Depopulation of rural landscapes exacerbates fire activity in the western Amazon

María Uriarte[a,1], Miquel Pinedo-Vasquez[b], Ruth S. DeFries[a], Katia Fernandes[c], Victor Gutierrez-Velez[a], Walter E. Baethgen[c], and Christine Padoch[d,e]

[a]Department of Ecology, Evolution and Environmental Biology, and [b]Center for Environmental Research and Conservation, Columbia University, New York, NY 10027; [c]International Research Institute for Climate and Society, Columbia University, Palisades, NY 10964; [d]Center for International Forestry Research, Bogor 16115, Indonesia; and [e]New York Botanical Garden, Bronx, NY 10458

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Destructive fires in Amazonia have occurred in the past decade, leading to forest degradation, carbon emissions, impaired air quality, and property damage. Here, we couple climate, geospatial, and province-level census data, with farmer surveys to examine the climatic, demographic, and land use factors associated with fire frequency in the Peruvian Amazon from 2000 to 2010. Although our results corroborate previous findings elsewhere that drought and proximity to roads increase fire frequency, the province-scale analysis further identifies decreases in rural populations as an additional factor. Farmer survey data suggest that increased burn scar frequency and size reflect increased flammability of emptying rural landscapes and reduced capacity to control fire. With rural populations projected to decline, more frequent drought, and expansion of road infrastructure, fire risk is likely to increase in western Amazonia. Damage from fire can be reduced through warning systems that target high-risk locations, coordinated fire fighting efforts, and initiatives that provide options for people to remain in rural landscapes.

rural migration | agricultural development | fire management

Fire has been used in tropical agriculture for clearing debris, recycling nutrients, and reducing pests for millennia. The potential dangers of agriculture-related fires, however, have gained greater importance within the context of global climate variability and change. Severe droughts in the Amazon in 2005 and 2010 confirmed that agriculture-related fires in the tropics has become a major and growing problem on a global level (1, 2). Throughout the tropics, a number of initiatives have been put into place to avoid or minimize the negative impacts of agricultural fires (e.g., refs. 3 and 4). These policies, however, will only be effective if they address the factors that promote fires. The biophysical and socioeconomic factors associated with fires and how they interact with climate variability are poorly understood. In part, this is because increased hazard and devastation caused by fire reflect not only changing patterns of drought and humidity but also broad shifts in many aspects of development around the tropics, including rapidly changing types and scales of land clearing and management, road construction, rapid urbanization, and shifts in the size and distribution of human populations (5–7).

Studies of fire in Amazonia have highlighted a number of proximate causes for the recent steep rise in fire incidence including physical factors such as drought (1), increased flammability of forests due to timber extraction (8) and repeated burning (9, 10), and extension and improvement of road access to forest areas (11). We consider here the additional influence of rapid demographic changes leading to increasing urban populations throughout the Amazon and declines in rural populations in many areas (Fig. S1). We consider these demographic factors because fire is the proximate result of activities of rural population even if these are ultimately driven by other factors (e.g., shifts in prices of crops) and there has been a large increase in the size of urban populations in the region along with considerable declines in rural populations in many areas (Fig. 1). We explore the links between outmigration and fire frequency at two scales: at the province level in the Peruvian Amazon and at the local scale, relying on farmer survey data.

This research focuses on the Peruvian Amazon where there has been far less research on fire use and damage than in the arc of deforestation along the southern and eastern fringe of the Amazon basin. The wetter conditions and less marked seasonality that generally prevail in the western Amazon could be expected to limit the danger of spreading fires (12). Extensive clearing of humid forests for cultivation and pasture especially along the eastern slope of the Andes has, however, undoubtedly increased the vulnerability of the region to escaped fires. The severe drought of 2005 set in motion conflagrations that burned more than 300,000 ha of forests in the neighboring Brazilian state of Acre (13). In the same year, according to government estimates more than 22,000 ha burned in the Ucayali region of Peru, a significant area but probably a very serious underestimate (14). Of the officially recognized burned area, about 16,000 ha were in forest, more than 5,000 in pasture, and the rest were fruit plantations, manioc fields, banana plantations, and the villages and homes of farming families (14). Increased fire risk in this region likely reflects a number of factors that interact with drought severity. These include economic policies that stimulate agricultural development (14, 15) and road construction (16, 17). By providing farmers with economic incentives and access to develop the land, both of these factors have led to increased fire activity elsewhere in the Amazon (11). Economic opportunities have also attracted migrants to the region (18), leading to higher population densities and, potentially, greater fire risk. Nevertheless, concomitant rapid urbanization (Fig. 1) and outmigration of people from rural areas could be expected to reduce the risk of agriculture-related fire. On the other hand, rural migration may result in labor shortages for fire control while the high fuel load of vegetation regrowth in fallow areas might make these areas susceptible to burning.

Here, we use spatially explicit analyses of climate, remote sensing, and census information to quantify the contribution of climate (drought), land use patterns, and socioeconomic factors, namely rural migration, to fire activity (occurrence and frequency) at the province scale in the Peruvian Amazon (936,240 km^2; Fig. S2) between 2000 and 2010. Severe droughts affected the region in 2005 and 2010 (19, 20). To identify the factors most strongly associated with fire activity at this scale, we rely on spatiotemporal regression models. Preliminary regional analyses indicated that the occurrence of fires (i.e., binary response) and its drivers

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[1]To whom correspondence should be addressed. E-mail: mu2126@columbia.edu.

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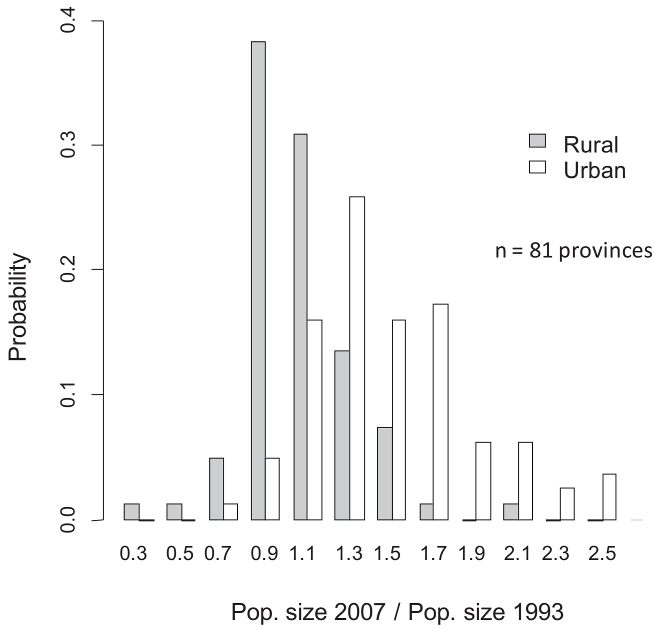

Fig. 1. Frequency distribution of the ratio of 2007–1993 population size in the Peruvian Amazon. Values lower than 1 indicate declines; values greater than 1 indicate increases. Rural populations increased in 46 of the 81 provinces included in the study and decreased in the remaining 35; urban populations grew in 76. Data are from Instituto Nacional de Estadística e Informática (www.inei.gob.pe/).

were qualitatively different from fire frequency (i.e., fire counts) so we modeled these two processes separately. We considered a total of seven correlates of variation in fire occurrence and frequency at the regional scale: drought severity [standardized precipitation index (SPI) between July and September], two factors related to agricultural activity (extent of pastures and crops), two related to transportation networks (distance to roads and rivers), and two demographic factors (population density and changes in the size of rural populations at the province level during the study period) (see Table S1 for sources and *Methods* for detailed description of covariates). In an effort to understand synergistic or antagonistic effects, we also included interactions between drought severity and the other variables.

To investigate the characteristics and activities of rural dwellers that may lead to increased fire frequency, we relied on burn scar data, land use information, and farmer surveys collected in 2010 for 37 communities in a smaller focus area (2,157 km^2; Fig. S3) located in the Ucayali Region near the city of Pucallpa (Fig. S3). We considered four correlates of burn scar frequency and extent at this scale: population density, land use, land owner place of residence, and degree of implementation of fire control methods (see Table S2 and *Methods* for detailed descriptions of covariates).

Results and Discussion

Our province-scale, regional model captured the spatial distribution of fire risk quite closely, revealing as expected a positive association of fire occurrence with drought severity, proximity to roads and rivers, and the extent of pastures and agricultural crops (Fig. 2 and Fig. S4; see Tables S3–S10 for goodness of fit, multicollinearity diagnostics, and model selection statistics). We also uncovered strong synergistic interactions between drought severity and the extent of agricultural crops and pastures, and proximity to roads (Fig. 2). For instance, in localities where agricultural crops covered more than 20% of land area, fire risk more than doubled from wet to dry years (Fig. 3). These results suggest that drought severity alone cannot explain the spatial distribution of fires. Rather, agricultural activity and proximity to roads and rivers determine the location of fires and modulate the impacts of drought severity.

Predictors of fire frequency (i.e., how many fires occurred in the same place) were distinctly different from those of fire occurrence (Fig. 2, Tables S3–S10). As before, regression analyses showed that fire frequency increased with drought severity and proximity to roads, but the extent of cattle pastures and agricultural crops had little impact on this metric of fire activity. The absence of an association between these land covers and fire frequency is not surprising given that data included in these analyses were restricted to areas where fires occurred, which, as our previous analyses indicated, consisted primarily of these two land covers. In contrast to the negligible effects of demographic variables on fire occurrence, declines in the size of rural populations at the provincial scale were associated with greater fire frequency (Figs. 2 and 4). Contrary to the expectation that rural outmigration would lead to less fire, this result identifies the demographic trend toward emptying rural landscapes as a factor that increases fire frequency.

Our results at the local scale highlight two potential mechanisms to account for the positive association between rural outmigration and fire frequency. First, communities with a larger percentage of land in fallow had a greater risk of more fires and larger burn scars (Tables 1 and 2). A greater amount of land in fallow was associated with lower population densities ($t = -2.0733$, df = 35, $P = 0.04$). Second, burn scars were larger in communities that had a greater proportion of farmers who did not reside in their properties (e.g., resided in urban dwellings) (Tables 1 and 2; see Tables S11 and S12 for regression diagnostics). Further analyses showed that collaborative group efforts in fire management and control were less likely in these communities (Pearson's $r = 0.46$, $t = 3.04$, $P = 0.004$), although this factor was not included in the regression because of collinearity.

There are two major implications of these results. First, trajectories toward continuing road development, conversion of forests to farms and pastures, and depopulation of rural areas in the Amazon carry risks of increasing fire susceptibility during dry years. Attempts to model the distribution of fire in Amazonia

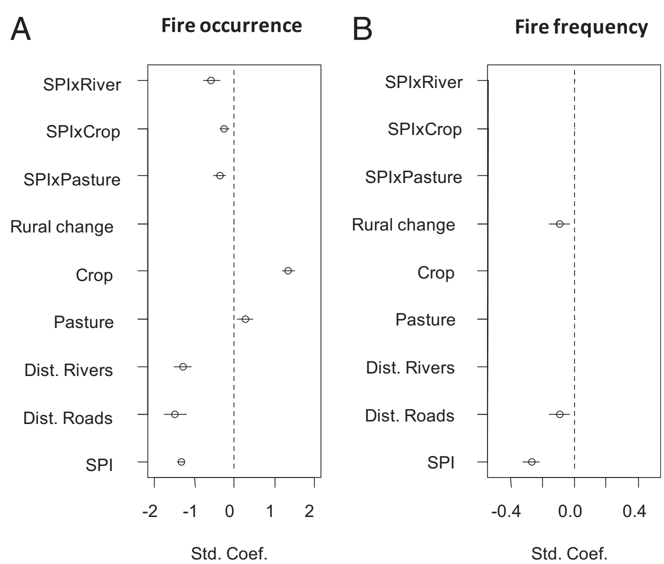

Fig. 2. Standardized regression coefficients and SEs for significant predictors of regional fire (*A*) occurrence and (*B*) frequency in regression models. See *Methods* for details on variable selection. All covariates were significant at $P < 0.00001$.

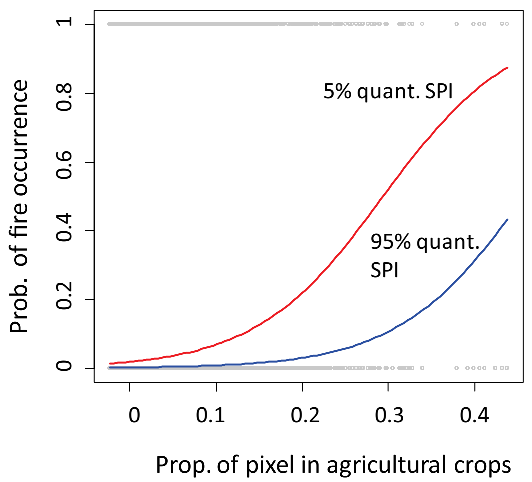

Fig. 3. Predicted probability of fire as a function of the proportion of a 100-km^2 pixel used for agricultural crops during a dry (red line, 5% quantile of observed SPI) and a wet (blue line, 95% of observed SPI) year. The gray dots show actual data. See *SI Text* for a description of methods used in calculating SPI.

have largely focused on biophysical drivers such as variation in forest biomass and soil moisture (e.g., ref. 11). Road development and human population size have been included in some fire models in Amazonia and elsewhere (e.g., refs. 21–23) but the mechanisms by which human activities influence fire activity over broad spatial and temporal scales are not well understood. Our study shows that land use, infrastructure, and demographic factors act with drought severity to determine fire activity patterns.

Second, demographic processes play a more important role than land use in modulating fire frequency where fire occurs. Our study suggests that rural outmigration is associated with increases in the frequency of fires and size of burn scars in the Peruvian

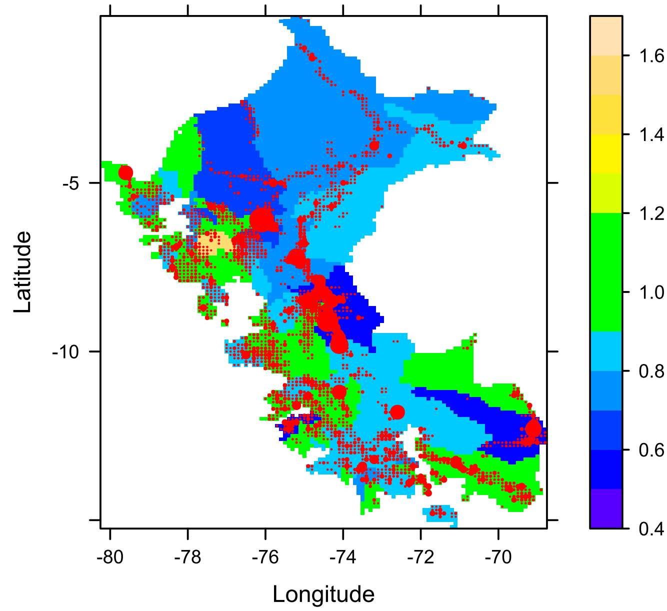

Fig. 4. Spatial distribution of the average number of fires (red dots) in a 100-km^2 pixel relative to the province level ratio of 2007–1993 rural population size (color legend). Ratio values <1 indicate decline in rural population, and >1 indicate increase. Average number of fires in a 100-km^2 pixel ranged from 0.1 to 8.16.

Table 1. Standardized coefficients, SEs, and statistical significance for regression predictors of mean burn scar size across 37 communities around the city of Pucallpa

Predictor	Mean	SE	t	P	Partial R^2
% community in fallow	62.72	26.05	2.41	0.021	0.13
% farmers who live on property	−85.71	26.05	−3.20	0.002	0.24

Overall adjusted model $R^2 = 0.24$.

Amazon. Fire is a cheap, labor-saving way of clearing and managing land, and, in a situation of rural labor shortage, its use may be increasingly important. On the other hand, with some household members, especially the young and able living at least part-time in the city, the capacity of households to control the fires they or their neighbors ignite may be declining (24). Communication among neighbors concerning fires may also be declining, reducing capacity to control fire (25).

Projected declines in rural population across Amazon countries (ref. 6; Table S13) and expansion of road infrastructure (17) combined with more frequent droughts predicted by some global climate models (26, 27) presage greater damage from fire in the future. However, it is possible to ameliorate risk to ecosystems and humans through the development of early warning systems that incorporate the factors that this study reveals as important in increasing risk of fires (i.e., differential warnings based on climate forecasts that account for recent changes in rural populations, distance to roads, etc.). To be effective, these early warning systems will require close coordination in fire-fighting activities among local government, regional civil defense, and of course, communities. Policies to promote low-fire land use systems (e.g., small-scale oil palm) in areas with high owner absenteeism and to provide options for people to remain in rural landscapes, such as access to education and health services, could also reduce fire. Provision of these services, which have been largely unavailable in rural communities, will enable people to reside in rural areas rather than seek services in urban centers.

Methods

Data. Data were collected at two spatial scales: the entire Peruvian Amazon (Fig. S2) and a smaller focal area near the city of Pucallpa (Fig. S3). Pucallpa is the urban center of Coronel Portillo, which is located on the Ucayali River, the main transportation thoroughfare of Peruvian Amazonia and connected to Lima via the Federico Basadre Highway. Because it is a hub of transport by both road and river, Pucallpa is an important market center and has attracted migrants from around Amazonia and from the mountain and coastal regions. Between 1961 and 1993, Pucallpa grew more than sixfold and now numbers about 300,000 (18). Facility of transport also has favored the establishment of large-scale industrial agriculture and cattle ranching, which spread from the edges of the urban zone into the smallholder agricultural landscapes located further away by both road and river. According to the Peruvian National Census, in 2007 more than 75% of the population of the Ucayali Region lived in urban places (18). Increasingly, many families are multisited, with residences in Pucallpa and in agriculturally productive rural and periurban zones; they maintain houses and economic activities in rural areas as well as in the city (28). More than one-half of the population resides in informal or squatter settlements.

At the regional scale, we conducted the analyses using data for the period 2000–2010. For the local scale, analyses were restricted to data collected in

Table 2. Standardized coefficients, SEs, and statistical significance for regression predictors of fire scar counts across 37 communities around the city of Pucallpa

Predictor	Mean	SE	t	P
% community in fallow	0.0009	0.0002	2.35	0.02

Overall adjusted $R^2 = 0.11$.

2010. Although burn scar data are available since 2000, human settlements around Pucallpa are extremely fluid, which prevented us from using survey data to examine fire activity before 2010.

Climate data. Because our focus is fire activity, our analyses aimed to identify years representing significant departures from average precipitation. To this end, we used the SPI, the number of SDs that observed cumulative precipitation over a defined period deviates from the climatological average (29). A continuous period of at least 30 y of precipitation data are necessary to accurately estimate the appropriate probability density function for a given SPI time interval. Once derived, the cumulative probability distribution is transformed to a normal distribution. SPI can then be interpreted as a probability using the standardized normal distribution, where SPI < -1 indicates drought and SPI > 1 pluvial.

For this study, we developed our own regional long-term gridded precipitation dataset as part of a collaboration work with the Peruvian Meteorological Service (Servicio Nacional de Meteorología e Hidrología). We complemented our station network with data obtained from the Brazilian Agência Nacional de Águas (http://hidroweb.ana.gov.br/). This second data set provided us with additional number of stations reporting nonmissing daily average precipitation data over the 1970–2010 period. All of the data were interpolated to 0.25° spatial resolution using the Cressman (30) method, which determines the average distance between the available stations at each time step and applies a multiplier factor to extend the radius of influence of neighboring stations on the target station. The daily interpolated precipitation is then averaged to monthly means, but only at grid cells with 75% of the days reporting nonmissing data. Monthly gridded precipitation data from 1970 to 2010 were used as the baseline period for the July–August–September (JAS) SPI calculation. Previous analyses have shown that SPI calculated for this period, the dry season in the region, correlates highly with fire anomalies (19). To make the data congruent with other raster datasets, we rescaled it to 0.1° spatial resolution (Table S1). Weather station data were not available for 4% of the 7,311 0.1° pixel-years, so these data were excluded from the analyses.

Remote sensing data. Regional scale. The active fire product from the moderate resolution imaging spectroradiometer (MODIS) sensor (31) provided a time series of fire activity over the study region from 2000 through 2010. This product consist of gridded fire pixels count at 1-km^2 resolution aggregated to a 100-km^2 grid and monthly time steps. We first calculated the total number of "hot" pixels in each 0.1° cell (roughly a 10×10-km grid). This value could range from 0 for no reported fires to 100 if all of the cells had fire activity in any given day. We then calculated the average annual value for each cell for the July–September period for 2000 through 2010. Although the MODIS product does not provide daily coverage in equatorial regions, the goal of our analyses is to evaluate the factors underlying relative variation in fire occurrence and frequency across the Peruvian Amazon. Undersampling might influence the magnitude of parameter estimates, but it is unlikely to change the sign, significance, or interpretation of the factors that influence fire activity.

To assess the impacts of human activities in the region, we used land use/land cover layers based on satellite data from 2000 (32) and calculated the proportion of each of the 0.1° cells that was used for agricultural crops or pasture. We also calculated the distance from the center of each cell to the nearest river and road. Road and river layers were obtained from Center for International Earth Science Information Network at Columbia University (Table S1).

Local scale. We used MODIS daily surface reflectance data (MOD09GQ) to quantify the number and size of burn scars that overlapped with the extent of each community in 2010. The spatial resolution of this product is ~250×250 m, meaning that burn scars <250 m were not detected. Communities were delineated using global positioning system and ranged in size from 298 to 4,810 ha (2.98–48.1 km^2) with mean area of 1,660 ha. Burn scars were mapped based on metrics characterizing temporal changes in bands 1 (620-670 nm), and 2 (841-876 nm) and normalized difference vegetation index associated with burning. These metrics were incorporated in a decision tree classifier (33) for burn scar classification. Calibration and validation data were obtained from field measurements of burned areas and from visual interpretation of burned and unburned areas in 2009 and 2010 using RGB composites of bands 5, 4, 3 from Landsat images. Accuracy was measured as the ability of the calibrated tree with data from 2010 to classify burned and unburned areas in time, using 2009 as the validation year. We further applied a postclassification sieving filter of 4 or less pixels to avoid misclassification of small isolated areas. Producer's accuracy was 82.4% and user's accuracy was 90.8%.

To assess the role of human land use in fire activity at this scale, we assembled Landsat data from 2010 for each of the 37 communities. Land cover was identified using Random Forest (34–35) and field data. Each 30×30 pixel in the study landscapes was classified as pasture, crop, fallow, or forest. Details on the methods and accuracy of the classification are provided in ref. 34.

Socioeconomic data. Regional scale. We collected socioeconomic data for the 81 provinces comprising the Peruvian Amazon from the Instituto Nacional de Estadística e Informática (18). Provinces range in size from 559 to 121,706 km^2 (Fig. S2). For each province, variables included population density in 2007 and the ratio of the 2007–1993 rural population.

Local scale. During the dry season months, generally between the last weeks of August through September and early October, smallholders clear new fields and pastures and leave the slash to dry in the clearing. In July 2010, we assigned one field worker per two sites and identified locations that were being prepared for burning. Throughout 2010 and 2011, we conducted semistructured interviews to establish landowner place of residence and degrees of implementation of fire control methods such as seeking help or constructing fire breaks (Table S2). We collected data for 732 households distributed in the 37 communities located within the study areas (Fig. S3). Surveys were conducted in Spanish in the farm house or within the farm plot. Before conducting the survey, we informed farmers of the general intent of our study and asked for permission to transcribe their responses. Only individuals who were actively managing the farm and making decisions about farm management were interviewed. These criteria included landholders or guardians and excluded temporary hired workers. Population density data for each community were obtained from community leaders.

Modeling fire incidence and frequency. To understand spatial and temporal patterns of fire activity in the study region as a function of climatic, landscape, and socioeconomic factors, we relied on time series data of fire activity detected using the MODIS fire product together with a number of covariates (Table S1). Preliminary analyses indicated that the occurrence of fires and its drivers were qualitatively different from fire frequency so we modeled these two processes separately.

At the regional scale, we examined a number of possible correlates of fire activity defined in terms of occurrence and frequency, including demographic, land cover, and transportation factors. We formally tested for collinearity using a number of regression diagnostics including variance inflation factors, condition indexes (ratios of eigenvalues), and variance decomposition proportions of the design matrix (36, 37) (Tables S4–S10).

We modeled fire occurrence at the regional scale using a Gaussian conditional autoregressive hierarchical Bayesian model with binary errors. To account for temporal autocorrelation, 10×10-km grid quadrats were modeled as random effects. To account for spatial autocorrelation, random effects for each were conditioned on the model predictions for neighboring quadrats. Parameters were estimated using WinBugs 1.4.3 with weak or noninformative priors. Initial analyses indicated that spatial autocorrelation did not influence parameter estimation and significance so we proceeded with mixed models with quadrat included as a random effect nested within province. We modeled fire frequency (i.e., annual counts) using a similar approach with the log of the average number of "hot" pixels in each 10×10 km as the response variable. Covariates included the precipitation index for the JAS period (JAS SPI), province-level population density in 2007, and the ratio of rural dwellers in 2007 and 1993, the proportions of each pixel used for pastures and agricultural crops, and distance to rivers and roads (Table S1). We also included interactions between climate (SPI) and the other covariates in our model. To speed up model convergence and facilitate interpretation, continuous covariates were standardized by taking each datum, subtracting the mean value and dividing by twice the SD (38). We used deviance information criterion for variable selection for binary responses (fire occurrence) and Bayesian information criterion for fire frequency (39).

We calculated model goodness of fit as the proportion of explained variance (R^2) at the sample (data) and site (quadrat) levels using methods modified from Gelman and Pardoe (40). At the sample or data level, R^2 was calculated as follows:

$$R^2_{\text{sample}} = 1 - \frac{E\left(V_{j=1}^{j=N_{\text{sample}}}\left(\log(y_j) - \beta X_j - \omega_{\text{site}(j)}\right)\right)}{E\left(V_{j=1}^{j=N_{\text{sample}}}\left(\log(y_j)\right)\right)}, \qquad [1]$$

where N_{sample} is the number of samples, E is the expected value, V is the variance, is the fire activity measure for the jth sample, is the sum of the products of the estimated coefficient and the predictors, and is the random effect associated with the quadrat (10×10 km) of the sample. The expected value of the variance was calculated by averaging the value of the variance obtained from 1,000 independent draws from the joint

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posterior distribution of the fixed and random effects. At the site, or random effect level, R^2 was calculated as follows:

$$R^2_{\text{site}} = 1 - \frac{E\left(V_{k=1}^{k=N_{\text{site}}}(\omega_k)\right)}{E\left(V_{k=1}^{k=N_{\text{site}}}(\beta \overline{X_k} + \omega_k)\right)}, \quad [2]$$

where N_{site} is the number of sites (quadrats), is the random effect for the kth site, and is the product of the estimated coefficients and the mean value of the predictors within the kth site.

Greater R^2 values at the data (sample) level indicate that the patterns are driven by temporal variation in covariates (i.e., changes in drought severity within a site over time), whereas a greater R^2 at the site level suggests that spatial variability in covariates among sites (e.g., land cover or socioeconomic covariates) accounts for variation in response variables. The approach used here allows us to separate the temporal signal from climate from that of spatial variation in covariates.

For the local-scale analyses, we used linear regression to examine a number of possible correlates of the number (i.e., frequency) and average size of burn scars that overlapped the extent of the 37 communities, including land cover (i.e., proportion of fallow, pasture, and crop cover), as well as the proportion of land owners who resided in their property and exercised some fire control practices (Table S2). To account for the possibility that larger farms would have a greater probability of overlapping burn scars, we also included community size as a covariate in the analyses of average burn scar size. We used the same procedures outlined for the regional analyses to standardize covariates (38) and evaluate regression results (37). We used Akaike information criterion for variable selection and calculated overall and partial R^2 for all of the covariates included in the final model. All analyses were conducted using R statistical software (41).

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Supporting Information

Uriarte et al. 10.1073/pnas.1215567110

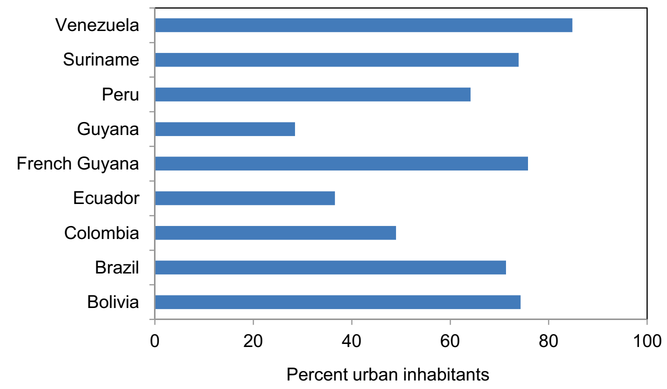

Fig. S1. Proportion of Amazonian inhabitants living in urban areas by country. Sources are refs. 1–8.

1. Instituto Nacional de Estadística de Bolivia (2001) *Censo de Población Vivienda* [*Population and Household Census*] (Instituto Nacional de Estadística de Bolivia, La Paz, Bolivia). Spanish.
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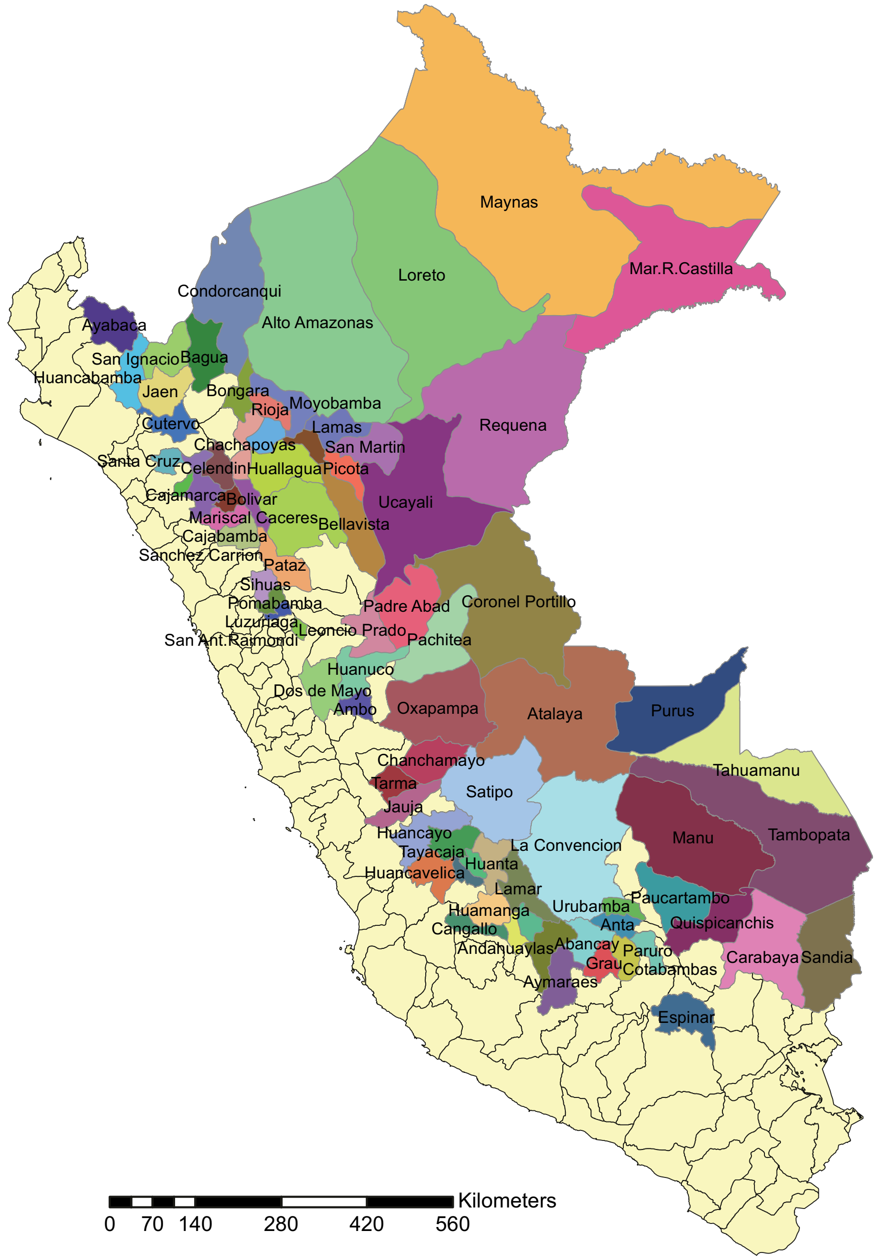

Fig. S2. Study region encompasses 81 provinces. A province was included in the study if its centroid fell within the wet tropical forest biome. Biome GIS layer used for selection was from ref. 1.

1. Olson D, et al. (2001) Terrestrial ecoregions of the world: A new map of life on earth. *Bioscience* 51:933–938.

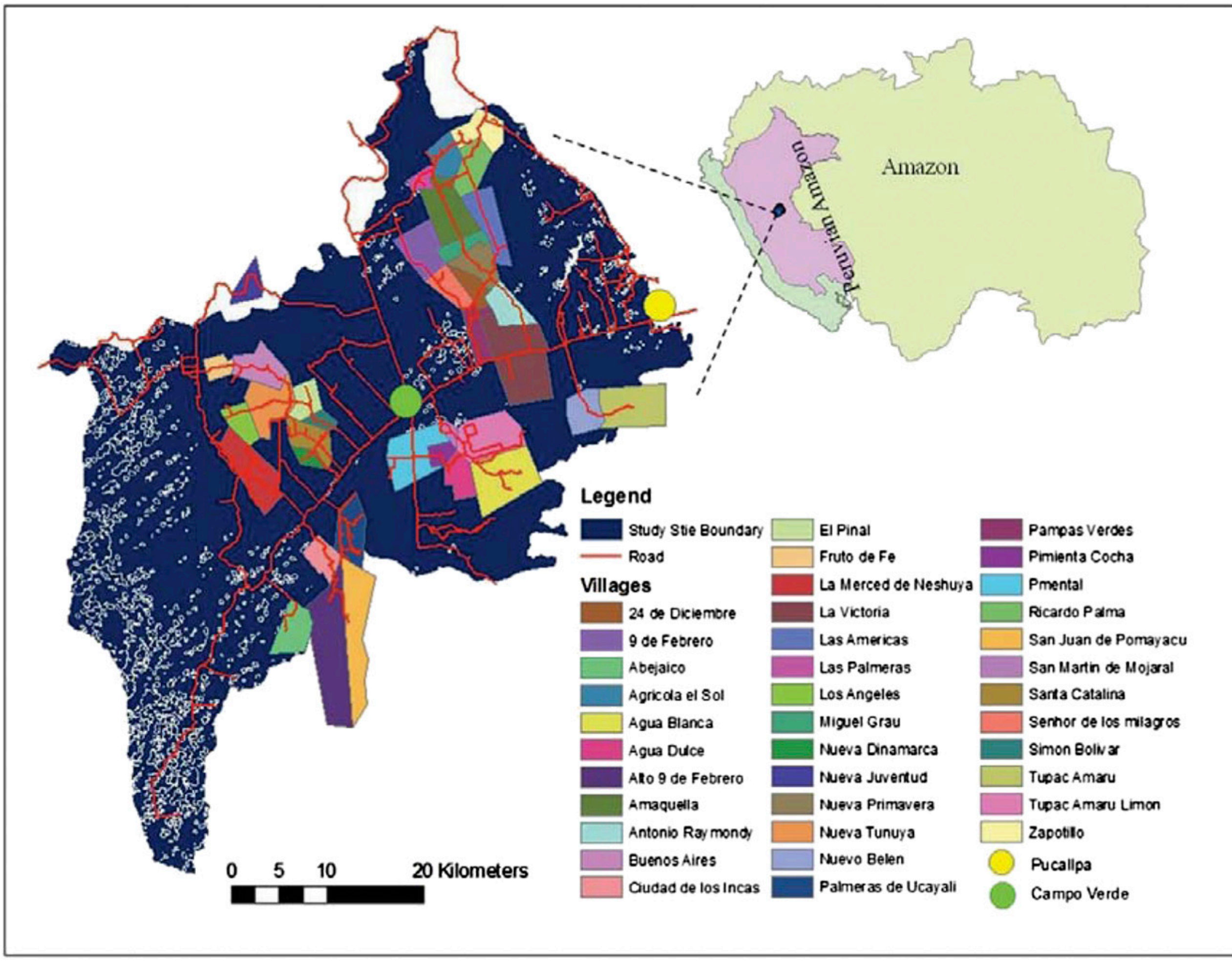

Fig. S3. Area of the local study, showing the 37 communities included in the analyses.

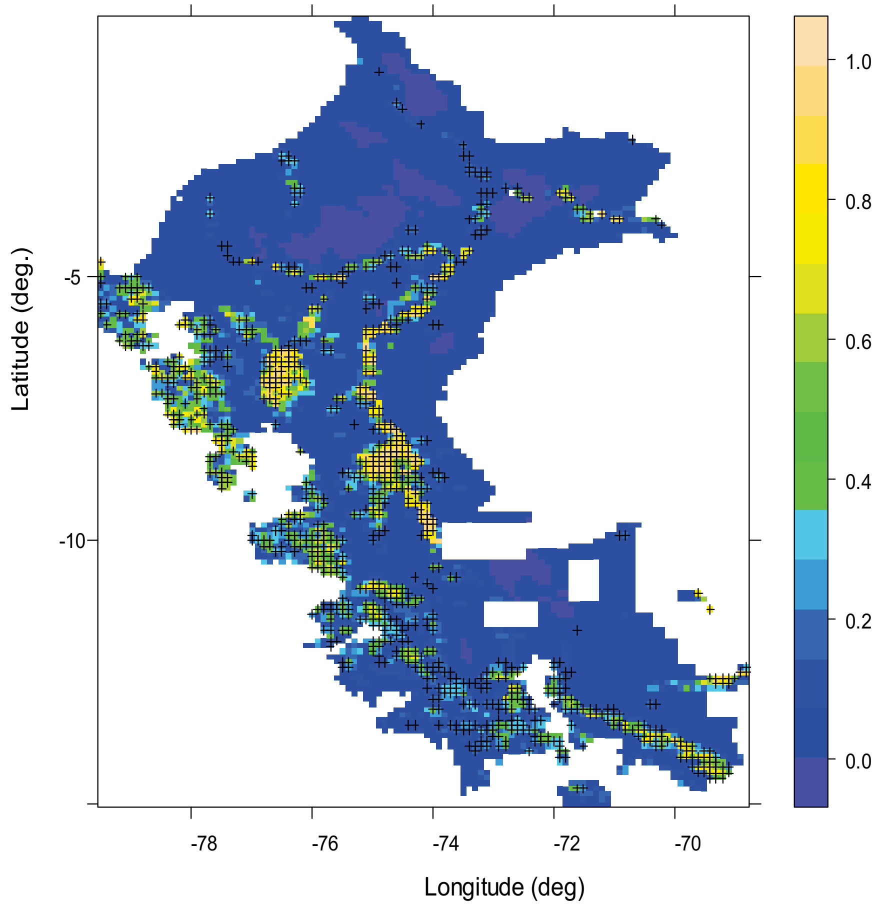

Fig. S4. Distribution of fire (black crosses) and predicted probabilities of occurrence (color legend) for 2005. The blank quadrats indicate missing climate data for those quadrat-years.

Table S1. Data variables included in the model with sources, and spatial and temporal scales at which they were used

Variables	Sources and scales
Fire activity	MODIS, no. of hot pixels 0.1°, 2000–2010 (NEO)
Biophysical	Rivers (CIESIN) 1 x 1 km, 2005
Infrastructure	Roads (CIESIN) 1 x 1 km, 2005
Demographic	Population density 2007 Rural population 2007/rural population 1993 INEI
Agricultural activity	Extent of pastures and crops 0.083° (1)
Climate	SPI-JAS, SENAMHI 0.1°, 2000–2010

See *Methods* for details. CIESIN, Center for International Earth Science Information Network at Columbia University (http://sedac.ciesin.columbia.edu/es/aglands.html); INEI, Instituto Nacional de Estadística e Informática (access at www.inei.gob.pe/); MODIS, moderate resolution imaging spectroradiometer; NEO, NASA Earth Observatory (http://neo.sci.gsfc.nasa.gov/); SENAMHI, Servicio Nacional de Meteorología e Hidrología; SPI-JAS, standardized precipitation index July–August–September.

1. Ramankutty N, Evan AT, Monfreda C, Foley JA (2000) *Global Agricultural Lands: Pastures, 2000. Data Distributed by the NASA Socioeconomic Data and Applications Center (SEDAC).* Available at http://sedac.ciesin.columbia.edu/es/aglands.html. Accessed July 6, 2011.

Table S2. Data variables included in the local model of fire frequency and size with sources, and spatial scales at which they were used

Variables	Sources, resolution, and values
Fire frequency	MODIS 1 x 1 km Fires/ha
Fire intensity	MODIS 250 x 250 m Maximum burn scar size (no. pixels)
Proportion of fallow land	Landsat 30 x 30 m
Population density	Survey data
% Farmers using fire control methods	Survey data, Community scale
% Farmers residing in their property	Survey data, Community scale

See *Methods* for details. MODIS, moderate resolution imaging spectro-radiometer.

Table S3. Explained variance at the data and site (quad) levels for best models of fire occurrence and frequency calculated using methods described in ref. 1

	Fire occurrence		Fire frequency	
	Data R^2	Quad R^2	Data R^2	Quad R^2
Best model	0.060	0.435	0.231	0.212

Values of R^2 at the data level indicate the importance of temporal variation in covariates in explaining fire activity; R^2 at the site level indicates importance of spatial variation in covariates.

1. R Development Core Team (2008) *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical Computing, Vienna).

Table S4. VIF for all of the variables initially included in the regressions for fire occurrence and frequency

Variable	VIF fire occurrence	VIF fire frequency
SPI	1.50	1.01
Pasture	1.44	1.26*
Agricultural crops	1.28	1.24*
Distance to roads	1.31	1.35
Distance to rivers	1.10	1.03*
Population density 2007	1.16*	1.02*
Rural population ratio (2007/1993)	1.13*	1.09

Variance inflation factor (VIF) should be <5 to avoid multicollinearity (1).
SPI, standardized precipitation index.
*Indicates variables not retained in the final models.

1. Belsey DA, Kuh E, Welsch RE (2004) *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* (Wiley, New York).

Table S5. Multicollinearity diagnostics for variables used in the regression at the regional scale: Fire occurrence

Parameter	Condition index	Intercept	SPI	Distance to road	Distance to river	Pasture	Crop	Population density	Rural change
Intercept	1.000	0.000	0.000	0.105	0.008	0.113	0.111	0.000	0.045
SPI	1.306	0.000	0.369	0.019	0.184	0.004	0.000	0.195	0.068
Distance to road	1.402	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Distance to river	1.413	0.000	0.050	0.011	0.370	0.000	0.001	0.467	0.089
Pasture	1.437	0.000	0.234	0.006	0.241	0.006	0.015	0.264	0.241
Crop	1.555	0.000	0.332	0.017	0.177	0.025	0.033	0.026	0.538
Population density 2007	1.782	0.000	0.008	0.791	0.003	0.058	0.338	0.029	0.004
Rural change (93–07)	1.962	0.000	0.007	0.051	0.017	0.793	0.502	0.019	0.014

Condition index should be <30 to avoid multicollinearity (1). SPI, standardized precipitation index.

1. Belsey DA, Kuh E, Welsch RE (2004) *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* (Wiley, New York).

Table S6. Multicollinearity diagnostics for variables used in the regression at the regional scale: Fire frequency

Parameter	Condition index	Intercept	SPI	Distance to road	Distance to river	Pasture	Crop	Population density	Rural change
Intercept	1.000	0.000	0.017	0.128	0.035	0.119	0.100	0.004	0.031
SPI	1.203	0.000	0.098	0.007	0.150	0.005	0.086	0.143	0.226
Distance to road	1.341	0.000	0.176	0.048	0.144	0.040	0.004	0.487	0.005
Distance to river	1.358	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pasture	1.425	0.000	0.667	0.001	0.184	0.000	0.023	0.087	0.081
Crop	1.536	0.000	0.000	0.005	0.298	0.179	0.066	0.053	0.536
Population density 2007	1.709	0.000	0.022	0.001	0.189	0.395	0.465	0.212	0.053
Rural change (93–07)	1.854	0.000	0.021	0.811	0.001	0.262	0.256	0.013	0.068

Condition index should be <30 to avoid multicollinearity (1). SPI, standardized precipitation index.

1. Belsey DA, Kuh E, Welsch RE (2004) *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* (Wiley, New York).

Table S7. DIC values for regression models of fire occurrence at the regional scale: Single-variable models

	Variable excluded?							
Single-variable models	SPI	Rivers	Roads	Pasture	Crop	Population density	Rural change	DIC
1								28045
2	Yes							29349
3		Yes						28196
4			Yes					28230
5				Yes				28061
6					Yes			28334
7						Yes		28048
8							Yes	28045
9						Yes	Yes	28045

We first tested a model with the nine covariates and compared deviance information criterion (DIC) values for models without each of the individual covariates. We then compared models with interaction terms of drought and covariates that had a significant influence on DIC as single factors. Lower DIC indicates a better fit. SPI, standardized precipitation index.

Table S8. DIC values for regression models of fire occurrence at the regional scale: Models with interactions

Models w/ interactions	Interaction excluded? SPI*river	SPI*road	SPI*past	SPI*crop	DIC
1					27931
2	Yes				27968
3		Yes			**27931**
4			Yes		27956
5				Yes	28252
6	Yes	Yes			27985
7	Yes		Yes		28000
8	Yes			Yes	27983
9		Yes	Yes		27958
10		Yes		Yes	28000
11			Yes	Yes	27985
12	Yes		Yes	Yes	28028
13		Yes	Yes	Yes	28003

We first tested a model with the nine covariates and compared DIC values for models without each of the individual covariates. We then compared models with interaction terms of drought and covariates that had a significant influence on DIC as single factors. Lower DIC indicates a better fit. SPI, standardized precipitation index.

Table S9. BIC values for regression models of frequency at the regional scale: Single-variable models

Single-variable models	Variable excluded? SPI	Rivers	Roads	Pasture	Crop	Population density	Rural change	BIC
1								14857
2	Yes							14957
3		Yes						14848
4			Yes					14860
5				Yes				14850
6					Yes			14846
7						Yes		14845
8							Yes	14889
9								
10		Yes		Yes	Yes	Yes		**14815**

We first tested a model with the nine covariates and compared Bayesian information criterion (BIC) values for models without each of the individual covariates. We then compared models with interaction terms of drought and covariates that had a significant influence on BIC as single factors. Lower BIC indicates a better fit. SPI, standardized precipitation index.

Table S10. BIC values for regression models of frequency at the regional scale: Models with interactions

Models with interactions	Interaction excluded? SPI*roads	SPI*rural	BIC
1			14829
2	Yes		14821
3		Yes	14826

We first tested a model with the nine covariates and compared BIC values for models without each of the individual covariates. We then compared models with interaction terms of drought and covariates that had a significant influence on BIC as single factors. Lower BIC indicates a better fit. SPI, standardized precipitation index.

Table S11. VIF for all of the variables initially included in the regressions for fire scar numbers

Predictor	No. scars ha
% community in fallow	1.12
% community in pasture*	1.32
% community in crops*	1.31
Population density*	1.28
% farmers who live on property*	1.42
% farmers who do not engage in fire control*	1.01

VIF should be <5 to avoid multicollinearity.
*Indicates variables not retained in the final models. Covariates were eliminated using stepwise regression. All condition indexes were less than 10.

Table S12. VIF for all of the variables initially included in the regressions for fire scar average size

Predictor	Mean scar size
% community in fallow	1.37
% community in pasture*	1.40
% community in crops*	1.35
Farm area*	1.27
Population density*	1.79
% farmers who live on property*	1.46
% farmers who do not engage in fire control*	1.09

VIF should be <5 to avoid multicollinearity.
*Indicates variables not retained in the final models. Covariates were eliminated using stepwise regression. All condition indexes were less than 10.

Table S13. Projected changes in rural population between 2010 and 2050 for countries in the Amazon basin

Country	Ratio of projected 2050–2010 population
Bolivia	0.78
Brazil	0.53
Colombia	0.76
Ecuador	0.64
Guyana	0.58
French Guyana	1.16
Peru	0.72
Suriname	0.63
Venezuela	0.67
Average	0.72

Data are from ref. 1.

1. United Nations (2009) *World Urbanization Prospects: The 2009 Revision* (United Nations, New York).