SUPPORTING INFORMATION

Appendix A. Background on the Study Area

Historically, the Shuar in the region of present day Morona-Santiago lived in dispersed, temporary settlements over large areas of forested land. This system persisted until missionaries entered the region beginning in the 1950s (Lopez, Beard and Sierra 2003). The newly established missions not only impacted traditional Shuar settlement patterns but also attracted mestizo colonizers from the southern highlands of Ecuador. This colonization process was also facilitated by a program of road construction to the area in the 1960s, which was part of a government push to move impoverished and mostly landless farmers from other parts of the country to regions in the Amazon with relatively low population levels. The Ecuadorian land reform programs of the 1960s and 1970s generally failed to cap estate size and redistribute land in coastal and highland regions (Rudel and Horowitz 1993), leaving the Amazon region as an attractive destination for landless migrants. Another outcome of Ecuadorian land reforms was to formalize the process of making a land claim on “open access” and “vacant” areas (*tierras baldías*) by putting land into productive use, which generally meant clearing forests for the cultivation of crops or ranching (Wasserstrom and Southgate 2013, Bennett and Sierra 2014).

Post-1950, the Shuar in Morona-Santiago began clearing forests themselves to establish pasture for livestock and to preemptively establish land claims against colonizing competitors. During this period, many Shaur adopted a new settlement pattern based on permanent community centers, thus moving away from their semi-nomadic lifestyle. Previously their land use was based on a combination of shifting agriculture, fishing, hunting and gathering activities. As the Shuar settled into communities they organized under groups such as FICSH (*Federación Indígena de Comunidades Shuar*) and presented a united front against government, migrants, and other outside users interested in their traditional lands. Later an additional Shuar indigenous organization FIPSE (Federación Independiente del Pueblo Shuar en Ecuador) was created, which further organized communities.

While some Shuar communities and colonizers obtained legal land recognition before 2000, particularly along the access road to the province capital, Macas, and the Upano Valley, according to PSUR documentation, regions of traditional Shuar territory remained mostly untitled (CARE 2007) or at least not titled in the eyes of the State. Most untitled or precariously formalized land was in the region known as Trans Kutukú, between the Kutukú and Condor ridges. The population in this area was composed of isolated Shuar communities located far from roads. This region was the setting for most PSUR activities that we evaluate in this study (Figure 1).

It is incorrect to view the entire pre-2000 period, characterized by the lack of legal land rights for both migrants and Shuar, as a period of open access with land grabs, land speculation, and rapid conversion of forests to other land uses. During periods of land reform and road construction into the region, many of the common characteristics of an agricultural frontier applied, but generally within about a decade of new road construction the frontier rush was over and informal agreements about land ownership between Shuar and mestizos were established (Rudel 1995). With informal and semi-formal controls in place, deforestation appears to have slowed following the initial period of migration into the region. The acceptance and enforcement of the new informal tenure rules appear to have made “clear to claim” logic unnecessary, allowing smallholders to divert human and economic resources to generating income within their allotted lands (Rudel 1995).

Within this informal tenure system, individual parcels within communal land could be sold between members, but not outsiders, or passed on to children. This method of transfer persisted after the communities received formal collective titles. The relative stability of informal institutions in Morona-Santiago, compared to other frontier regions in Ecuador and South America, is based on several contextual factors. For example, when compared to regions farther north on the Colombian border, Morona-Santiago is more remote, had more limited government and private investment, and has a limited history of high-value commodity extraction. These factors did not promote a large influx of migrant labor and the expropriation of commodity-rich lands common in other parts of South America.[1]

As noted, cattle play a significant role in land use dynamics in the region. Cattle serve as a clear visual claim for cleared land, as transportable capital, as a store of value, and as a source of protein. Micro-credit programs in the region support the acquisition of cattle (CARE 2007). Additionally, in recent years, many second-generation mestizos have left the region to work in urban areas or abroad and cattle ownership has become a means to invest incoming remittances in the region. This cattle from remittance dynamic is less common with the Shuar as they typically have less access to credit to purchase cattle, although in some areas of Morona-Santiago Shuar communities have begun leasing their land to mestizos for cattle ranching (Rudel, Katan and Horowitz 2013).

By the 2000s, the political climate in Ecuador had changed with more support for the rights of indigenous groups and recognition within national policy-making processes of the value derived from environmental assets. Indeed, the Ecuadorian government became the first government to codify the rights of nature and the environment in its constitution (Articles 10, 71-74) giving inalienable rights for ecosystems to exist and flourish. This was a marked departure from earlier policies that encouraged forest clearing to establish ownership. These recent pro-environmental and pro-indigenous policies have created

[1] In contrast to the northeastern portion of Ecuador’s Amazon, Morona Santiago has not been the site of oil exploitation and has only limited mining. Only recently has the Ecuadorian government revealed plans to grant new concessions for oil and mine exploration in the province.

a receptive environment for land tenure programs that seek to secure title for individuals and groups.

Since 2008, laws and regulations that create sole and inalienable ownership of mining, gas, and oil resources for the state have now superseded some of the constitutional protections for indigenous people and the environment. This situation leaves rural populations occupying oil, mining and gas rich areas with uncertain land tenure. In addition, overlapping governance structures and jurisdictions form a complex web of land tenure institutions in the study region (Holland et al. 2014). Chief among these competing jurisdictions are the Ministry of the Environment (MAE), which manages “hard” and “soft” protected areas, and the Ministry of Agriculture, Livestock, Aquaculture and Fisheries (MAGAP)[2], which administers and adjudicates other rural lands. The lack of a clear legal framework delineating responsibilities between these two ministries has created a patchwork of legal instruments for securing title to forested lands. As a solution, these ministries negotiated a series of inter-ministry agreements and co-management agreements with local groups as land claims arose (Morales, Naughton-Treves and Suarez 2010). Currently, forested land under the MAE or MAGAP can be claimed by indigenous communities, collective associations and cooperatives, or individuals. However, the differing pathways to to title via the differing agencies results in a myriad of differing restrictions and conditions. Each combination produces different levels of access, exclusion, security and certainty for local populations with respect to land tenure, permitted land uses, and the consequences of not meeting title requirements (Table 1).

Table A1. Usage restrictions associated with different types of forest tenure in Ecuador

	Hard Conservation Protected Areas (Environment)	**Soft Conservation** BNP / PFE forests (Environment)	**Other Rural Lands** (Agriculture)
Indigenous -communal only -Cannot be sold/exchanged, sub-partitioned	Cutting forest only for subsistence (co-management agreements)	-Restricted forest extraction -Requires management plan	No limitations as long as there is no conflict with other properties
Collective and Individual	No use allowed (unless there is a co-management agreement)	-Restricted forest extraction -Requires management plan	No limitations as long as there is no conflict with other properties

Notes: SNAP is Protected Areas System; PFE and BNP are National Patrimony and Protector Forests. Source= Inter-ministry agreements (MAE 2003, 2006, 2007) Forestry Law 1981 (Congreso Nacional de Ecuador)

The pre-existence of settlements prior to the establishment of “hard” protected areas has forced

[2] Originally it was the role of the Institute for Agricultural Development (INDA), whose functions were later absorbed by the Subsecretariat of Lands and Agricultural Development of MAGAP.

the MAE to devise co-management agreements rather than titles with indigenous or ancestral populations residing in protected areas such as the protected forest area of Kutukú in Morona-Santiago. In these cases, groups must demonstrate occupation and cultural links to land before the establishment of protected areas. In any other case, no human activity is allowed inside “hard” protected areas. In “soft” protected areas, only limited livelihood uses and managed forestry operations are permitted. In both “hard” and “soft” areas, the unauthorized extraction of forest resources and conversion of forests can lead to sanctions, including fines and in some cases annulment of the adjudication agreement that leads to a land title (Morales, Naughton-Treves and Suarez 2010). It must be noted that some Shuar communities question the status of the Kutukú ridge as protected forest claiming that a formal declaration was never concretized in the 1990s. It is in this context that the PSUR program carried out land titling activities. In 2002, when the program began, jurisdictional issues between the MAE and the MAGAP were not fully resolved and the requirements for the legalization plan were incomplete.

The land titling component of the PSUR program formalized land rights according to the PML legalization planning process. However, the later wave of the PSUR program from 2003 onwards included supplementary management activities that aimed to improve living conditions for populations in the area. Activities included micro-finance and commercial fairs for income generation, increased access to water, sanitation, and health services, natural resource management planning, evaluation, and training, and support activities for local government. Planes de Manejo Integral (PMIs), or integral management plans, were part of the PSUR natural resource management package, but they could only be produced after the titling process and they needed Ministry of Environment approval because they implied a use of forest resources.

APPENDIX B. ROBUSTNESS OF MODEL RESULTS

We report additional results here that supplement the results reported in the main text. These results include balance measures for the matching analysis, reestimates of the main models within a subset of the data that are known to be inhabited by Shuar communities, as delimited by the Nature Conservancy (Geoplades 2010), and models that account for proximity to the Peru border.

As displayed in Figure 3, Panels C/D in the main text, we searched for a set of control observations that are similar on measures of other factors that are associated with changes in forest cover. We search for a matched set of control plots with similar background factors to isolate the direct impact of the PSUR program from targeting decisions. After searching for a matched set of control observations, we improve balance between treatment and control groups in almost all cases, usually by very significant margins. Table B1 reports pre- and post-matching balance statistics for the covariates in the models reported in the main text.

Table B1. Pre- and post-matching balance summaries for covariates

	PML-only Analysis	PMI Analysis
Forest Loss within 5 km^2 (m^2 at *t-1*)	m-t: 4261 pre-m-c: 21794 post-m-c: 3218	m-t: 9089 pre-m-c: 21794 post-m-c: 8450
Forest Cover Percent (m^2 at *t-1*)	m-t: 823861 pre-m-c: 802232 post-m-c: 826594	m-t: 840682 pre-m-c: 802232 post-m-c: 841722
Distance to Major Roads (m)	m-t: 17988 pre-m-c: 7403 post-m-c: 17473	m-t: 4064 pre-m-c: 7403 post-m-c: 4288
Distance to Electric Grid (m)	m-t: 14893 pre-m-c: 19766 post-m-c: 16322	m-t: 15209 pre-m-c: 19766 post-m-c: 14627
Distance to River (m)	m-t: 3856 pre-m-c: 3041 post-m-c: 3470	m-t: 3177 pre-m-c: 3041 post-m-c: 3121
Distance to Disturbed Land Classification (m at *t-1*)	m-t: 11464 pre-m-c: 13141 post-m-c: 10197	m-t: 16854 pre-m-c: 13141 post-m-c: 16333
Indigenous Shuar Land (binary)	m-t: 0.98 pre-m-c: 0.44 post-m-c: 0.98	m-t: 0.73 pre-m-c: 0.44 post-m-c: 0.68
Protected Area Status (binary)	m-t: 0.00 pre-m-c: 0.31 post-m-c: 0.00	m-t: 0.57 pre-m-c: 0.31 post-m-c: 0.57
Elevation (m)	m-t: 1251 pre-m-c: 1216 post-m-c: 1337	m-t: 715 pre-m-c: 1216 post-m-c: 708
Slope (degrees)	m-t: 16.7 pre-m-c: 11.6 post-m-c: 15.7	m-t: 13.1 pre-m-c: 11.6 post-m-c: 13.0
Population Density within 5 km^2 (persons/km^2 at *t-1*)	m-t: 6.41 pre-m-c: 4.33 post-m-c: 5.73	m-t: 0.89 pre-m-c: 4.33 post-m-c: 0.92

Notes: m-t is mean of the treated group; pre-m-c is mean of the control group before matching; post-m-c is mean of the control group after matching. All unit measures are contained in column 1.

The PSUR program was formally targeted to support Shuar indigenous communities in gaining formal land title, strengthening collective decision-making, and improving access to legal institutions. According to secondary data, however, some of the PSUR programming fell outside of areas with known Shuar communities. As a consequence and to check the robustness of our models, we examine only areas that were identified by USAID and its partners (CARE 2007) as being inhabited by Shuar communities at the time of the PSUR program. In this analysis, the main result is substantively unchanged. We do not find that the PSUR program reduced forest loss in the first five years after implementation both aggregated over five years and on a year-to-year basis. In the figures below, we show the results displayed in the main figures above for the subset of observations that fall within Shuar territory. Figures B1 and B2 report the results of the Shuar subset analysis for the first wave of the PSUR program that only included land titles and legalization plans (PMLs). Figures B3 and B4 report the results of the analysis on the Shuar subset for the second wave of the PSUR program from 2003 onwards that included land titles, legalization plans, and enhanced community management plans (PMIs).

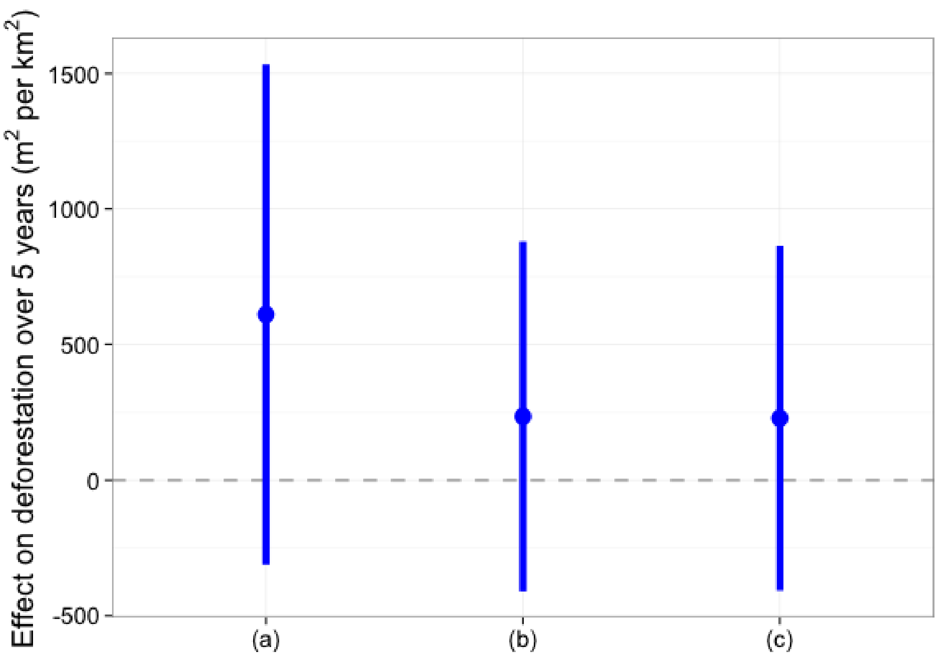

Figure B1. Difference in differences over five years for PSUR plots with legalization plan (PML) and title versus non-PSUR plots with no plan or title, 2002-2012
Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching

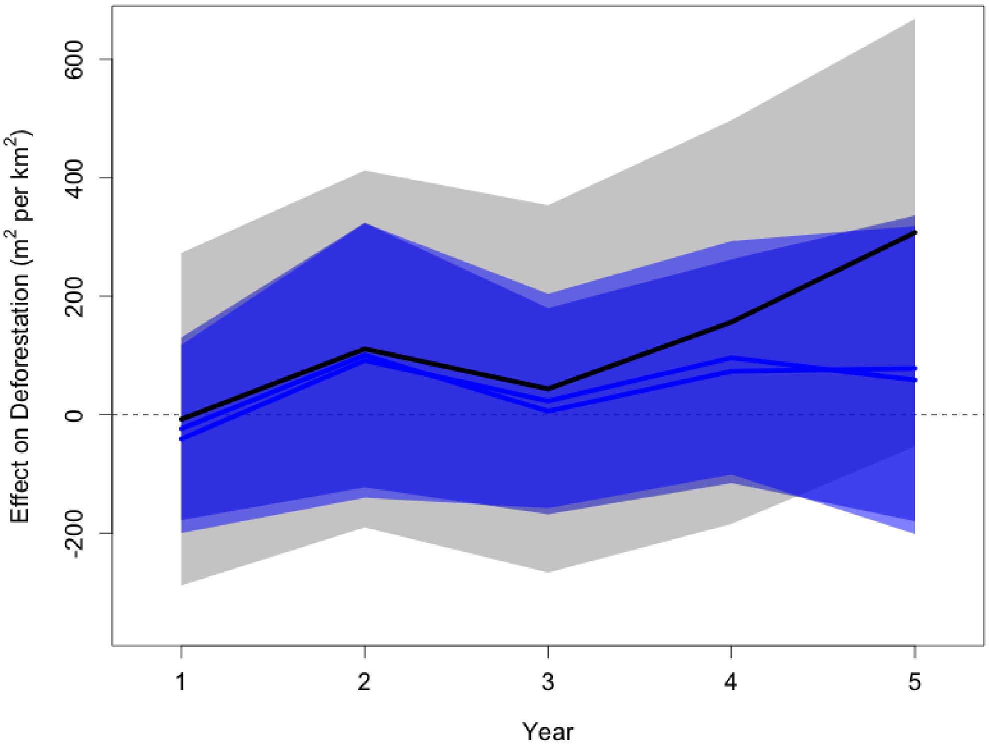

Figure B2. Year by year effects for PSUR plots with legalization plan (PML) and title versus non-PSUR plots with no plan or title in Shuar areas, 2000-2012

Notes: The black line / grey error bars are regression without pre-matching; The blue lines and error bars are regression estimates with pre-matching both with (dark blue) and without (light blue) covariates. The error bars show two standard errors

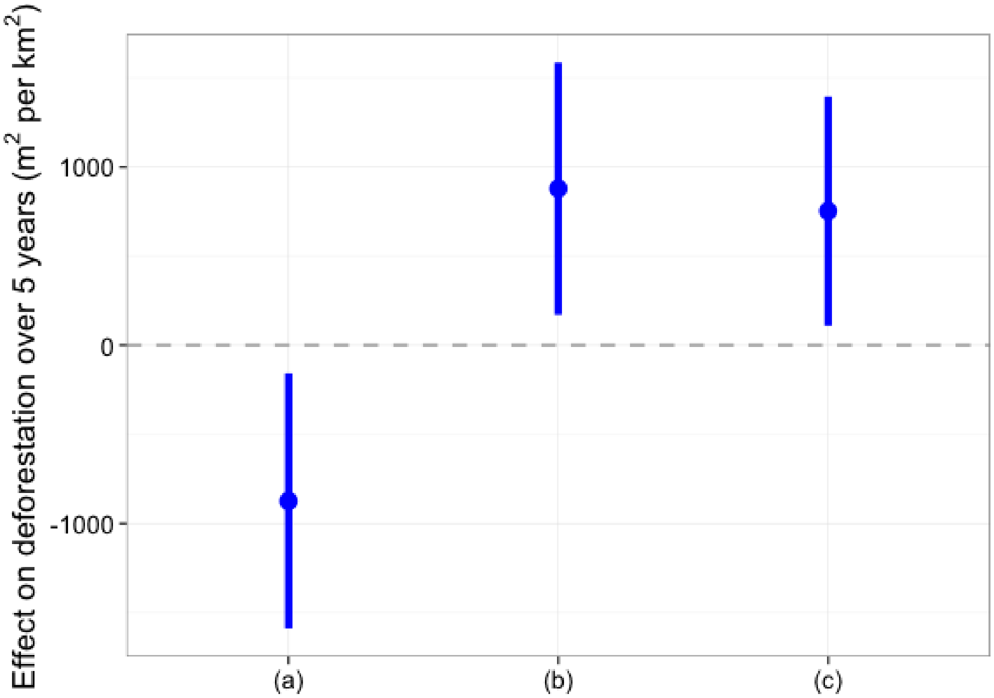

Figure B3. Difference in differences over five years for PSUR plots with title and USAID-funded management plan (PMI) versus non-PSUR plots with no title in Shuar areas, 2002-2012
Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching

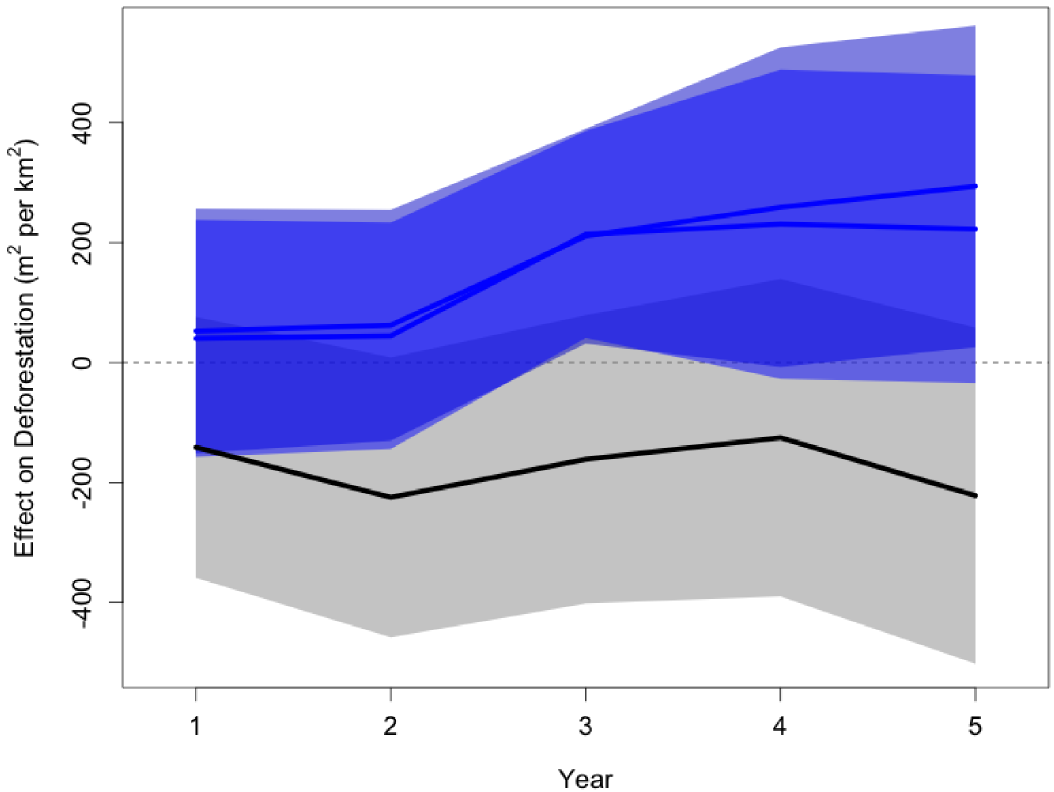

Figure B4. Year by year effects for PSUR plots with title and USAID-funded management plan (PMI) versus non-PSUR plots with no title in Shuar areas, 2002-2012
Notes: The black line / grey error bars are regression without pre-matching; The blue lines and error bars are regression estimates with pre-matching both with (dark blue) and without (light blue) covariates. The error bars show two standard errors

It is possible that categorical land classification measures will not capture degradation to forests that do not involve conversion to other land cover types. To explore this possibility, we completed the same analyses reported above using changes in Enhanced Vegetation Index (EVI) over five years as the outcome variable. EVI is a standard vegetation index that has proven to be effective for detecting changes to forests in areas of high greenness, such as tropical rainforest (Huete et al. 2002). Because EVI changes in part based on annual variations in rainfall and cloud cover that we cannot fully capture in covariate measures, the EVI analysis only matches treatment plots to control plots in the same pre-treatment years for covariate values. For example, if a plot enters the PMI designation in 2003, we search for plots with similar pre-treatment values in 2002 for both treatment and control plots and then compare differences in EVI from 2003-2008. Because each starting year of the data has a strong effect on five year differences, matching within temporal waves reduces noise due to inter-annual regional variations in weather. We match on the same covariates as the models reported in the main text, except that we use the baseline EVI value for matching, rather than the amount of forest cover.

Because we are interested in separating significant episodes of forest degradation from natural variation in EVI over time, we examine whether the PSUR interventions make it less likely that a plot will experience a significant downward shift in EVI over five years. We take downward shifts that are approximately two standard deviations from average change in EVI shift over five years as our outcome variable. For ease of exposition, we round this number (~0.96) to a -0.1 shift in EVI over five years as the primary outcome variable. As before, we examine the effect of both legalization alone (PML) and legalization with a complementary community management plan (PMI).

For PSUR treatment areas that only include legalization, downward shifts to EVI mirror the results reported in the main text and earlier in this technical appendix (Figure B5). The regression results without matching (a) indicate that undergoing legalization decreases the probability of a downward shift in EVI over five years. However, after matching this effect reverses and is consistent in post-matching regressions both without (b) and with (c) covariates. Using EVI as the outcome variable, we find no evidence of a decrease in downward EVI shifts based on legalization plans.

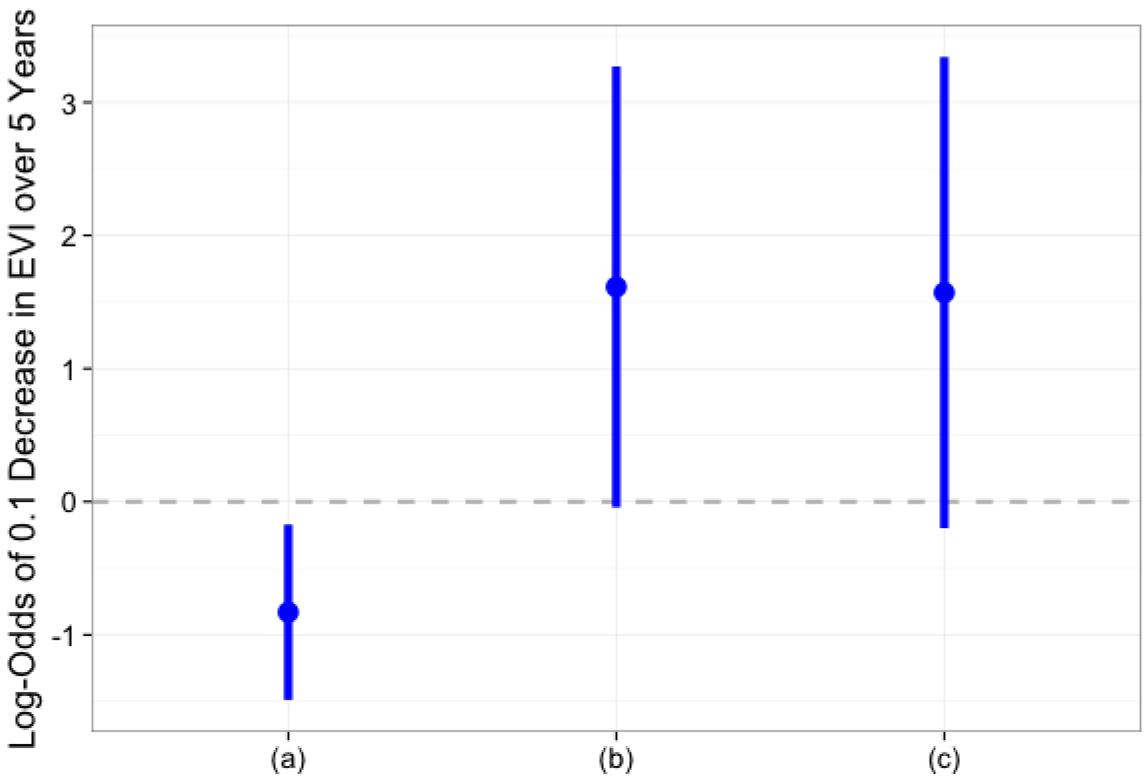

Figure B5. Changes in the probability of a 0.1 downward shift in EVI over five years for PSUR plots with legalization plan (PML) and title versus non-PSUR plots with no plan or title, 2002-2007
Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching

For PSUR treatment areas that include both legalization and community management planning, we also fail to find evidence that the program decreased the probability of downward shifts in EVI (Figure B6). The regression results without matching (a) indicate that undergoing legalization and community management planning increases the probability of a downward shift in EVI over five years. However, after matching this effect is no longer present in post-matching regressions both without (b) and with (c) covariates. Using EVI as the outcome variable, we find no evidence of a decrease in downward EVI shifts based on legalization and community management planning.

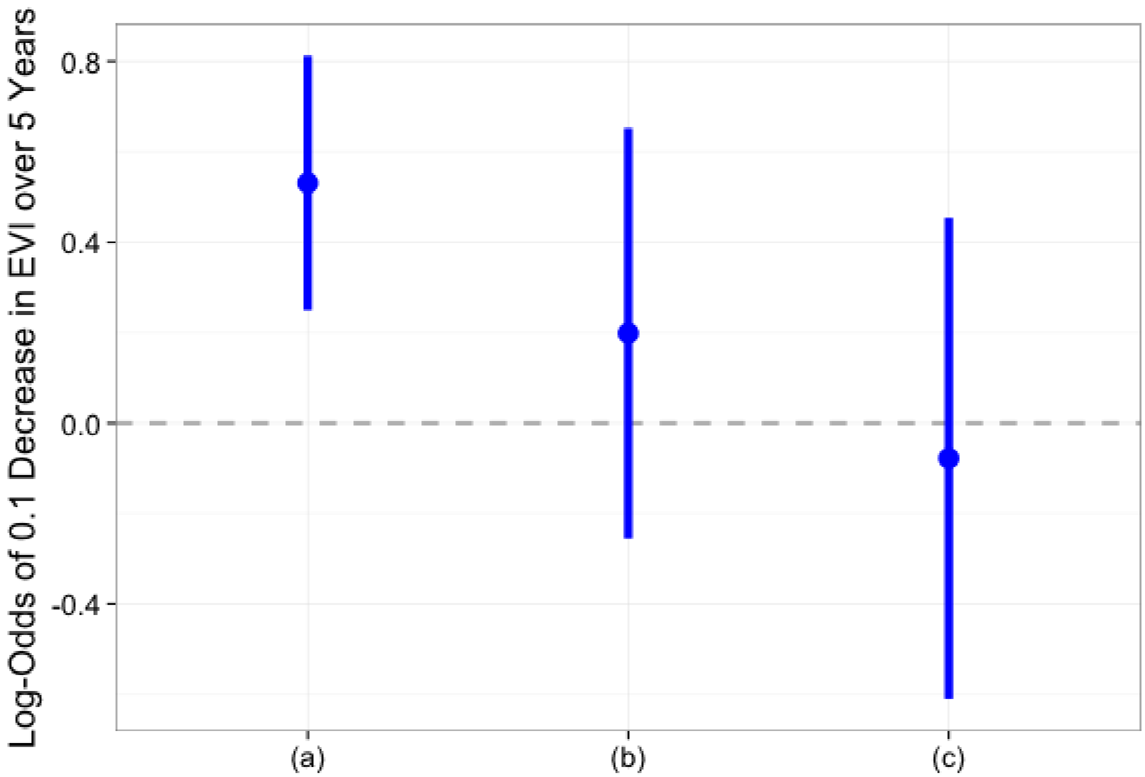

Figure B6. Changes in the probability of a 0.1 downward shift in EVI over five years for PSUR plots with title and USAID-funded community management plan (PMI) and title versus non-PSUR plots with no plan or title, 2003-2012

Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching

Our GIS dataset only includes information on the Ecuadorian side of the border with Peru. This raises the possibility that population or colonization pressures from Peru could be driving land use dynamics differently near the border, as compared to areas further away from the border. We do not expect this to be the case based on a visual examination of the land cover data, since the Peruvian side of the border is much less populated, with no road access, and limited deforestation (Figure B7). To ensure that distance to the Peruvian border is not driving our results, we completed supplementary analyses where we use distance measures for regression adjustment and matching. We do not find that distance to the border predicts land cover change or that this alters our estimates of PSUR effects.

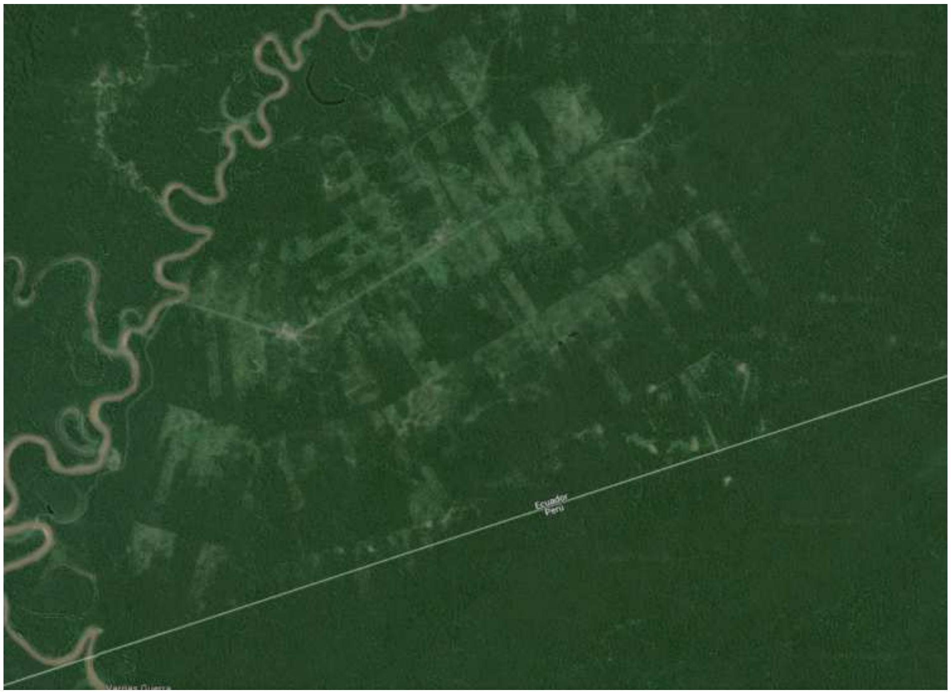

Figure B7. Aerial photograph of Ecuador-Peruvian border region from 2012. Dark green is forest and light green is land converted to agriculture.

For PML plots that underwent legalization planning in 2002 as part of the first wave of the PSUR program, we are unable to find a good matched set when including a continuous measure of distance to the Peruvian border. When we instead include the categorical variable that the plot is within 10 km of the border, which is the outmost hunting range of most indigenous communities in the area, we find a good matched set, but not below the threshold of 0.1 standard deviations between treatment and control covariate means that we used to stop the matching algorithm in the main text. Nonetheless, distance to the border does not have a direct effect in the matched sample and does not change estimates of the PSUR program effect (Figure B8).

For PMI plots, which underwent both legalization planning and supplementary community-level natural resource management planning, we are able to find a good matched set after including distance to the Peruvian border in kilometers. Like the PML plots, this variable does not influence land cover change in either the unmatched or matched samples directly and does not change estimates of the PSUR program effect (Figure B9).

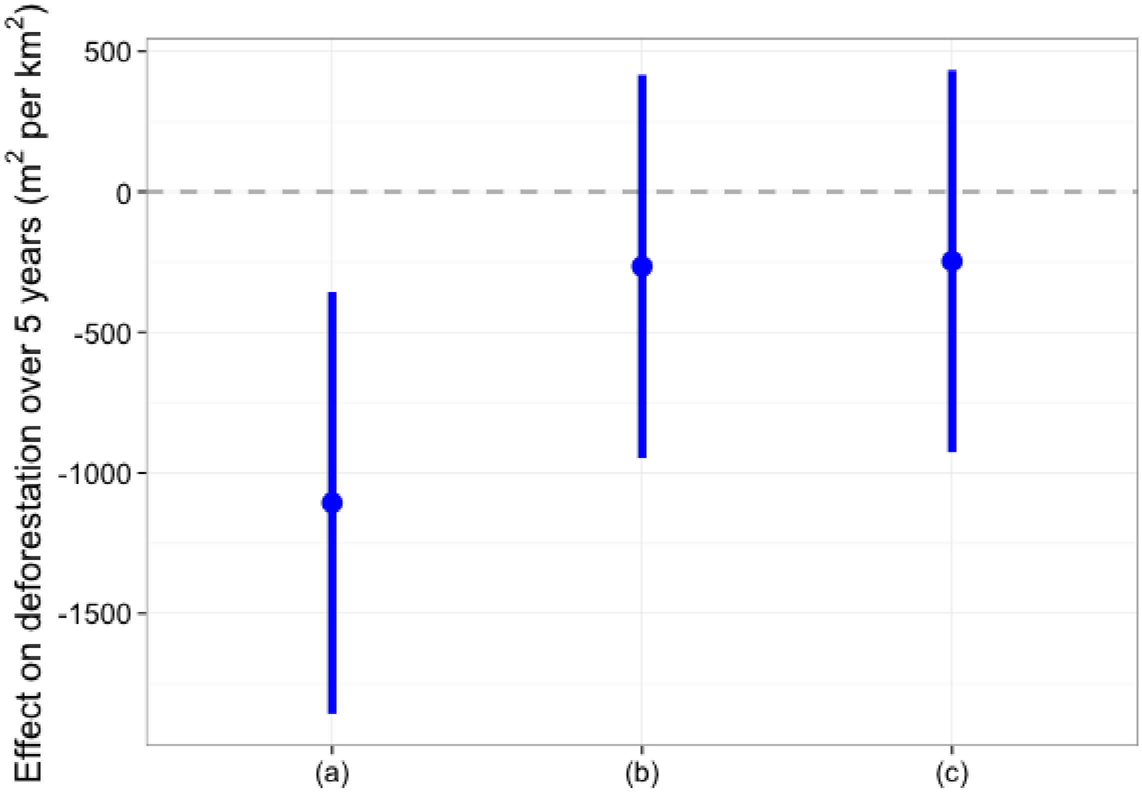

Figure B8. Difference in differences over five years for PSUR plots with legalization plan (PML) and title versus non-PSUR plots with no plan or title with distance to Peruvian border included in regression adjustment and matching, 2002-2012

Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching

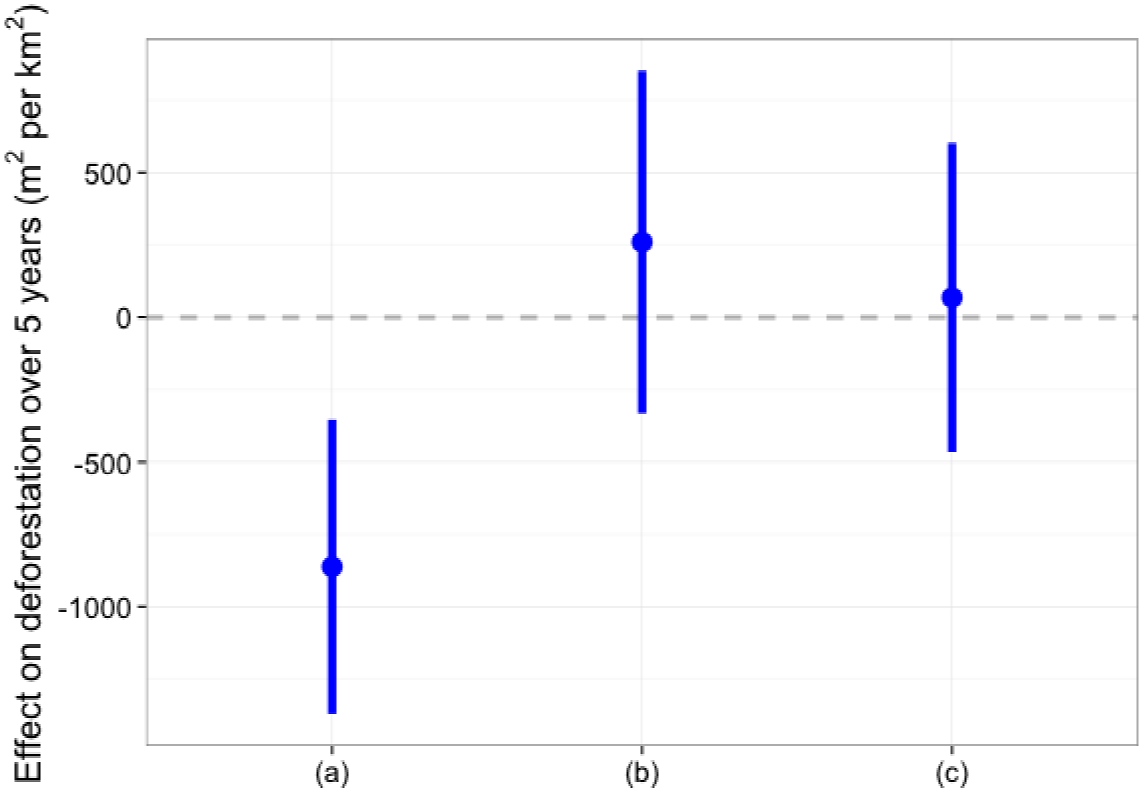

Figure B9. Difference in differences over five years for PSUR plots with title and USAID-funded management plan (PMI) versus non-PSUR plots with no title in Shuar areas, 2002-2012

Notes: Figure shows treatment effect of tenure status for models as follows: (a) covariates, no pre-matching; (b) no covariates, pre-matching; (c) covariates, pre-matching

APPENDIX C. STATISTICAL METHODS

Both observable and unobservable differences between treatment and control areas can confound estimates of the effects of policies or programs. When the treatment state, in this case land tenure and management status, is correlated with observed or unobserved factors that also affect the outcome, it is not possible to distinguish the effect of the intervention from the effect of the correlated factors without the additional assumption in Equation 1.

(1) $E[X_i , Z_i \mid T_i = 1] = E[X_i , Z_i \mid T_i = 0]$

where X_i are observed covariates for each unit and Z_i are unobserved covariates for each unit that encompass all causes of the outcome Y_i other than the treatment state T_i. When X or Z have a causal relationship with the outcome of interest, then the expected untreated value of the untreated units will not be the same as the expected untreated value of the treated units, where $Y_i(0)$ is the expected value of units had they not been assigned to treatment (Equation 2). This makes it difficult to distinguish the treatment effect of the intervention from the baseline difference in expected outcomes, also referred to as the selection effect.

(2) $E[Y_i(T_i = 0) \mid T_i = 0] \neq E[Y_i(T_i = 0) \mid T_i = 1]$

We adopt a matching framework to construct a set of control plots that have similar pre-treatment characteristics as the plots that were assigned to treatment under the PSUR program. We compile spatial data on other variables that have strong associations with forest loss in the extant literature (Table 2). We then iteratively search through sets of control observations outside the PSUR intervention area to select a set of control units that have distributions of each covariate that are not statistically different from the covariate distributions of the treatment plots.

We also exclude observations from the control set that have covariate values that are never realized in the set of treatment observations. This reduces concerns about biased inference that might result from choosing a set of control observations that have many outliers with no similar observations in the treatment group (King and Zeng 2007).

We carry out statistical matching using a genetic algorithm that both weights and discards control plots that do not serve as comparable units to the treatment plots (for statistical derivation, see Sekhon

2007; Diamond and Sekhon 2013). We apply a genetic algorithm that iteratively searches through many sets of potential control plots to maximize balance on the observed covariates. Matched sets with good balance, those that have a large *minimum p*-value on paired *t*-test for differences of means between treatment and control observations across all covariates are passed onto the next generation, along with mutated sets to ensure the full space of combinations of observations for the control set is explored. In our particular application, we ran the algorithm until no improvement in balance between the treatment group and the 500-2000 control sets considered in each generation was observed for 20 generations. In the end, this produces a set of control plots for analysis that are close to observationally equivalent with the treatment plots, where ρ is the observed values in the selected set of treatment and control groups (Equation 3).

(3) $\rho(X \mid T = 1) \approx \rho(X \mid T = 0)$

Matching does not ensure that sets of treatment and control observations are similar for unobserved variables Z. Since we do not observe unobserved covariates, we are forced to make one additional assumption before proceeding to estimation. We assume that any unobserved variable Z that affects the outcome is captured in the pre-treatment value of the outcome variable (Equation 4), where t=0 is the pre-intervention time period and t=1 is any post-intervention time period. Matching studies are frequently able to reproduce the results of more reliable experimental studies when a pre-intervention measure of the outcome is used for matching (Cook et al. 2008). We use two derivatives of the outcome to increase the possibility that we have captured the effects of unobserved variables on forest loss and partially accounted for spatial autocorrelation: the amount of pre-treatment forest cover in the subject plot and the pre-treatment rate of forest loss within 5 km^2 of the plot.

(4) $E[Y_i(t=1) \mid Y_i(t=0), X_i] = E[Y_i(t=1) \mid Y_i(t=0), X_i, Z_i]$

By ensuring that we have a comparable set of control plots with respect to observed covariates, our results are less dependent on parametric modeling assumptions that are built into regression analysis (Rubin 1973, Rubin 1979, Ho et al. 2007). The treatment and control observations that remain after the genetic matching process are used to estimate the treatment effect by weighted least squares, where the weights are assigned on the basis of how often each control plot matches to a treatment plot. We only examine treatment and control plots that are forested at the baseline year, since our outcome of interest is the conversion of forests to other land cover types.

APPENDIX D. SPATIAL DATA LAYERS

Hansen et al. (2013) forest loss/gain data is available under a creative commons license at http://earthenginepartners.appspot.com/science-2013-global-forest. All other spatial data layers are provided as a supplementary submission in ESRI shapefile format for use in GIS software, in csv format for statistical packages, and in Excel format for general analysis.

Global Forest Change (GFC) data from Hansen et al. (2013) was utilized for tree cover percentage for the year 2000. GFC defines tree cover as the percentage of canopy closure for all vegetation taller than 5 m in height. We aggregated the GFC data to approximately 1 km^2 and converted the units from percentage per grid cell to forest area per grid cell. Additionally, a focal sum process created forest density measures at the 5 km^2 neighborhood level. That is the measure of how much forest exists per 5 km^2 for each 1 km^2 grid cell. The native resolution of GFC is approximately 30m, the temporal resolution is annually from 2000 - 2012, and the attribute resolution is 0 - 100 as a percentage of tree cover. In the GFC data, forest loss and gain were validated using a probability-based stratified random sample of 120 m blocks per biome, including tropical areas (Hansen et al. 2013).

Forest loss was also taken from Hansen et al. (2013), who not only provides forest cover as a percentage in 2000 but also provides forest loss and gain in subsequent years. The GFC forest loss metric is a disaggregation of total forest loss to annual time scales. These data are encoded as 2001 to 2012 at the the pixel level with the pixel value indicating the year of loss. Again, we aggregated the GFC forest change data to 1 km^2 and produced a focal sum for forest loss at the 5 km^2 level for each 1 km^2 analysis cell. The native resolution of GFC forest change is approximately 30 m, the temporal resolution is annually from 2000 - 2012, and the attribute resolution is 2001 - 2012 indicating year of loss.

Therefore, combining 2000 GFC forest cover with 2001 to 2012 GFC forest change the GFC dataset produces an unbiased consistent year-to-year estimation of forest loss at the ~30 m pixel level. The dataset is unique in that it provides both the temporal and spatial resolutions to examine forest loss at the community scale. The dataset has been criticized for not distinguishing between types of forest and this shortcoming may result in underestimation of ecologically important forest losses. For example, Tropek et al. (2014) note that within Ecuador forest conversion from tropical forest to oil palm is not captured in the GFC dataset and such transitions likely have significant biodiversity and ecological implications. Although this issue clearly exists within the dataset, GFC still provides the most accurate representation to date of global forest change since 2000 and allows for a high-resolution repeatable analysis of annual forest change. The GFC accuracy level is reported as 99.5 percent (n = 628, se = 0.1) for areas of loss or no loss and 99.7 percent (n = 628, se = 0.1) for areas of gain or no gain with the tropical regions (Hansen et al. 2013).

EVI was taken from MODIS using product MOD13Q1. The data was aggregated to annual averages temporally and aggregated to 1 km^2 pixel resolution. EVI was selected over NDVI due to the increased ability of EVI to differentiate between exceptionally high levels of greenness over land cover such as tropical rainforest whereas NDVI tends to saturate over such dense green canopy.

Major roads were aggregated from vector data provided by Open Street Map, Vector Map of the World Level 1, and the official roads product from the Ministry of Environment (MAE) within Ecuador. Road presence or absence was encoded into the 1 km^2 analysis cell. A simple Euclidean distance to roads layer was then created for all 1 km^2 grid cells that have no roads present. It should be noted that aside from the western edge of the analysis area, that did not produce matches, few if any roads exist in this area. The native data model is vector with varying temporal resolutions from 1993 to 2012.

Distance to rivers and distance to the electricity infrastructure were obtained using the same process as distance to roads outlined above but with data from MAE and Vector Map of the World Level 1 data. The native data model is vector with varying temporal resolutions from 1993 to 2012.

Disturbed land was delineated from MODIS product MCD12Q (Friedl et al 2010). MCD12Q1 provides pixel-based information for five common land cover classification systems as well as quality information for each pixel. The data is obtained from annual composites from the Terra and Aqua satellite systems. We utilized the IGBP global vegetation classification scheme that identifies 17 land cover classifications (FAO 2000). We extracted classifications that relate to human disturbance such as cropland and urban classifications. Once extracted, a distance to these classifications was constructed utilizing a simple Euclidean distance measure. The native resolution is approximately 500 m and was aggregated to the 1 km^2 pixel, the temporal resolution is annually from 2001 - 2012, and the classification system was a nominal land cover classification system.

The indigenous Shuar region and protected area status were both obtained from TNC and are current as of 2012. Both are vector products converted to binary rasters at the 1 km^2 pixel level.

Elevation and slope were derived from over 1 million digitized elevation points within the Ecuadorian topographic map series. The points were interpolated into the 1 km^2pixel with slope then calculated from the elevation model using an eight-neighbor maximum rate of change of change approach from cell center to cell center. These data are a one-time snapshot.

Population count data was obtained at 1 km^2 resolution from the Landscan data repository. The temporal resolution is 2000 to 2012. These data were converted from the 1 km^2 pixel count measure to a focal density of 5 km^2 using a neighborhood function.

We considered a number of alternate approaches to the pixel approach including objects (communities) but settled on the pixel approach as it best preserves the dataset and results in less loss of information. Each pixel is coded with canton and parroquia, various measures of population and population density, as well as protected status, indigenous status and others. This allows for objects to easily be compiled from pixels by running a simple selection but if the data are presented as generalized objects they cannot be disaggregated back into pixels or other smaller units. Other researchers can now compile data back into clusters or objects of their choosing as long as the objects or groupings are larger than 1 km^2.

The minimum mapping unit based on one of our least resolute input datasets (population density from Landscan) and this allowed for many GFC pixels to feed into each unit of analysis. This prevents one or two cells with bad information in GFC or other datasets causing poor matches in our database. At the same time, using 1 km^2 cells allows us to account for the fact that not all areas within a community have the same probability of converting from forest to other land cover types because of slope, elevation, population density, etc. We tested our results with EVI as well to ensure that the results were robust across different measures of the outcome.

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