]	[0.115]
Castanhal municipality	0.233	-0.210*	0.406*	-0.313***
	[0.387]	[0.109]	[0.227]	[0.068]
Igarapé Açu municipality	0.054	-0.277**	0.322	-0.107*
	[0.393]	[0.111]	[0.211]	[0.063]
Constant	0.304	1.594***	1.485	2.734***
	[1.393]	[0.393]	[0.957]	[0.284]
Observations	236	236	271	261
R-squared	0.74	0.90	0.74	0.65

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%