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Integrating remotely sensed fires for predicting deforestation for REDD+

Dolors Armenteras,[1,5] Cerian Gibbes,[2] Jesús A. Anaya,[3] and Liliana M. Dávalos[4]

[1]*Grupo de Ecología del Paisaje y Modelación de Ecosistemas ECOLMOD, Departamento de Biología, Facultad de Ciencias, Universidad Nacional de Colombia, Edificio 421, Cra 30 # 45-03, Bogotá, 111321 Colombia*
[2]*Department of Geography & Environmental Studies, University of Colorado, Colorado Springs, Colorado 80918 USA*
[3]*Facultad de Ingenierías, Universidad de Medellín, Carrera 87 Nro. 30–65, Medellín, 050026 Colombia*
[4]*Department of Ecology and Evolution and Consortium for Interdisciplinary Environmental Research, Stony Brook University, Stony Brook, New York 11794 USA*

Abstract. Fire is an important tool in tropical forest management, as it alters forest composition, structure, and the carbon budget. The United Nations program on Reducing Emissions from Deforestation and Forest Degradation (REDD+) aims to sustainably manage forests, as well as to conserve and enhance their carbon stocks. Despite the crucial role of fire management, decision-making on REDD+ interventions fails to systematically include fires. Here, we address this critical knowledge gap in two ways. First, we review REDD+ projects and programs to assess the inclusion of fires in monitoring, reporting, and verification (MRV) systems. Second, we model the relationship between fire and forest for a pilot site in Colombia using near-real-time (NRT) fire monitoring data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS). The literature review revealed fire remains to be incorporated as a key component of MRV systems. Spatially explicit modeling of land use change showed the probability of deforestation declined sharply with increasing distance to the nearest fire the preceding year (multi-year model area under the curve [AUC] 0.82). Deforestation predictions based on the model performed better than the official REDD early-warning system. The model AUC for 2013 and 2014 was 0.81, compared to 0.52 for the early-warning system in 2013 and 0.68 in 2014. This demonstrates NRT fire monitoring is a powerful tool to predict sites of forest deforestation. Applying new, publicly available, and open-access NRT fire data should be an essential element of early-warning systems to detect and prevent deforestation. Our results provide tools for improving both the current MRV systems, and the deforestation early-warning system in Colombia.

Key words: *edge; fire; forest loss; modeling; Moderate Resolution Imaging Spectroradiometer; monitoring.*

Introduction

Fires are a central force shaping the Earth system, and have particularly large effects on tropical landscapes. Although climate, human actions, and their interactions strongly influence fire incidence (Bowman et al. 2009), tropical fire dynamics are currently changing. Tropical fires have increased in frequency and extent (Cochrane 2003, Barlow et al. 2012, Chen et al. 2013), for reasons ranging from decreases in rainfall and increases in extreme climatic events, to the expansion of human activities (Bowman et al. 2009, Aragao and Shimabukuro 2010, Bowman and Murphy 2011, Brando et al. 2014). Anthropogenic tropical fires, in particular, have many uses and intents, most frequently being associated with agricultural activities (Morton et al. 2007, 2013, Chen et al. 2013). Fires are used in agricultural practices including traditional uses (e.g., charcoal production), and intensive agro-industry (e.g., soy bean, sugar cane; Morton et al. 2008, Alencar et al. 2015). Fires are also used as a forest clearing tool, ultimately resulting in land cover change (Fearnside 2005, Chen et al. 2013). This particular use makes fires potentially predictive of forest fragmentation and deforestation, as well as important factors in forest degradation.

From an ecological perspective, the first and most obvious consequences of forest fires are increased tree mortality (up to 50% of trees), and biomass loss (up to 80% after a third fire, depending on previous fires and land use history; Barlow et al. 2012). These consequences are followed by the release of significant amounts of carbon emissions that in drought years exceed the quantities emitted from deforestation alone (Houghton et al. 2000, Barlow et al. 2012, Houghton 2012). Recurring fires can have dramatic consequences for the mortality of all trees, regardless of whether fires are used for forest clearing or understory management. For example, recurring fires can lead to functional deforestation (Barlow et al. 2012), or unintentional (Cochrane 2003) deforestation. Further fire effects on both forest structure and species composition (Cochrane and Schulze 1999, Barlow and Peres 2008) can affect ecosystem function

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[5]E-mail: darmenterasp@unal.edu.co

and reduce the rates of carbon sequestration capacity in tropical forests (Balch et al. 2015).

Complex feedbacks also exist among fire, deforestation, and forest fragmentation/degradation, often resulting in higher vulnerability to future fires (Cochrane et al. 1999, Cochrane and Laurance 2002, Cochrane 2009). In general, fire incidence is higher in areas of deforestation where fire is used as a tool for forest clearing (Aragão et al. 2008, Silvestrini et al. 2011, Armenteras et al. 2013*a*). Once the landscape has shifted from majority forest to majority agriculture, forest fires may increase from edge effects and higher exposure of remaining forest fragments, while understory fires may become more common from accidental/escaped burns from adjacent farms (Soares-Filho et al. 2012). Indeed, fragmentation increases the susceptibility of forests to fire by increasing the extent of edges, and through biomass collapse and associated microclimate changes (low relative humidity, high wind exposure) exacerbated during droughts (Cochrane 2003, Armenteras et al. 2013*a*). Recurring understory fires also make forest recovery more challenging, and therefore prone to further degradation and tree cover loss.

Given the high incidence of fires, observed and potential increases in burning activity, and the effects of forest fires on regional and global carbon cycles, several authors have highlighted the importance of fires in Reducing Emissions from Deforestation and Degradation [REDD+] and enhancing forest carbon stocks (Aragão and Shimabukuro 2010, Barlow et al. 2012). Surprisingly, the extent to which REDD+ considers and incorporates forest fires in implementing programs varies greatly from local to international levels. A recent revision of REDD projects for their biodiversity co-benefits reports only four projects out of 80 would monitor fire as a threat to biodiversity (Panfil and Harvey 2016). Although forest fires have critical consequences for REDD+, the 2011–2015 global UN-REDD strategy did not explicitly contemplate fires as a main focus areas (Barlow et al. 2012). Several non Annex I countries, however, have addressed biomass burning in their national strategies or action plans by including fires and fire-related forest loss in their greenhouse gas emissions to the United Nations Framework Convention on Climate Change (UNFCCC), or by including fires in the development of their monitoring, reporting, and verification (MRV) systems (Romijn et al. 2012). In fact, most countries have achieved great progress in mapping and monitoring deforestation, but perhaps less on biomass burning. Fire data collection and management, analyses, and incorporation into MRV systems, or even the estimation of emission factors remains a crucial capacity gap (Romijn et al. 2012).

The existing gap in forest fire accounting has the potential to limit mechanisms such as REDD+, as well as national monitoring efforts seeking to inform decisions on forest and emissions. Even though implementation of fire monitoring is highly uneven, currently available remotely sensed data sources could be used to quickly improve biomass burn and forest change mapping, and predicting deforestation. Remotely sensed data, such as Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) products offer systematic measures of the Earth's surface with a relatively high frequency. The daily active fire product derived from MODIS, in particular, can provide near-real-time (NRT) monitoring of fires. Integrating such data sets with existing frameworks based on the relationship between fire and forest fragmentation, and associated feedbacks, can improve forest management and monitoring efforts in many places. Additionally, using frequent Earth observations to understand processes related to deforestation and degradation can improve the implementation of mechanisms such as REDD+, and contribute to reducing emissions from tropical forests, while helping conserve forest carbon stocks and reduce susceptibility to unintended fires.

Here, we address the critical gap in fire accounting in two ways. First, we review and synthesize the current ways in which REDD+ programs monitor fire and its consequences in non-annex I countries. Second, we use near real time (NRT) fire monitoring to examine the relationship between spatial patterns of fire, and forest fragmentation (i.e., forest edge) and deforestation. These analyses address the potential to extend current mapping and monitoring strategies by deploying NRT fire detection and spatial analysis to predict forest loss. We aim to help develop early-warning systems to identify deforestation-prone areas using NRT fire data, and therefore improve resource allocation and land management. We focus spatial analyses on a pilot area within a deforestation hotspot in Colombia, and test models to predict deforestation hotspots using simple measures such as the distance to the nearest fire and the distance to the forest edge. We assessed the potential for integrating these spatial relationships into the current early-warning system by comparing the officially published deforestation early-warning results for 2013 and 2014 derived from Colombia's REDD program (IDEAM 2013, IDEAM 2014). Finally we provide the prediction of deforestation for 2015 for the pilot area.

Methodology

Study area

The study site is located in the northwest region of the Amazon basin corresponding to an area of ~1378350 ha between the municipalities of San José del Guaviare and El Retorno in Guaviare, Colombia (Fig. 1). The southern part of the study area overlaps with the Nukak national natural reserve and includes five indigenous groups. The altitude ranges between 100 and 200 m with a tropical very humid and mono-modal climate, annual rainfall varying from 2800 to 3500 mm, and an average annual temperature of 24.5°C. This region supports high floristic and ecological complexity as a result of its geological,

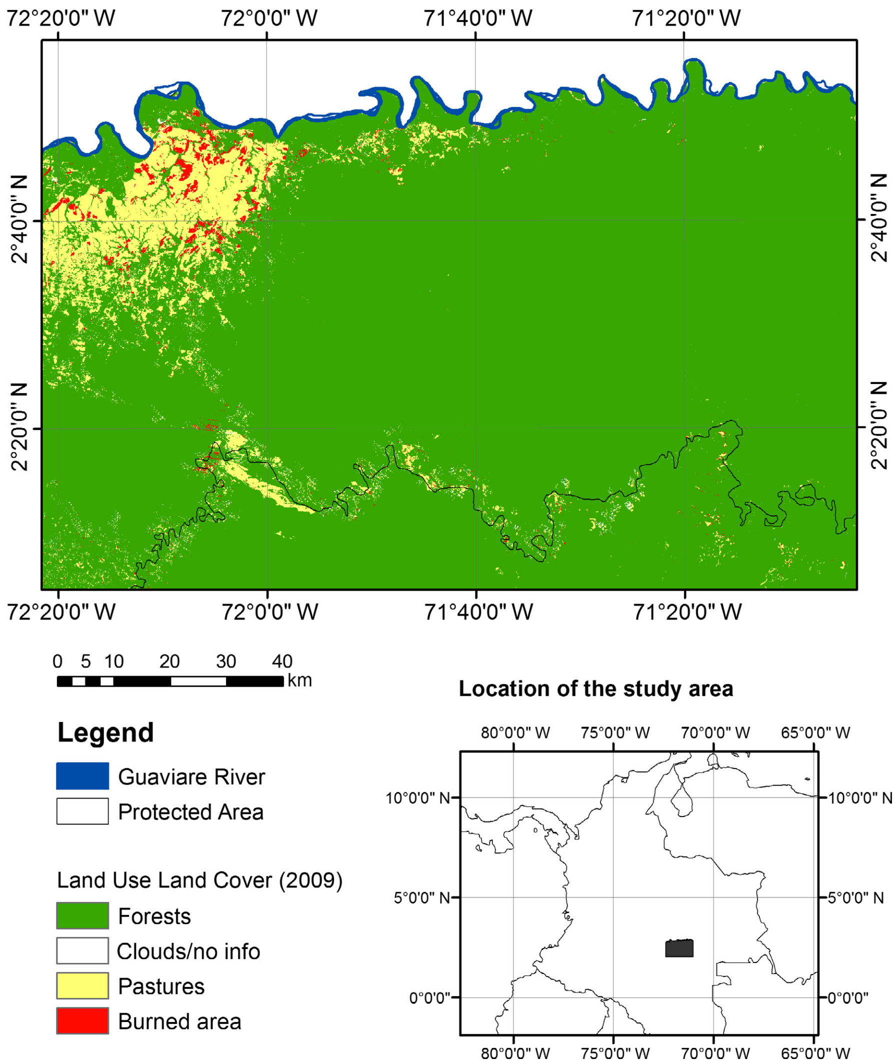

FIG. 1. Land use land cover map for 2009 and location of the study area in Colombia. [Colour figure can be viewed at wileyonlinelibrary.com]

topographic, soil, and water gradients and includes several tropical rain forest systems (Armenteras et al. 2013*b*).

Economic activities in the region are primarily related to natural resource extraction, followed by the establishment of pastures and crops (Ariza et al. 1998). Economic and land use activities directly related to fire are largely driven by local agricultural practices, in particular, the maintenance and creation of pastures for grazing. Livestock is primarily concentrated near municipalities with ongoing development of infrastructure and roads. The study area lies on the edge of an active colonization front, with dynamic land use and land cover change and high deforestation rates (Dávalos et al. 2011, 2014, Armenteras et al. 2013*b*). Fire occurrence in the study site can typically be divided into three categories: (1) maintenance of current pasture land, in which fire is primarily used to stimulate grass regeneration; (2) clearing of vegetation to create new areas for agriculture; and (3) escaped fires associated with pasture maintenance that spread into nearby forests. For monitoring purposes, it is important to discriminate intentional deforestation and escaped fires from other types of fire. Escaped fires, in particular, affect forest edge health, and increase the susceptibility of the forest to future deforestation. We used 2001 as the starting year for analyses because of the availability of high quality geographic data for this area, which has been extensively validated with in situ observations (Armenteras et al. 2013*b*). The remoteness of the study area reinforces the need for maximizing the use of remotely sensed Earth observations for monitoring purposes.

Data and analysis

Review of fire monitoring in REDD programs or projects.— To discover where fire monitoring was integrated within

MRV-REDD systems, we conducted a document review approach focused on REDD+ programs in non-annex I countries. The review was limited to project documentation for non-annex I countries available online up to December 2015. We focus here on non annex I countries, as REDD deforestation efforts emphasize these countries. Relevant key terms were identified throughout each document, including: fire, monitoring, emissions, deforestation, forest degradation, burning, and forest loss.

In the document review, we identified the presence of specific fire monitoring efforts, and the approaches used in these efforts. The context of these terms was used to determine the presence of, and approach used, for specific fire monitoring objectives of the REDD projects. Through an iterative process—first by the lead author, then by the primary co-author, and finally through a joint review by all authors—these documents were categorized based on the presence and treatment of fire monitoring. Additionally, the geographic distribution of fire monitoring strategies was mapped. The results from this review offer a measurement of the prevalence and nature of the strategies used to monitor fires. We reviewed a total of 55 documents, including both REDD project documents and peer reviewed articles related to specific REDD projects or initiatives at regional, national, or subnational levels.

Fire data.—We used the Collection 6 active fire detections derived from MODIS on board Aqua and Terra (Giglio et al. 2003, 2016). This data set is free and publicly available. Daily files covering January 2001 to December 2014 were downloaded in ASCII format (monthly files comprising Terra and Aqua; *available online*).[6] The MODIS fire data provided the center coordinate of 1-km nominal pixels with detected fire activity. Each observation in the MODIS product included a confidence level (Giglio et al. 2003). To reduce the chances of including observations unrelated to fire incidence, we selected only observations with medium to high confidence levels (confidence value ≥30). The final data set consisted of fire occurrences between 2001 and 2014 for the study area during the prevailing fire season (January to March).

Forest data.—Forest cover was assessed in two ways. First, we used a global annual forest cover product consisting of two classes (forest and non-forest) and based on Landsat 4, 5, 7, and 8 satellite data (Hansen et al. 2010). We used this forest cover product for the years of 2001–2014 to assess the dynamics of forest loss in the pilot area. A second land cover classification data set consisting of four land classes (forest, secondary forest, pasture, and burned area), in addition to clouds and shadows (classified as missing data) was derived from 2009 Landsat TM imagery (Armenteras et al. 2013*b*). That regional classification scheme was accomplished using a maximum likelihood supervised classification method and validated using in situ observations. This single-year, regionally adjusted land classification data set was used for contextual purposes and later reclassified into a binary (forest and non-forest) format to match the Hansen et al. (2010) data set.

Statistical approach.—To control for spatial autocorrelation, we grouped observations into sub-municipal units or *veredas*, roughly equivalent to U.S. census tracts, obtained from an online database (OCHA Colombia et al. 2016). These units were then used to calculate a neighbor matrix as outlined below. The relationship between fires and deforestation was quantified by the $\log_{10}$(distance) (in kilometers) between all pixels and the nearest fire in old growth or secondary forest the preceding year. Analyses encompassed fire observations from 2001 to 2014, and forest lost since 2002 through 2015. A total of 1271713 ha of forests were modeled in 3605 pixels for 13 yr. The final data set encompassed 46865 dated pixels.

To measure the ability to predict deforestation based on forest fires, we used spatially explicit landscape models. The neighbor matrix within ~55 km of each sub-municipal unit was calculated for every one of 45 sub-municipalities. Deforestation was modeled as a binomial response in multi-level regressions. The spatial component was defined by a random vector at the level of sub-municipalities, given by:

$$x_i | x_j, i \neq j, \tau \sim \mathcal{N}\left(\frac{1}{n_i}\sum_{i\sim j} x_j, \frac{1}{n_i \tau}\right) \quad (1)$$

where n_i is the number of neighbors of the political unit i, $i{\sim}j$ are the two neighboring units i and j, and τ, the precision parameter, is the variance of the effect across different sets of neighbors (Besag and Kooperberg 1995). The relationship between deforestation and the distance to the nearest fire the preceding year was fitted as a fixed, or sample-wide coefficient.

We fitted regressions with several combinations of predictors using nested Laplace approximations to approximate Bayesian inference for latent Gaussian models (Rue et al. 2009) In particular, we fitted models with and without bins based on the $\log_{10}$(distance) (in km) to the edge of the forest. Four bins of distance to the edge were included as an additional random effect defined by a random walk of order 2 (rwr2) assuming independent second-order increments, with density defined by

$$\tau^{(n-2)/2} \exp\left\{-\frac{1}{2}\mathbf{X}^T\mathbf{Q}\mathbf{x}\right\} \quad (2)$$

where $\mathbf{Q} = \tau\mathbf{R}$, $\mathbf{R}$ is the structure of the neighborhood in time steps for the model, and τ accounts for the variance in structure. The year in which deforestation was recorded was also included as a potential rwr2 random effect. We used the INLA package v.0.0-1455098891 (Rue et al. 2016) implemented in R v.3.2.4 (R Development Core Team 2016) to fit all models. Data and scripts are deposited in the Dryad Digital Deposit (see *Data Availability*).

[6]ftp://fuoco.geog.umd.edu

Table 1. Spatial models, log marginal likelihoods, and log Bayes factors (BF).

Sample-wide (fixed) terms	Group-specific (random) terms	log marginal likelihood	log BF
None	spatial	−5238.95	—
Distance to nearest forest fire	**spatial**	**−1679.33**	**3559.64**
Distance to nearest forest fire, distance to edge	spatial	−4794.66	444.29
Distance to nearest forest fire	spatial, year	−4961.39	277.56
Distance to nearest forest fire, distance to edge	spatial, year	−4813.92	425.03

Notes: Bayes factors compare the evidence in favor of the statistical model compared to the first, purely spatial, model. BF >10 represents decisive evidence for the model given (Kass and Raftery 1995). The best-supported model is shown in boldface type.

We used Bayes factors to compare models, using a purely spatial model based on sub-municipal units (Eq. 1) without any predictors (i.e., considering neither distances to fires the previous year, nor distance to the forest edge) as the baseline model. The Bayes factor summarizes the evidence in favor of one statistical model compared to another based on the empirical data (Kass and Raftery 1995), given by

$$\log \mathrm{BF} = \log(\mathrm{mL}(\mathrm{model}_1)) - \log(\mathrm{mL}(\mathrm{model}_2)) \quad (3)$$

where mL is the marginal likelihood of a model, and model_2 in this case corresponds to the purely spatial model. We follow guidelines by Kass and Raftery (2012) to interpret Bayes factors: BF <-2 suggests preference for model_2, BF >2 for model_1, $6<$ BF <10 strong evidence for model_1, and BF >10 represents decisive evidence for model_1. Table 1 summarizes the models, their log marginal likelihoods and Bayes factors. We then used the best-supported model to predict deforestation. Posterior distributions of parameters for the best-supported model are shown in Table 2.

We used the area under the curve (AUC) of the receiver-operator characteristic (ROCR) to quantify the success for the model in predicting deforestation (Hanley and McNeil 1982). This statistic measures the probability that a randomly selected cell is correctly classified as 1 or 0, based on the log-odds predicted by the function obtained from the model. The AUC ranges from 0 to 1, with 0.5 indicating a completely random model, and 1 indicating a perfect model (Hanley and McNeil 1982). The main advantage of using this statistic is the ability to separate location from quantity in the performance of deforestation models (Pontius and Batchu 2003), generating an unbiased assessment of error in predictions. The ROC and corresponding AUC were obtained using the ROCR R package (Sing et al. 2005). The OptimalCutpoints R package (López-Ratón et al. 2014) was used to calculate confidence interval of the AUC. We also calculated the AUC and its confidence interval from existing early-warning system predictions for 2013 and 2014. Finally we provide the prediction for 2015 deforestation.

Results

Document review revealed 58% (32 documents) of the projects fail to (1) explicitly identify fire as a driver of deforestation and/or forest degradation and/or (2) consider fire monitoring as a REDD objective. Fire was referred to as a tool used for preparing agricultural lands and identified as a forest disturbance in 24 of the documents reviewed. Thirteen documents identified a clear relationship between fire and deforestation, in which fire is considered a driver of deforestation. Yet, with regard to emissions, fire is primarily associated with land cover change from forest to agriculture, as opposed to direct emission resulting from the fire occurrences themselves. Fire monitoring has a more limited representation, mentioned in only four documents. The majority of the documents, 17 out of the 23 documents that do mention fire, state the intent to develop fire monitoring processes as related to deforestation and forest degradation. These monitoring strategies are centered on the use of information from satellite data, e.g., MODIS satellite imagery or LANDSAT for mapping burnt areas.

High annual variability was found in the active fire data between 2001 and 2014 (Figs. 2, 3A). The number of active fires detected ranged from 158 to 487, with a 10-yr average of 236 ± 91. The year with the most active fires was 2007, followed by 2004 with 263 and 2010 with 253, while 2001, 2002, and 2011 were the year with fewest active fires detected. The inter-annual variability in forest loss is also evident during that period, with 2006, 2008, and 2010 showing the highest forest loss totaling, in order, 2902, 2735, and 3832 ha (Figs. 2, 3B).

Table 2. Posterior distributions of parameters for the best-supported model.

Parameter	Type	2.5th percentile	Mean	Median	97.5th percentile
Intercept	sample-wide (fixed)	−3.18	−2.84	−2.84	−2.51
Distance to nearest forest fire	sample-wide (fixed)	−2.39	−2.06	−2.06	−1.72
Precision spatial	sub-municipality-specific (random)	0.0629	0.1528	0.1403	0.3154

Note: See Table 1 for Bayes factor in favor of this model.

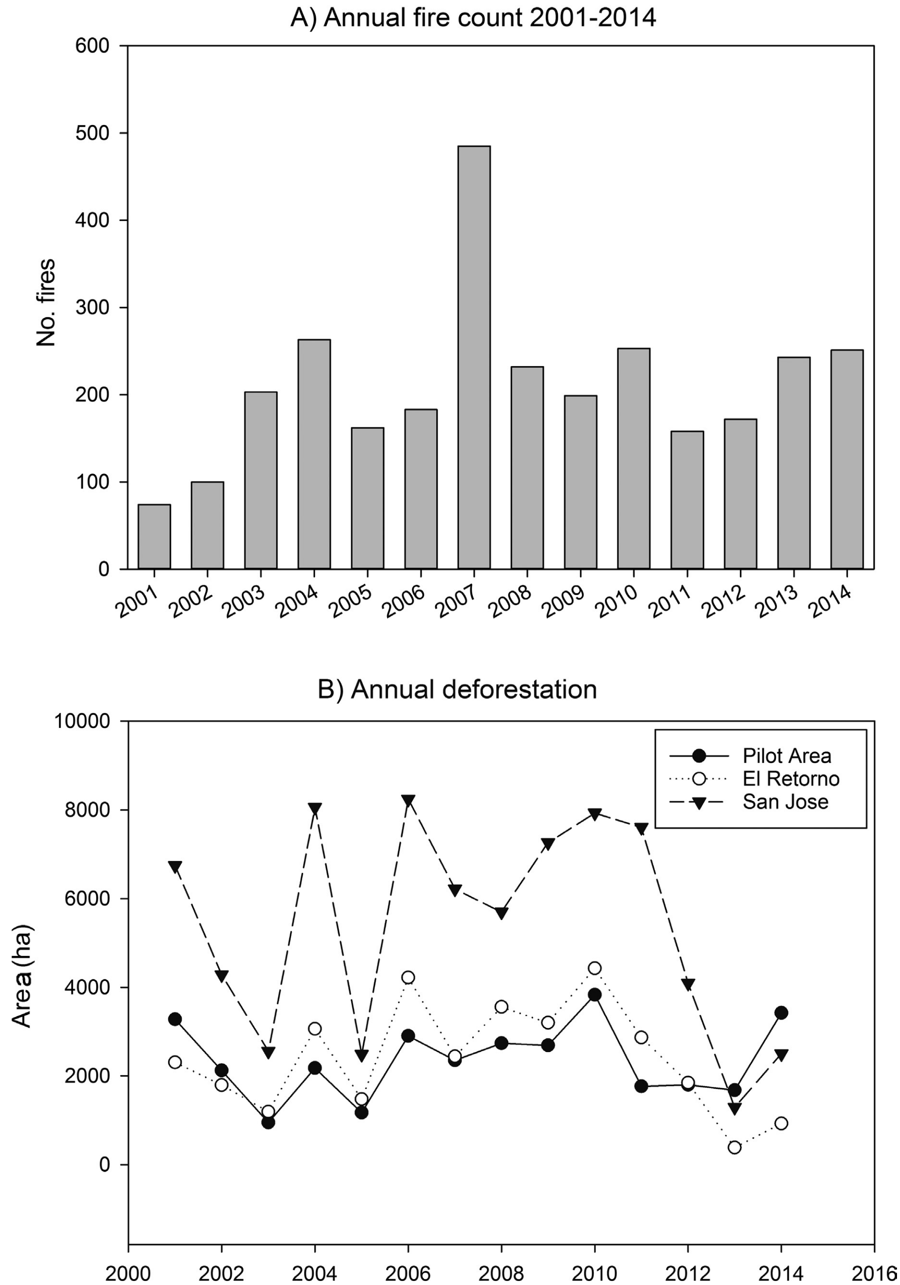

Fig. 2. (A) Number of MODIS satellite active fire pixels detected and (B) hectares of forest loss between 2001–2014 for the pilot area.

The best-supported model of deforestation had the distance to the nearest forest fire the preceding year as a strong and negative predictor of the probability of losing forest (Tables 1 and 2, Fig. 3C). The bin of the distance to the forest edge was not indicative of deforestation in the best-fit model (Tables 1, 2). The year of occurrence was not included in the best-fit model, suggesting annual effects are small and the relationship between deforestation and distance to fires was similar across years. The probability of deforestation drops with distance to the nearest forest fire the preceding year, and is highest at the distance of 0, meaning sites where the fires occur have the highest possible probability of deforestation the following year (Table 2). The resulting best-fit model was validated with observed deforestation, scoring an AUC of 0.818 (resampling confidence interval of 0.794 to 0.842, Fig. 3D).

The official deforestation early-warnings maps for 2013 and 2014 can be seen in Fig. 4A and B. Predictions from the fitted model were conducted for 2013 and 2014 by excluding the deforestation response data from each

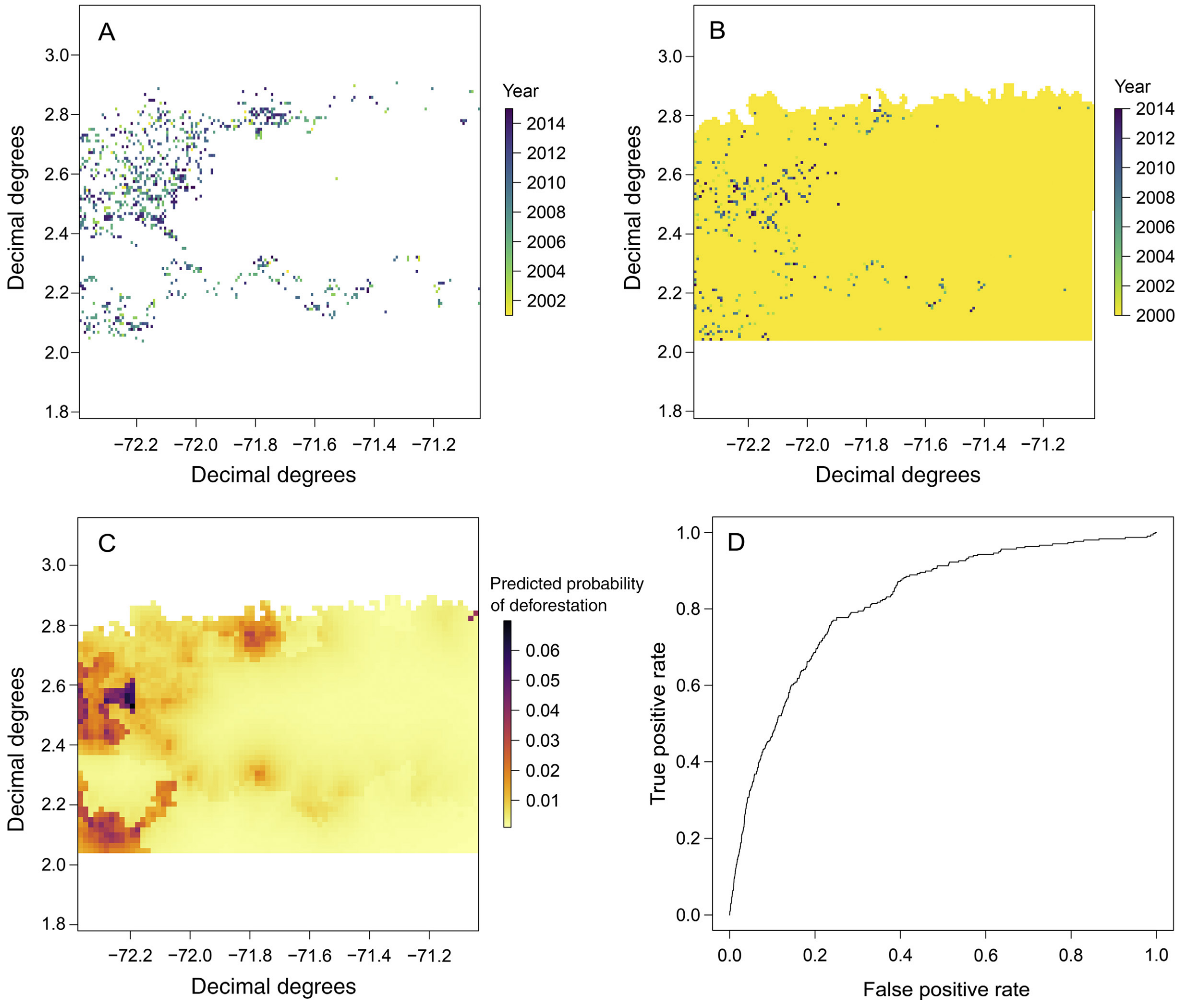

FIG. 3. Modeled probability of deforestation as a function of distance from fires the preceding year. (A) Observed fires, (B) observed deforestation, (C) best-fit multiyear model, (D) area under the curve (AUC). [Colour figure can be viewed at wileyonlinelibrary.com]

of the two years (Fig. 4C, D). The resulting models were similarly predictive with AUCs of 0.811 (95% confidence intervals = 0.786, 0.834). The early-warning system for 2013 had an AUC of 0.519 (95% confidence interval = 0.432, 0.606), while the early-warning system prediction for 2014 had an AUC of 0.681 (95% confidence interval = 0.583, 0.779; Fig. 4). For each of these two years, the fitted model outperformed the early-warning system.

Discussion

Given the central role of fire in shaping landscapes and contributing to regional and global cycles, it is important to elucidate its dynamics in order to minimize the negative effects of tropical fires, and link fire dynamics to direct interventions within REDD+. We investigated how countries are considering fire as a tool to monitor and/or predict deforestation within REDD programs or projects, and found most of them do not use available fire near-real-time (NRT) data for this purpose. We also aimed to determine whether basic spatial relationships, distances to fire and to the forest edge, were good predictors of deforestation. We found distance to the nearest fire is an excellent predictor of future deforestation. It is likely that collinearity with the fire distance alters the effect of the distance to the edge of the forest. These results demonstrate proximity to an active fire as detected through NRT fire observations is a useful early indicator of areas most likely to be deforested in subsequent years. Given the extensive geographical area monitored for deforestation in many countries, simple spatial relationships, such as those presented here, can help focus deforestation monitoring and management efforts (Fig. 5).

It has been recently suggested that countries should link forest area changes to specific driver activities and follow-up land use (Salvini et al. 2014). In our case study area, the majority of deforestation supports the expansion

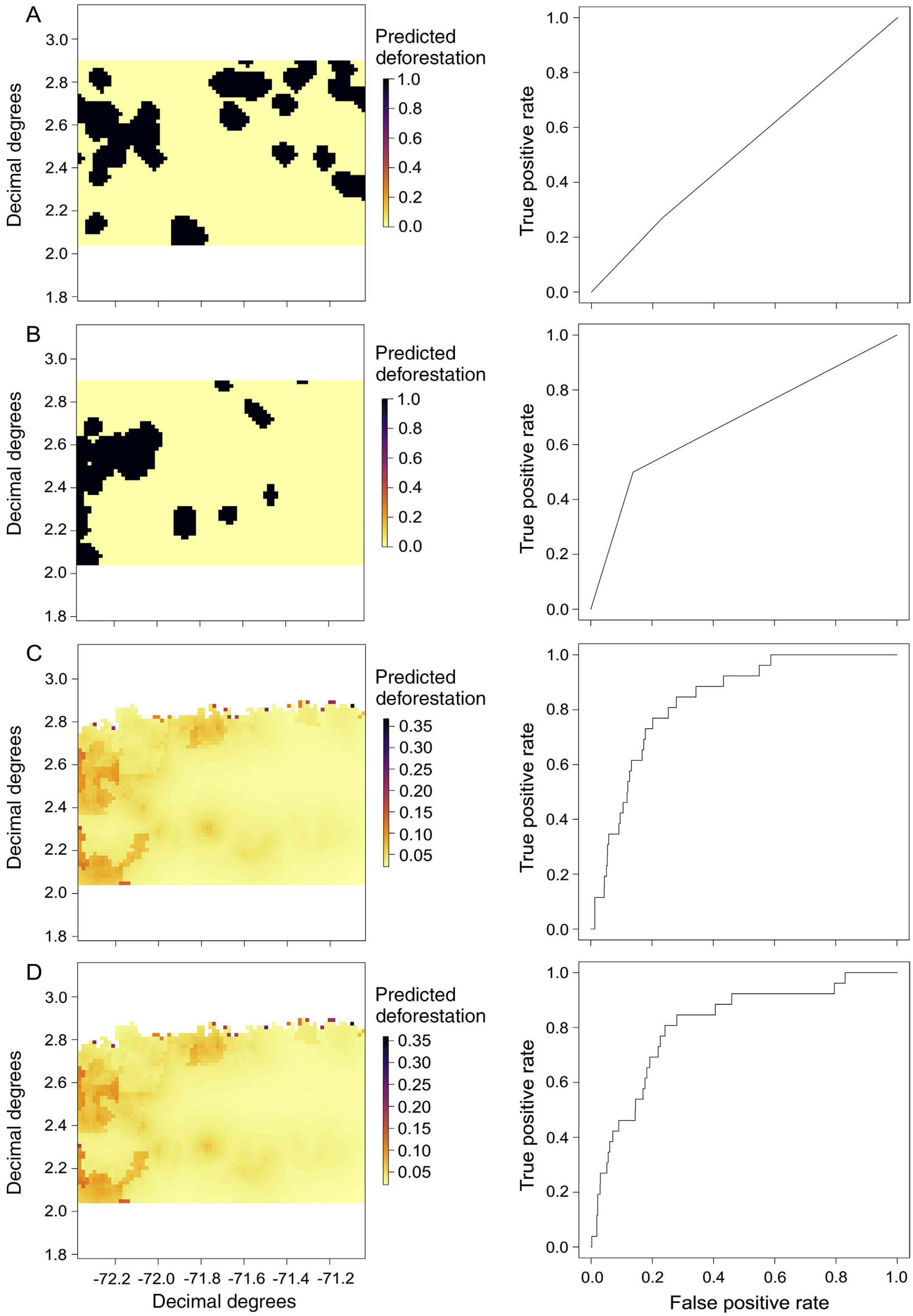

FIG. 4. Comparison of official deforestation early warnings and their AUC for (A) 2013 and (b) 2014 with deforestation predicted by the model of Table 2 for (C) 2013 and (D) 2014. [Colour figure can be viewed at wileyonlinelibrary.com]

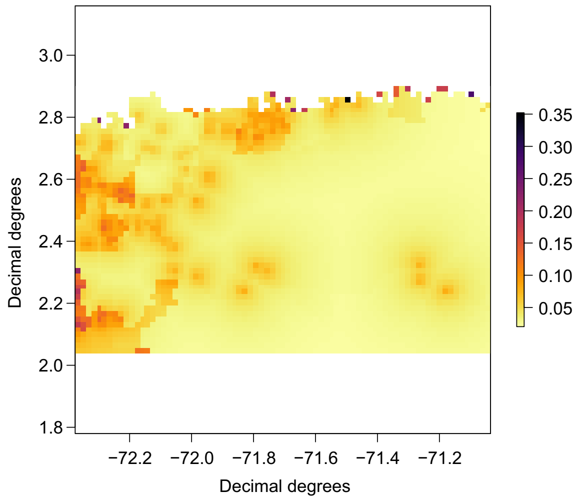

FIG. 5. Prediction for 2015 deforestation. [Colour figure can be viewed at wileyonlinelibrary.com]

of pasture. As escaped fires contribute to forest loss, forest degradation, and emissions, monitoring and potentially managing such fires is crucial to REDD+ efforts. We therefore recommend that in countries where fire is a concern, monitoring strategies should be extended both improve deforestation predictions, and to monitor effectiveness of any fire management and control plan they might propose as an intervention within REDD+ national strategies (Salvini et al. 2014).

The approach proposed here intentionally seeks to use freely available data and statistical approaches, to limit data and analysis inputs in the monitoring and management frameworks, and deploy basic spatial relationships, distance, as a starting point for improvement of such frameworks. Taken together, the free data and modeling approaches identify a simple spatial pattern: distance to fires predict the detection of areas of concern for future deforestation. These findings are in accordance with similar works (Salvini et al. 2014). The approach presented here in the Colombia case study supports high feasibility for national monitoring offices in many parts of the tropics with limited staff and technical capabilities, and few resources. Updating and tailoring the basic analytical approach used here is simple, and only requires coding annual observations in a grid. While the benefit of the approach to national monitoring offices would be refined identification of areas warranting concentrated monitoring and management efforts due to risk for future deforestation.

Incorporating active fire data into deforestation and emissions monitoring frameworks, however, remains challenging because the fire data have limitations. Currently available fire data have limited resolution, and cloud cover can obstruct the detection of fires, underestimating fire occurrence (Giglio et al. 2006, Schroeder et al. 2008). This challenge is somewhat addressed by focusing on detecting fires during the dry season, when cloud cover is typically lower. Although this framework may also underestimate fire occurrence, this is also true of comparable approaches (see for example Müller et al. 2013).

The resolution (1-km) of the MODIS fire data is another potential limitation when analyzing fire–forest spatial patterns. The resolution of the data could limit the fire–forest relationship detected. We anticipate the higher resolution (375 m) Visible Imaging Infrared Radiometer Suite (VIIRS) will become widely available, improving active fire data. As this improved data set becomes fully available, it will be critical to reexamine the fire–forest relationship, at higher resolution. The archives of VIIRS data are not yet available, but weekly data is freely available to the public. Currently, potential early-warning locations for deforestation monitoring might be advanced with the VIIRS fire observations. For retrospective analysis, however, available MODIS data, still offers observations useful for initial examinations of fire–forest relationships despite lower resolution.

Finally, improvements in the available data combined with the changing nature of fire in the tropics, requires adaptive fire-oriented deforestation warning systems. The modeling framework presented here can be easily expanded, and thereby constantly evolve to accommodate improved measures of fire and forest cover, as well as changes in spatial relationships and patterns of fire and forest cover.

CONCLUSIONS

Current mechanisms focused on minimizing forest loss and degradation will benefit from integrating continuously improving fire and forest cover observations, as well as modeling the spatial relationships between fire and forest. We found that quantifying the distance to an active fire is a simple and easy method to identify areas at risk of deforestation. The modeling approach is also easy to implement, allowing national agencies responsible for monitoring forest cover to quickly define the spatial relationship between fire and forests. The distance relationship can then be integrated into early-warning systems used for monitoring and managing fires in Colombia. The free, easily accessible nature of the data, and the simple approach to measuring spatial relationships, distance, allows for transferability to other regions in the tropics. Additionally, this added value to early-warning systems can be used by government and monitoring institutions for which funding is often limited. The efficiency of the methods presented here can be used by many national monitoring offices more effectively than complex modeling.

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Data Availability

Data associated with this paper have been deposited in the Dryad digital repository https://doi.org/10.5061/dryad.1925k