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Climate, landowner residency, and land cover predict local scale fire activity in the Western Amazon

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ABSTRACT

The incidence of escaped agricultural fire has recently been increasing in the Western Amazon, driven by climate variability, land use change, and changes in patterns of residency and land occupation. Preventing and mitigating the negative impacts of fire in the Amazon require a comprehensive understanding not only of what the drivers of fire activity are, but also how these drivers interact and vary across scales. Here, we combine multi-scalar data on land use, climate, and landowner residency to disentangle the drivers of fire activity over 10 years (2001–2010) on individual landholdings in a fire-prone region of the Peruvian Amazon. We examined the relative importance of and interactions between climate variability (drought intensity), land occupation (in particular, landowner absenteeism), and land cover variables (cover of fallow and pasture) for predicting both fire occurrence (whether or not fire was detected on a farm in a given year) and fire size. Drought intensity was the most important predictor of fire occurrence, but land-cover type and degree of landowner absenteeism increased fire probability when conditions were dry enough. On the other hand, drought intensity did not stand out relative to other significant predictors in the fire size model, where degree of landowner absenteeism in a village and percent cover of fallow in a village were also strongly associated with fire size. We also investigated to what extent these variables measured at the individual landholding versus the village scale influenced fire activity. While the predictors measured at the landholding and village scales were approximately of equal importance for modeling fire occurrence, only village scale predictors were important in the model of fire size. These results demonstrate that the relative importance of various drivers of fire activity can vary depending on the scale at which they are measured and the scale of analysis. Additionally, we highlight how a full understanding of the drivers of fire activity should go beyond fire occurrence to consider other metrics of fire activity such as fire size, as implications for fire prevention and mitigation can be different depending on the model considered. Drought early warning systems may be most effective for preventing fire in dry years, but management to address the impacts of landowner absenteeism, such as bolstering community fire control efforts in high-risk areas, could help minimize the size of fires when they do occur. Thus, interventions should focus on minimizing fire size as well as preventing fires altogether, especially because fire is an inexpensive and effective management tool that has been in use for millennia.

1. Introduction

Although humans have long influenced fire regimes on earth, recent anthropogenic drivers are causing major shifts in fire activity in some parts of the world and are expected to further alter global fire regimes in the near future (Bowman et al., 2011; Krawchuk et al., 2009; Turner, 2010). These changes will have consequences for biodiversity, conservation, and ecosystem processes, along with human health, economics, and wellbeing (Bowman et al., 2009; Lohman et al., 2007). Adapting to and mitigating the effects of changing fire regimes requires an understanding of the drivers of both broad scale and local heterogeneity in fire activity, and of the links, interactions, and interdependencies of the multiple drivers of these changes.

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An ideal region in which to examine such questions is the western Amazon. Although humans have used fire to clear land for agriculture and improve hunting grounds in the Amazon for thousands of years (Bowman et al., 2008; Bush et al., 2008), the incidence of escaped agricultural fires has been increasing in recent decades (Alencar et al., 2011; Aragão et al., 2007; Aragão and Shimabukuro, 2010; Armenteras and Retana, 2012; Asner and Alencar, 2010). Because there are few natural ignitions, fires are associated with human activities (Cochrane and Laurance, 2008; Nepstad et al., 2001). Fire is still a common tool used to prepare land for agriculture or grazing, but today, these fires are prone to escaping into adjacent forest or non-forested land, particularly in dry years (Alencar et al., 2004; Nepstad et al., 1999). Amazonian fires can be major sources of greenhouse gas emissions (DeFries et al., 2002, 2008), degrade forests, affect biodiversity and ecosystem services (Cochrane and Schulze, 1999; Gerwing, 2002), and cause property loss and respiratory disease (de Mendonça et al., 2004). Although fire is most prevalent in the southern and eastern parts of the Amazon basin, its incidence is growing in the western Amazon as well (Brown et al., 2011). For example, in the 2005 drought, 22,000 ha burned in the Ucayali region of Peru (Gobierno Regional de Ucayali, 2006).

Fire can only occur when conditions are favorable; it requires fuels, an ignition source, and sufficiently dry weather conditions to ignite and spread. Fire regimes, the spatial and temporal patterns of fire observed in an ecosystem, are the result of vegetation, climate, and ignition controls acting simultaneously (Moritz et al., 2005). Human activities can affect fire regimes by interfering with any of these controls. For example, land use and management activities can change fuel amounts, composition, and configuration and affect the number and spatiotemporal patterns of ignitions (Nepstad et al., 1999), while roads can act as fire breaks, but also can be a source of anthropogenic ignitions (Archibald et al., 2009; Bowman et al., 2011; Cardille et al., 2001; Hawbaker and Radeloff, 2013). Promoting grazing, introducing exotic plants, engaging in fire suppression, and other activities can similarly affect patterns of fire (Bowman et al., 2011).

The degree to which various controls on fire activity limit fire depends on the study location (Bowman et al., 2009; Krawchuk et al., 2009; Krawchuk and Moritz, 2011; Parisien and Moritz, 2009). For example, in places with wet climates where productivity, and thus fuel availability, is high, fire is limited by fuel moisture. In very dry climates where fuels are almost always dry enough to burn, fuel quantity can be limiting instead (Krawchuk and Moritz, 2011). Where natural ignitions are very rare, the availability of anthropogenic ignitions changes the degree to which ignitions limit fire (Cochrane and Laurance, 2008; Nepstad et al., 2001).

The spatial scale of analysis also affects which drivers best explain patterns of fire activity (Parisien and Moritz, 2009; Parks et al., 2012). Climate exerts control across broad areas, while topography and vegetation are important in driving finer scale heterogeneity. Within broad fire-prone regions there can be considerable spatial and temporal heterogeneity in frequency, intensity, and severity of fires, and local patterns of fire activity are the result of climate, fuel, and ignition controls acting simultaneously and to different degrees, and reflect the ways humans influence each of these controls. Thorough understanding of a fire regime requires examining patterns of fire at a number of different spatial scales: focusing on broad scales might blur out the drivers of local scale heterogeneity, while focusing only on very local scales may miss informative and important regional patterns in fire activity. For example, a focus on climate may overlook the role of topography in driving local variation in fire regimes, while a focus on the way topography influences patterns of fire might not detect the role of interannual climate variability in driving regional synchrony and year-to-year variability in fire activity.

Similarly, the most important biophysical factors predicting fire occurrence (defined as whether a particular place burns or not) may be different from those predicting other metrics of fire activity such as fire intensity or fire size. In ecosystems where natural ignitions are rare, availability of ignitions could be the most important driver of fire occurrence, but once a fire starts, fuel quantity could be the strongest predictor of fire intensity and the spatial configuration or connectivity of fuels could be most important for fire size. In ecosystems where ignitions are frequent but conditions are rarely dry enough for fires to start, fuel moisture might be the most important factor limiting fire occurrence, intensity, and size.

Here, we combine multi-scalar data on land use, climate, and landowner residence from remote sensing, meteorological stations and socio-economic surveys to further disentangle the drivers of two different metrics of fire activity – fire occurrence and fire size – over 10 years on individual landholdings in a fire prone region of the Peruvian Amazon. We focused on the following questions:

1) What is the relative importance of climate, landowner place of residence, and land cover for predicting fire activity in the Ucayali region of the Peruvian Amazon and how do these drivers interact?

We expected that climate would exert the strongest control on fire, but in dry years, variables related to human activities would play an important role in determining finer scale patterns of fire activity.

2) To what extent do characteristics of a particular landholding, as opposed to characteristics of the village or region around it, predict fire activity on that landholding?

Because most landholdings are relatively small and thus potentially highly susceptible to fire spread from adjacent properties, we expected that characteristics of the village around a landholding would be a stronger predictor of fire activity than conditions on a landholding itself.

3) Are the drivers of fire occurrence different from those of fire size?

We expected that the predictors of fire occurrence would be different from those of fire size: fire occurrence would be more closely associated with spatial and temporal patterns of ignition sources (related to patterns of human activity) while fire size would be associated with variables that affect fuel quantity and moisture, in particular land cover and drought intensity, and that reflect social control, in particular the number of landowners present in the village.

2. Material and methods

2.1. Study area

This study focused on an area within the Ucayali region of Peru, near the urban areas of Pucallpa and Campo Verde (Fig. 1). Elevation ranges from 150 to 250 m, and annual mean precipitation averages 1500–2500 mm/year with an annual dry season from July to September (Gutiérrez-Vélez and DeFries, 2013). The study region has been connected to Lima and other urban centers in the coast and mountains of Peru by a highway and networks of roads for more than six decades. It has attracted many migrants from elsewhere in Peru in recent years (Uriarte et al., 2012) and has undergone extensive land-use change and deforestation including

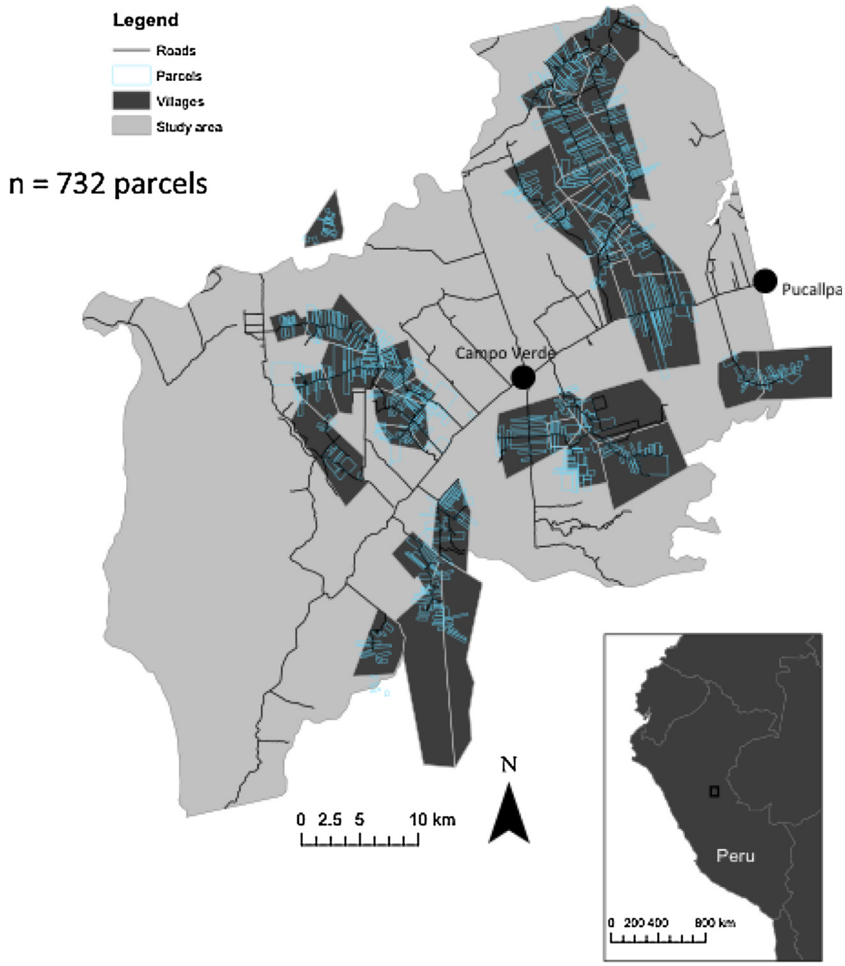

Fig. 1. Map of study area. Inset shows location in Peru (black rectangle).

conversion of forest to oil palm (Gutiérrez-Vélez and DeFries, 2013; Oliveira et al., 2007). Since the early 1980s, there has been significant rural-to-urban migration, with 75% of the population living in cities as of 2007, up from 56% in 1972 (Instituto, 2009). Many households are multi-sited, with property and activities in rural and urban areas (Padoch et al., 2008).

Several studies have examined the drivers of recent fire activity in the western Amazon, and have found it is correlated with repeated droughts over the 2000s, which in turn are associated with positive anomalies in the North Atlantic sea surface temperature (Chen et al., 2011; Fernandes et al., 2011). Recent fires in the Peruvian Amazon have been concentrated in provinces where rural-to-urban migration is high, and, within the study area, in villages with high levels of landowner absenteeism (Uriarte et al., 2012). This may be due to decreased capacity to control fires in areas where landowners are rarely present on their land, and/or to an increase in flammable fallow land. Gutiérrez-Vélez et al. (2014) found that land cover composition is significantly correlated with fire probability in individual burned pixels but that the magnitude and sign of the correlation depends strongly on drought intensity, successional stage of regrowing vegetation and oil palm age. Here, we build on these findings to further disentangle the drivers of fire occurrence over 10 years on the scale of individual landholdings in the Peruvian Amazon. Previous analyses of drivers of fire activity in the region have been on disparate scales: province, village, burned 250 m pixel. Conducting analyses on the scale of individual landholdings allows us to simultaneously compare the relative importance of the climate, residency, and land cover drivers previously identified as important, at a scale relevant for local management and prediction of finer scale patterns of fire occurrence.

Data were compiled from a number of sources including weather stations, satellites, and farmer surveys (Table 1). We focused our analyses on 732 farms within 37 villages in the region (Fig. 1).

2.2. Climate data

Drought is a major climatic driver of fire in the Amazon (Alencar et al., 2006; Fernandes et al., 2011; Nepstad et al., 2004). To quantify drought intensity, we used the Standardized Precipitation Index (SPI), calculated as the number of standard deviations that cumulative precipitation over a defined period deviates from the long-term average: here, 1970–2010. SPI values < -1 indicate drought, while SPI > 1 wet years. We used a map of SPI at 0.25° spatial resolution developed by Fernandes et al. (2011) to assess the relative and interactive influence of drought intensity on fire occurrence and size. The map was derived by interpolating meteorological stations' precipitation data from the Peruvian Meteorological Service (Servicio Nacional de Meteorologia e Hidrologia-SENAMHI) and the Brazilian Agência Nacional de Águas (http://hidroweb.ana.gov.br/) using the Cressman method (Cressman, 1959). Previous analyses have shown that July–August–September (JAS) SPI is the most accurate predictor of fire activity

Table 1
Variables used and their sources.

Variable	Source	Citation
Response variables		
Fire occurrence	MODIS	Gutiérrez-Vélez et al. (2014)
Burn scar size	MODIS	Gutiérrez-Vélez et al. (2014)
Predictors–household scale		
Land cover (focal landholding)	Landsat	Gutiérrez-Vélez and DeFries (2013)
Does landowner live on farm?	Landowner survey	Uriarte et al. (2012)
Farm size	Landowner survey	Uriarte et al. (2012)
Predictors–village scale		
Land cover (village)	Landsat	Gutiérrez-Vélez and DeFries (2013)
% Landowners residing in village	Landowner survey	Uriarte et al. (2012)
Predictors–regional scale		
Climate (SPI)	Peruvian Meteorological Service and Brazilian Agênia Nacional de Águas	Fernandes et al. (2011)

for the Peruvian Amazon (Fernandes et al., 2011), so we used JAS SPI as the climate variable in our analyses to predict fire activity. Because of the coarse spatial resolution of the SPI data, there were only six different values of SPI across the study area each year. Thus, variation in SPI mainly represents inter-annual variation in precipitation, as opposed to spatial variation.

2.3. Fire mapping

Annual burn scar maps for every year between 2001 and 2010 were obtained from a previous study (Gutiérrez-Vélez et al., 2014). Burn scars were mapped using the daily surface reflectance product from the Moderate Resolution Imaging Spectrometer (MODIS) satellite (MOD09GQ) at 250 m × 250 m resolution, based on temporal changes in NDVI and in bands 1 (620–670 nm) and 2 (841–876 nm). The presence of smoke, haze, and clouds during burning can prevent the detection of fires at the time of burning. The method used for burn scar mapping minimizes these effects in a number of ways. First, the MODIS surface reflectance product incorporates an algorithm that reduces the effects of smoke and other aerosols (Vermote et al., 2002). Second, the method implements a filtering algorithm to remove unreliable pixel observations. Third, the method takes into consideration minimum NDVI values measured throughout the entire dry season, July through November. Detection of fires that occur toward the end of this period may be reduced somewhat, but relatively few fires occur during this time period (Gutiérrez-Vélez et al., 2014).

Due to the minimum pixel size required for detection, sub pixel-sized fires, such as controlled agricultural fires, are not likely to be detected, and the method is most reliable for burn scars larger than 10 ha (Gutiérrez-Vélez et al., 2014). Therefore, though it is not possible to discriminate controlled vs. escaped fires using this method, the majority of fires included in our models likely represent large escaped fires, as controlled agricultural fires are generally smaller than 2 ha (Gutiérrez-Vélez et al., 2014). Therefore, this method allows us to detect and model the drivers of large fires; the drivers of small fires may be different.

In addition, there may be some error in the size of mapped burn scars in both directions, due to the lack of information on date of burning. The same fire event may correspond to multiple separate mapped burn scars if they are connected through areas smaller than the minimum detectable burn scars, leading to some underestimation of fire size. On the other hand, single burn scars could correspond to areas burned in different fire events during the same year and close enough to be mapped as an individual burn scar, leading to some overestimation.

2.4. Land cover mapping

Land cover maps were obtained from a previous study (Gutiérrez-Vélez and DeFries, 2013). They were classified at the 30 m × 30 m resolution using a combination of Landsat TM and ETM optical data and ALOS-PALSAR radar data. We excluded 2007 from analyses because there was not a suitable Landsat TM image of the region available. Each pixel was classified as oil palm, deforested, fallow, forest, pasture, secondary vegetation, bare, or water with an overall accuracy of 93%.

2.5. Socio-economic data

During 2010 and 2011, we conducted semi-structured interviews at 732 farms in 37 villages across the study area (Fig. 1). A farm is defined here as one spatially continuous landholding with one owner. Villages are defined as communities with more than 40 school-aged children (the minimum number needed for a private school) and are delineated by the local government. We selected these 37 villages via a preliminary survey of fire history and landholding types (smallholders versus large holdings). Households were selected from within these communities from the population who potentially used fire as a management tool or were potentially affected by escaped fires using snowball sampling, in which individual respondents helped recruit future respondents from their acquaintances (Goodman, 1961). Only heads of households or individuals actively involved with farm management were interviewed. Each individual was asked about the landowner's place of residence and fire use and management practices. If the current landowner acquired the farm more recently than 10 years ago, they were included in analyses for all years after they acquired it. Otherwise, they were included for all 10 years of the study. This resulted in 5387 farm-year observations. We assumed that their answers in 2010–2011 reflect conditions since the acquisition.

Farm boundaries were mapped using GPS points. Mean farm size was 32.5 ha. If any burn scar overlapped with a farm in a given year, that farm was classified as "burned" for that year, for the model of fire occurrence. Otherwise landholdings were marked as unburned. For farms that burned, we calculated the total area of the burn scars that overlapped with the farm for use in the model of fire size. For each farm, we tallied the proportion in each land cover class for each year between 2001 and 2010. In addition, we calculated the proportion of land cover class in each village and the proportion of landowners residing on their property to use as community-scale predictors in our models of fire activity.

2.6. Statistical analysis

We used a hierarchical Bayesian modeling framework to predict annual fire activity from 2001 to 2010 at the scale of individual farms. We expected that the predictors of fire occurrence would be different from those of fire size. Therefore, we built two models to predict fire activity: first, to predict the probability that fire occurs on a farm in a given year, and second, for the subset of farms that did burn in a particular year ($n = 1095$), the total area of burn scars overlapping with each farm. Considering fire size in this way allows us to understand the characteristics of farms that are associated with large escaped fires.

Predictors varied at the regional (i.e. whole study area), village, and individual farm scale and comprised drought intensity (SPI), farm-level land cover (proportion of pasture and fallow), place of residence of landowner (on the farm or elsewhere), village land cover (proportion pasture and fallow), and percent of landowners residing within the village (Table 1). We also included interactions between SPI and each other predictor. Because we were interested in how the relative importance of predictors varied across models, and not in finding the best model to predict each metric of fire occurrence, we fit a full model for both fire probability and fire size. Farm size (hectares) was included as a covariate to control for the fact that fire is more probable in large farms because they cover more area. We included only the fallow and pasture land cover classes as predictors to avoid collinearity between land cover predictors and because both have been identified as being associated with fire in previous analyses (Gutiérrez-Vélez et al., 2014). Collinearity was less than 0.36 for all pairs of predictors (Table A.1).

Fire occurrence (y_{occ}) was modeled as a Bernoulli process as follows:

$$y_{occ,ij} \sim \text{Bernoulli}(p_{ij}) \tag{1}$$

where p_{ij} is the probability of fire on farm i in year j. We modeled the logit of p_{ij} as a linear combination of the predictors (x), regression coefficients β, and a farm-specific intercept α_i:

$$\ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = \alpha_{ij} + \beta_1 x_{1,ij} + \cdots + \beta_n x_{n,ij} \tag{2}$$

The size of fires overlapping with a farm was log transformed, as a few very large fires resulted in a long-tailed distribution. We modeled fire size (y_{fs}) using a gamma density function as follows:

$$y_{fs} \sim \text{gamma}\left(\frac{\mu_{ij}^2}{\sigma}, \frac{\mu_{ij}}{\sigma}\right) \tag{3}$$

$$\mu_{ij} = \alpha_{ij} + \beta_1 x_{1,ij} + \cdots + \beta_n x_{n,ij} \tag{4}$$

where μ_{ij} is the predicted fire size associated with farm i in year j and σ is the estimated variance. In all models for both fire occurrence and fire size, we modeled random effects (α_i) for farm i in community k drawn from a normal distribution with parameters μ_k and τ_k determined by the community in which they were located. These parameters were in turn derived from a normal distribution whose mean (μ_{com}) and precision (τ_{com}) were estimated as hyperparameters. Including random effects for village helps account for the fact that a farm may be more likely to burn simply because it is located in a more fire-prone village.

Models were specified using uninformative priors. Posterior distributions for parameters were estimated using Markov Chain Monte Carlo (MCMC) sampling. Models were run for 3 chains and 10,000 iterations burn-in, and then for 10,000 total iterations. Convergence was assessed visually by examining chains and the shapes of the posterior distributions of parameters and using the Gelman and Rubin Diagnostics (Brooks and Gelman, 1998). If the 95% credible interval of the posterior distribution of a parameter did not overlap with 0, that parameter was determined to be statistically significant. The estimated parameters were used to calculate predicted values of fire probability and fire size for each landholding; the predictions were plotted against observations to assess model predictive ability (Figs. A.1 and A.2). All statistical analyses were conducted in R (R Core Team, 2012) using the rjags interface (Plummer, 2003).

3. Results

3.1. Fire occurrence model

The model of fire occurrence was able to reproduce the patterns observed in the data (Fig. A.1). Main effects for all predictors were significantly different from zero (Fig. 2). Consistent with expectations, greater drought intensity (lower SPI values) was associated with greater fire occurrence (Fig. 2), and the magnitude of the effect of drought intensity on fire probability stood out as far larger than the effects of any other predictors; it was more than double the magnitude of the next largest effect (farm size). The probability of fire increased with the percent of the farm in fallow and to a slightly lesser extent, in pasture. The presence of a landowner on a farm decreased the probability of fire, and fire was less likely on farms located in villages with a higher percentage of landowners residing in that village. The predicted probability of fire was higher on farms located in villages with a larger percent in fallow, but was reduced in villages with a large proportion of pasture.

There were significant interactions between the index of drought intensity and both percent fallow on the farm and village-scale landowner absenteeism. The magnitude of the effect of percent fallow on a farm on the probability of fire was higher in drought years (Fig. 3a). In wet years, probability of fire increases only slightly as the percent of a farm in fallow increases. In dry years, the overall probability of fire is much higher, but also increases more quickly as the percent fallow on a farm increases. There was a positive interaction between drought intensity and the percent of landowners in a village who live locally. In dry years, farms located in villages with high levels of landowner absenteeism were more likely to burn than those in villages where more landowners are present (Fig. 3b).

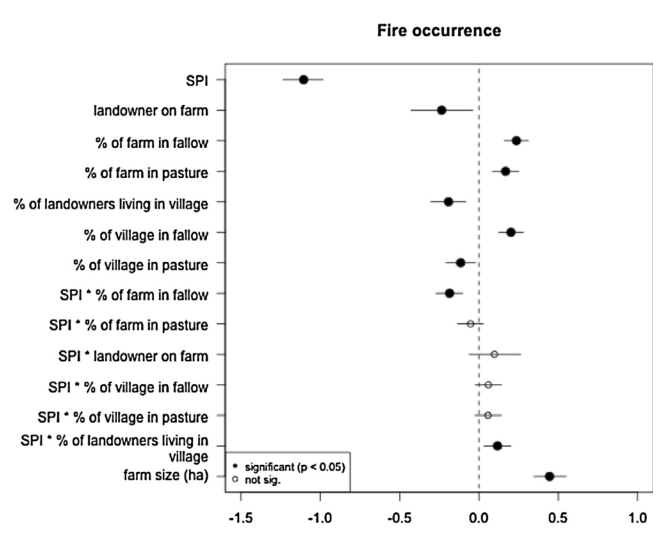

Fig. 2. Standardized regression coefficients for model predicting fire occurrence.

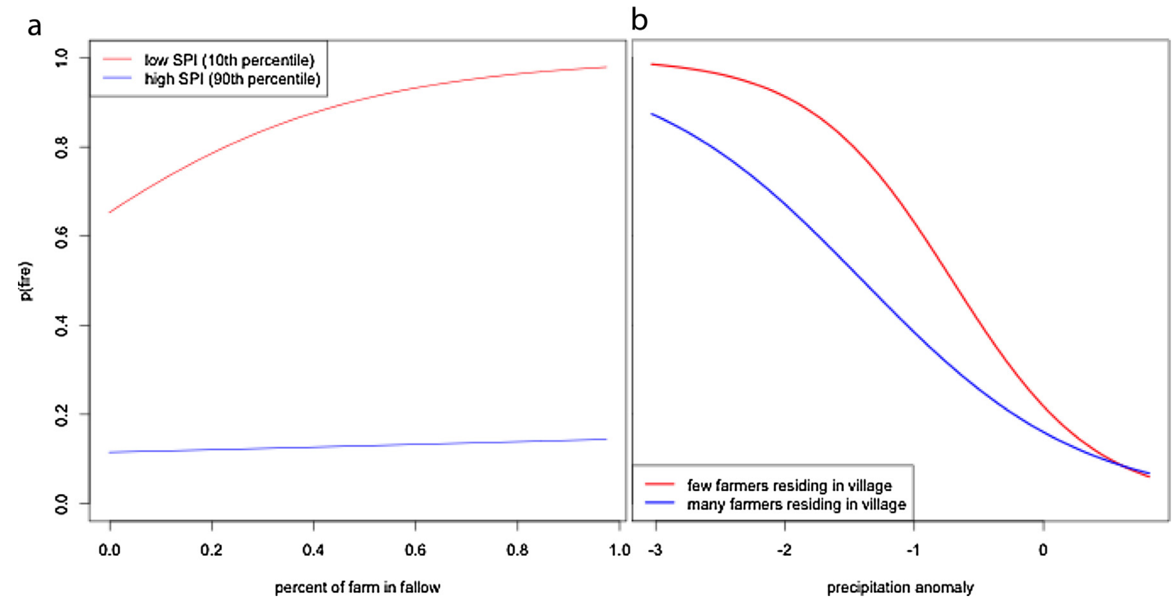

Fig. 3. (a) Predictions for probability of fire as a function of percent farm in fallow. When SPI is high (wet year), fire probability is low regardless. In dry years, fire probability is higher overall, but increases with percent fallow on a parcel. (b) Predicted probability of fire as a function of SPI. Blue line depicts predictions for village with a high percent of landowners residing in the village (90th percentile) while red line is for villages with a low percentage of farmers residing in village (10th percentile). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

3.2. Fire size model

Results from the model to predict fire size (the total area of fires overlapping with an individual farm in a given year) were qualitatively different from the results from the fire occurrence model (Fig. 4). While the model of fire size accurately reproduced the trend in the observed data, the model under-predicted the size of large fires (Fig. A.2). SPI was negatively correlated with fire size, meaning that fires are larger in drier years. However, unlike the model of fire occurrence, here there were other predictors that had effects of almost the same magnitude as that SPI. Several of the village level predictors had effects comparable in magnitude to that of SPI, with larger fires associated with farms within villages with a high percent cover of fallow and in villages with fewer landowners residing on site. The only farm-level predictor that was significant was percent of farm in fallow, with farms with a large percent in fallow being associated with larger fires.

As in the previous model, there were several significant interactions between SPI and the other predictors, but the nature of these interactions was different. The negative interaction term between percent of a village in fallow and SPI means that farms located in villages with a high percent of fallow land cover tend to be associated with large fires regardless of SPI, whereas when there is small area of fallow in a village, climate is more important in determining fire size (Fig. 5). In other words, the relative effect of SPI is greater in villages with less percent cover of fallow.

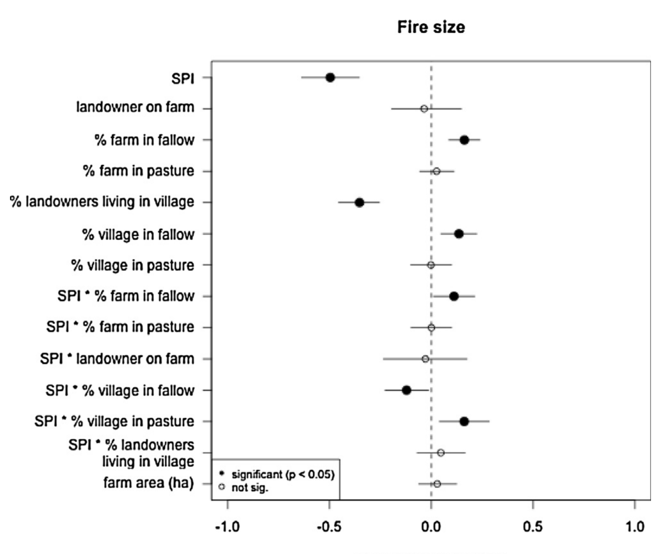

Fig. 4. Standardized regression coefficients from the model to predict fire size.

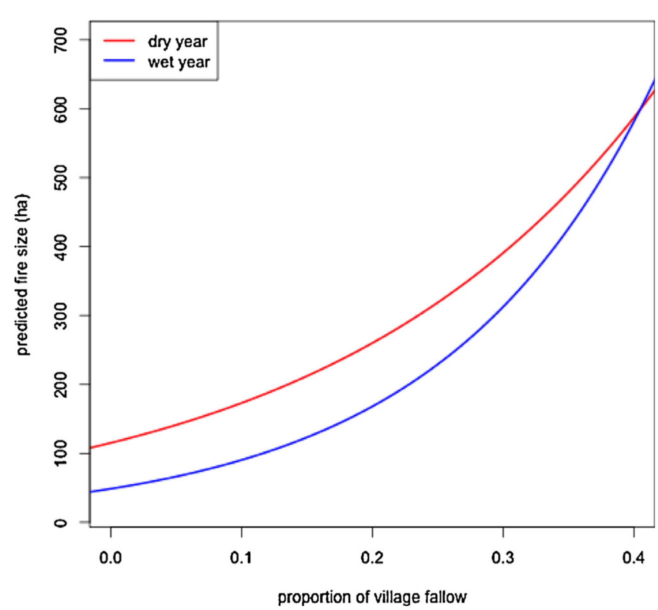

Fig. 5. Predicted fire size as a function of the proportion of a village in fallow. Red line shows predictions for a dry year (10th percentile SPI) and blue line shows predictions for a wet year (90th percentile SPI). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

4. Discussion

We combined data from meteorological stations, remote sensing, and landowner surveys to examine the relative importance of and interactions between multiple drivers of fire activity in the Peruvian Amazon. As expected, drought intensity is an important predictor of fire occurrence and fire size, although its relative importance compared to other significant predictors is far greater in the model of fire occurrence than in that of fire size. We also found that the relative importance of predictors varies depending on the scale at which they are measured: in the model of fire occurrence, the predictors at both household and village scales are important, but in the model of fire size, the importance of village scale predictors outweighs that of the household scale predictors. These differences across scales and across metrics of fire activity have implications for understanding future fire regimes and for fire prevention and mitigation activities.

4.1. Relative importance of climate, patterns of landowner residency, and land cover for predicting fire activity

Other studies have shown that because much of the Amazon is so wet, climate exerts a strong control on fire (Alencar et al., 2011, 2004; Fernandes et al., 2011; Nepstad et al., 2004). Because almost all ignitions are caused by human activities, at some level fire occurrence is limited by whether or not there are people present and whether or not they are using fire. However, in dry years, fires are more likely to escape, spread further and burn a larger area, which increases the likelihood that any given farm is burned by a fire large enough to be detected by satellites. While variables associated with human activities were important in our models, we found that climate was the most important driver of fire occurrence. In the model of fire occurrence, the effect of drought intensity overwhelms the effects of other predictors, with an effect about twice the magnitude of any others. Fire is more common in the drier and more seasonal eastern Amazon than it is in the more humid western Amazon (DeFries et al., 2008; van der Werf et al., 2009), so the constraint of climate on fire occurrence may be particularly strong in Ucayali and other regions of western Amazonia. This is consistent with the varying constraints hypothesis, which implies that in wet regions fire should be constrained by fuel moisture conditions (Krawchuk and Moritz, 2011). If it is too wet, agricultural fires will rarely escape control, regardless of land cover type, landowner place of residence, or management practices. Climate also exerts a strong influence on fire size, with big fires more likely in dry years.

However, within dry years, there is still considerable heterogeneity in spatial patterns of fire, driven by factors other than climate. Our results were consistent with other studies that have examined the role of human activities in driving patterns of fire in the Amazon. While conventional wisdom has said that more people and more land preparation mean more fires in the Amazon, recent findings, including those presented here, indicate that this relationship is more complex than previously thought. In the Brazilian Amazon, fire occurrence has increased in the majority of the areas where deforestation rates have declined (Aragão and Shimabukuro, 2010). Morton et al. (2013) found high levels of understory fire activity in Mato Grosso, even as deforestation rates were some of the lowest in recent decades. Uriarte et al. (2012) found that fire activity in the Peruvian Amazon was more extensive in provinces with high levels of rural-to-urban migration and in villages with high levels of landowner absenteeism. Our results extend this finding to a finer spatial scale, demonstrating that fine scale analysis can help explain the mechanism behind the observed broad scale trends.

Land cover type was significantly related to fire activity in both the fire occurrence and size models, although the role of land cover was weaker than that of climate in the model predicting fire occurrence. Although not all measures of land cover were significant in both models, fallow and pasture were both correlated with fire activity. There are multiple plausible mechanisms for the relationship between land cover and fire activity, which could be biophysical or related to human activities and decisions. The biophysical explanations relate to differences in flammability: fallow land could be more flammable because there are more fuels that can dry out relatively quickly compared to forest (Gutiérrez-Vélez et al., 2014). Alternatively, the reason fallow land is more prone to fire could be because people frequently burn fallow land for various management purposes. Fire is a common tool for land preparation and agricultural management in the Amazon (Bowman et al., 2008; Carmenta et al., 2013), and so the association between fallow land and fire could represent people's uses of fire for land preparation or pasture management. However, because of the minimum fire size necessary for satellite detection, the fires mapped for this research likely represent escaped fires, suggesting that factors that affect the likelihood of fire escaping, i.e. biophysical factors not directly related to ignitions, are responsible for this association (Gutiérrez-Vélez et al., 2014).

There were significant interaction terms in both models. These interactions illustrate that the nature of the relationships between local-scale variables and fire can change depending on the prevailing climate conditions within a year. For example, percent of farm in fallow has little effect on the probability of fire in wet years, but once it starts getting drier, the amount of the farm in fallow can greatly increase the probability of fire (Fig. 3a). Gutiérrez-Vélez et al. (2014) found that the relationship between land cover types and fire on the pixel scale covaried with climate. They found a particularly strong interaction between secondary forest and fire activity: the direction of the relationship between secondary forest and fire occurrence switches from a negative correlation during wet years to a positive correlation during dry years. In the Brazilian Amazon, human activity is key for determining seasonal and annual trends in fire occurrence, but the effect of drought can overwhelm that of anthropogenic activities, leading to high-fire years when land conversion is low (Aragao et al., 2008). Our results are consistent with these findings, which demonstrate a strong interaction between the effects of human activities and the effects of climate.

4.2. Importance of conditions within vs. around a farm

Fire can occur on a farm in two ways: the ignition can occur in the landholding, or it can spread onto a property from a fire ignited in the area surrounding it. For that reason, we included land cover and landowner residency predictors calculated at both the individual landholding and the village scale, to compare to what degree landscape context (i.e. characteristics of the village in which farms are located) versus characteristics of a property itself are important.

The importance of variables at the village and individual landholding scale varied depending on which metric of fire occurrence was being considered. In the fire occurrence model, the parameters for variables measured at the individual farm and village scale were approximately of the same magnitude. On the other hand, in the model for predicting fire size, the effects of variables at the village scale (percent of landowners living in village and percent of village in fallow) were much larger than those at the individual farm scale, of which only one predictor, percent of property in fallow, is significant. This suggests that efforts to control fire size should target communities, perhaps working to build fire control and firefighting capacity or working to manage fallows in a way that would reduce flammability, in addition to targeting management practices of individual households. This also corroborates the hypothesis that large fires are related to a limited capacity to control fire (Uriarte et al., 2012), as fire control can be a community effort (Bowman et al., 2008; Brondizio and Moran, 2008).

4.3. Drivers of fire occurrence vs. fire size

As expected, there were differences between the models predicting fire occurrence and fire size (total area of fires overlapping a farm), mostly in terms of differences in the relative magnitudes of the coefficients of the various predictors. Fewer of the predictors found to be significant in the model of fire occurrence were significant in the model of fire size. This could relate to the fact that the model of fire size in general did a poorer job predicting the observed data (Fig. A.2) and suggests that there may be factors important for predicting the size of fires overlapping with a farm that we did not measure or include in our model, such as landscape configuration or fuel connectivity on or around a farm. Gutiérrez-Vélez et al. (2014) found that the degree of aggregation and patchiness of some land cover types affected fire spread, i.e. the number of pixels burned around a focal pixel. Including such a measure of the degree of connectivity or fragmentation of particular fuel types might have improved our predictions of fire size. A lower predictability of fire size might also be influenced by limitations in fire detection given the relatively coarse resolution of the satellite source (250 m pixel size) used for burn scar mapping, the absence of data on the time of burning, and possible errors in estimation of fire size, as discussed in Section 2.3.

One key difference between the models of fire occurrence versus fire size was the difference in the strength of the effect of climate relative to the strength of the other significant predictors. Climate is an important predictor of fire occurrence and size, but its influence relative to other predictors is smaller in the model of fire size. Fires are bigger in dry years, but several other predictors also have quite large contributions; in particular, larger fires are associated with landholdings located in villages with high levels of landowner absenteeism and in villages with a high percent cover in fallow.

The significant interaction terms in the model predicting fire size also illustrate that the dynamics in models of fire size are different than in those for fire occurrence (Fig. 5). Once a fire is ignited, it is likely to be large in villages with a high percent cover in fallow regardless of a year's climate conditions. On the other hand, if there is small area of fallow, predicted fire size is much smaller overall, but is significantly larger in dry years than in wet years. In this case, local conditions are more important in determining fire size, with big fires happening when village conditions are favorable with comparatively less influence of climate conditions. This is in contrast to the dynamics observed in models predicting fire probability, where only in dry years do conditions such as landowner place of residence and land cover type elevate the probability of fire.

These results suggest that studies should consider multiple aspects of fire regimes to gain full understanding of the relative importance of and interactions between different drivers of fire activity. In our study area, conclusions about which fire prevention and mitigation activities are most likely to be effective could vary depending on the model being considered. The model of fire occurrence suggests that management to lower the probability of fire should mainly focus on responding to anticipated climate conditions. Fire prevention interventions to this end include early warning systems meant to inform farmers of extreme weather conditions that create high risk of escaped fires (Goldammer, 1998), coupled with education about how drought affects the risk of escaped fire and under what conditions it is safer to burn. However, other variables, which could imply different management responses, become equally relevant when fire size is considered. For example, targeting fire-fighting efforts and building community fire-control capacity in areas with high levels of absenteeism, or building fire breaks in areas with extensive fallow land may also be effective at minimizing the occurrence, size and effects of escaped fires. Area burned, not just fire occurrence, is important for emissions and property loss. Management interventions could usefully focus on minimizing fire size and not just preventing people from using fire, especially because fire is an inexpensive and effective management tool that has been in use for millennia (Bowman et al., 2008; Carmenta et al., 2013).

4.4. Future research

By simultaneously using data on climate variability, landowner residence and land cover type to model two different metrics of fire activity, this study provides a deepened understanding of the relative importance and interactions between the multi-scalar drivers of fire activity. Yet we still require a further understanding of the sources, numbers, and spatio-temporal patterns of ignitions. Fires cannot occur without ignitions, and all ignitions in this region come from human activities. Changing the spatial and temporal patterns of ignitions could have a major effect on patterns of fire activity. While some of the predictors considered in this analysis may reflect differences in ignitions–for example, ignitions might be more common in pasture as it is frequently burned for management – a more direct examination of the sources and patterns of ignitions would help our understanding of the degree to which ignitions are limiting in the region.

Additionally, fire activity may have positive feedbacks: a place that burns once may be more likely to burn again in the future because of fire-induced changes to fuel structure. This phenomenon has been observed elsewhere in the Amazon (Nepstad et al., 2001); however, it has not been investigated in this region. Alternatively, in places that burn frequently, there may be a negative fire feedback as fine fuels may become slower to accumulate (Balch et al., 2008). Analyses of repeat burns could provide insights into whether or not this phenomenon occurs in the wetter Peruvian Amazon as well, which would have implications for our understanding of fire regimes in the region and for fire management.

5. Conclusions

Climate variability and change, land use change, and other shifts in human activity and demographics are expected to alter future fire regimes around the world (Bowman et al., 2011; Krawchuk et al., 2009), and are projected to lead to increases in future fire activity in the Amazon (Chen et al., 2011; Silvestrini et al., 2011). Better understanding of the drivers of fine scale patterns of fire activity provides insight into appropriate actions to minimize the risk of escaped fires and decrease the risk of property loss to fire in these landscapes (Carmenta et al., 2013; Sorrensen, 2009). By focusing on the individual farm scale, we were able to combine climate and land cover data, along with data on patterns of landowner occupation to better elucidate how these variables affect patterns of fire on a relatively fine scale. This study adds to the growing literature demonstrating that fire in the wet tropics is not simply a byproduct of deforestation and may continue to spread even as deforestation declines (Aragão and Shimabukuro, 2010; Morton et al., 2013; Uriarte et al., 2012). Additionally, the differences we found between the models of fire occurrence and fire size demonstrate that the metric of fire activity being considered can influence results, and highlight the importance of considering multiple aspects of fire regimes. A full understanding of drivers of fire, their relative importance, and their interactions can help to identify the most effective interventions to prevent and mitigate escaped fires in the tropics.

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Appendix A

Table A.1
Correlation matrix between predictors used in analyses.

	SPI	Fallow (farm)	Pasture (farm)	Land owner present?	Fallow (village)	Pasture (village)	% Landowners living in village	Farm area
SPI	1							
Fallow (farm)	0.043	1						
Pasture (farm)	0.072	−0.098	1					
Land owner present?	0.002	0.090	0.034	1				
Fallow (village)	0.031	0.278	−0.105	0.081	1			
Pasture (village)	−0.002	0.053	0.386	−0.0359	0.169	1		
% Landowners living in village	0.019	0.170	0.017	0.359	0.211	−0.087	1	
Farm area	−0.010	−0.072	−0.042	−0.139	0.027	0.096	−0.105	1

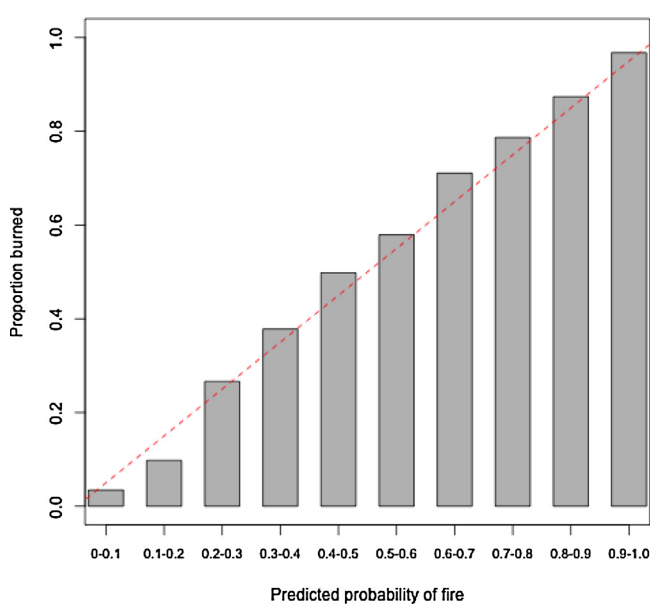

Fig. A.1. Plot of proportion of parcels with predicted probability of fire that actually burned. The red dashed line indicates the expected value for a model that perfect predicts probability of fire. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

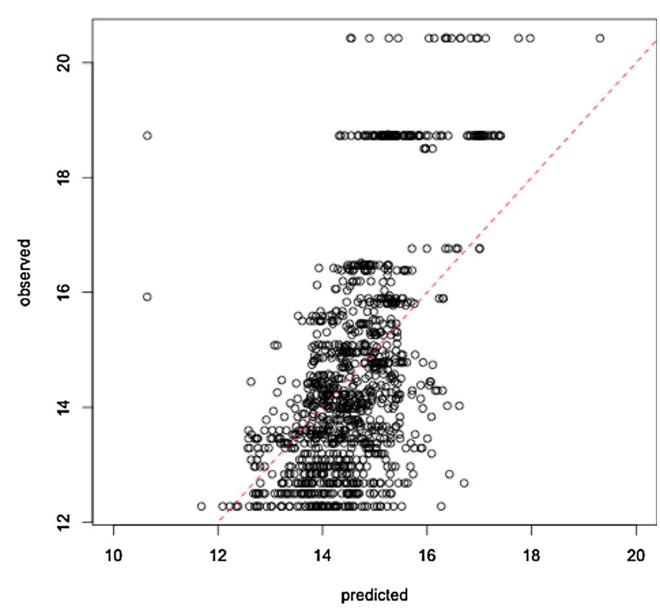

Fig. A.2. Observed fire size vs. predicted fire size. Our model underpredicts large fires.

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