Ecological Applications, 23(3), 2013, pp. 565–582

Human and biophysical influences on fire occurrence in the United States

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Abstract. National-scale analyses of fire occurrence are needed to prioritize fire policy and management activities across the United States. However, the drivers of national-scale patterns of fire occurrence are not well understood, and how the relative importance of human or biophysical factors varies across the country is unclear. Our research goal was to model the drivers of fire occurrence within ecoregions across the conterminous United States. We used generalized linear models to compare the relative influence of human, vegetation, climate, and topographic variables on fire occurrence in the United States, as measured by MODIS active fire detections collected between 2000 and 2006. We constructed models for all fires and for large fires only and generated predictive maps to quantify fire occurrence probabilities. Areas with high fire occurrence probabilities were widespread in the Southeast, and localized in the Mountain West, particularly in southern California, Arizona, and New Mexico. Probabilities for large-fire occurrence were generally lower, but hot spots existed in the western and south-central United States The probability of fire occurrence is a critical component of fire risk assessments, in addition to vegetation type, fire behavior, and the values at risk. Many of the hot spots we identified have extensive development in the wildland–urban interface and are near large metropolitan areas. Our results demonstrated that human variables were important predictors of both all fires and large fires and frequently exhibited nonlinear relationships. However, vegetation, climate, and topography were also significant variables in most ecoregions. If recent housing growth trends and fire occurrence patterns continue, these areas will continue to challenge policies and management efforts seeking to balance the risks generated by wildfires with the ecological benefits of fire.

Key words: fire occurrence; MODIS active fires; wildfire risk; wildland–urban interface.

Introduction

Wildfire management in the United States must balance the ecological benefits of fire with the risks wildfires pose to society. On one hand, fire suppression is necessary to limit the damage to property and threat to public life. On the other hand, fire is an important disturbance process in many ecosystems and necessary to maintain ecosystem composition and structure (Pyne et al. 1996, Bond and Keeley 2005). In the United States, fire policies, management directives, and funding are national in scope (Stephens and Ruth 2005), and thus national-scale models of fire occurrence are needed to help inform fire management decisions. Our goal was to fill this knowledge gap by comparing the relative influence of human and biophysical drivers of fire occurrence using predictive models for the conterminous United States.

The cost of fighting wildfires and the damage wildfires cause are substantial. For example, in October 2007, wildfires destroyed more than 3000 structures and forced the evacuation of one-half million people in southern California (Grossi 2007). In 2003, wildfires in southern California also destroyed 3361 houses (Keeley 2004). Furthermore, the destruction of homes by wildfires is not limited to southern California. In 2010, the Fourmile Canyon fire near Boulder Colorado burned 6200 acres (∼2509 ha) and destroyed 169 homes, In 2000, the Cerro Grande fire burned 235 homes in New Mexico (National Park Service 2006) and, in 1998, wildfires destroyed 340 homes in Florida (Butry et al. 2001).

Even beyond the loss of homes, fighting wildfires has become an increasingly costly endeavor. Federal fire suppression expenditures exceeded $1 billion in four of the seven years between 2000 and 2006 (U.S. Department of Agriculture 2006, National Interagency Fire Center 2009). Wildfires also have high indirect costs. By reducing timber supply and tourism income, and by

Manuscript received 18 October 2012; accepted 15 November 2012. Corresponding Editor: A. D. McGuire.
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increasing health care costs, the economic impact of the 1998 wildfires in Florida was greater than a category 2 hurricane (Butry et al. 2001). Because the expense of fighting fires is high and the consequences of uncontrolled wildfires are great, there is a pressing need to better understand and predict fire occurrence at the national scale.

The expense of preventing and suppressing fires is stretching public land management agencies thin, leaving few resources for other management activities, including those needed to allow fires to burn for their ecological benefits (Dombeck et al. 2004, Noss et al. 2006). This is unfortunate, because fire is an important disturbance process in many ecosystems (Pyne et al. 1996, Bond and Keeley 2005) and maintaining fire regimes within their historic range of variability is a benchmark for conservation success (Hunter 1993, Morgan et al. 1994, Landres et al. 1999). However, fire return intervals have increased by an order of magnitude in many areas (Cowell 1998, Rollins et al. 2001, Cleland et al. 2004, Grissino-Mayer et al. 2004) with negative ecological consequences. In the dry ponderosa pine forests of the Southwest, fire regimes have shifted from frequent low- and mixed-severity fires to less frequent, high-severity fires (Covington and Moore 1994, Baker et al. 2007). Changes in southwestern dry forests have influenced policies implementing fuel treatments to reduce fire risk, but the changes experienced by southwestern forests have not occurred everywhere (Schoennagel et al. 2004). In eastern deciduous forests, fire-tolerant species, such as oak, have decreased in dominance while fire-intolerant species, such as maple, have increased in dominance following years of fire suppression (Foster et al. 1998, Abrams 2003). This change in dominance has resulted in a positive feedback, further limiting fires because litter in maple forests is less conducive to burning (Abrams 2005). In other places, such as southern California, human ignitions have increased fire frequency far above the historic range of variability, causing shrub-dominated ecosystems to switch to grasslands (Syphard et al. 2006, 2007*b*).

Human development and activity can push disturbance regimes beyond the historic range of variability through two primary direct mechanisms: fire ignition and suppression. Human activities correlated with roads and housing cause novel ignition patterns different from patterns generated by lightning-caused ignitions (Chuvieco and Congalton 1989, Cardille et al. 2001, Kasischke et al. 2002, Stephens 2005, Syphard et al. 2007*b*). Suppression occurs through altered ignition patterns, fuel treatments, and fire fighting (Rideout and Omi 1990, Prestemon et al. 2002). The influence of suppression is especially pronounced in the wildland-urban interface where the number of potentially vulnerable homes and the potential costs of uncontrolled fires are great (Cohen 2000, Radeloff et al. 2005*b*, Syphard et al. 2007*b*). Humans can affect fire regimes also indirectly due to landscape-level alteration of the arrangement and types of fuels (Turner et al. 1989, Finney 2001, Duncan and Schmalzer 2004). Furthermore, the magnitude of human influence on fire occurrence may vary with the size of fires (Cardille et al. 2001) and suppression efforts may be overwhelmed by large fires occurring under extreme weather conditions (Bessie and Johnson 1995, Keeley et al. 2004, Cary et al. 2009). Thus, human variables may be more relevant when predicting ignition patterns and less relevant when predicting large fires and the total area burned (Cardille et al. 2001, Syphard et al. 2007*b*). However, human influences on fire occurrence have been studied only from landscape to regional scales, and how they vary across the nation is unknown. Understanding national-scale relationships between humans and fires is important because the strong relationship between human development and fire, and because human factors affecting fire patterns are much more amenable to policy and management actions than other drivers such as climate.

In addition to human activities, fire occurrence is also a function of topography, vegetation, climate, and weather, which together influence fuel type and production, moisture levels, and fire behavior (Pyne et al. 1996, Schoennagel et al. 2004, Moritz et al. 2005, Westerling et al. 2006). Weather conditions are especially important when predicting short-term fire behavior on an hourly or daily basis. For example, short-term changes in precipitation, humidity, temperature, and solar radiation can affect fuel moistures, or sudden changes in wind can have a large effect on fire spread (Rothermel 1972, Bessie and Johnson 1995, Cary et al. 2009). The short-term effects of weather conditions are moderated by vegetation type and topographic influences (Rothermel 1972, Rollins et al. 2004). Climate becomes more important over the long term, in determining fire patterns over annual, decadal, or longer time periods. Climate interacts with topography and vegetation to determine patterns of moisture availability, which determines the types of fuels present at a site, as well as the volume and flammability of those fuels (Neilson 1995, Rollins et al. 2004, Bond et al. 2005). Deviations from long-term precipitation patterns, in particular, can result in drought and increased fire activity (Simard et al. 1985, Swetnam and Betancourt 1990, Veblen et al. 2000, Schoennagel et al. 2004). Biophysical conditions clearly have strong effects on fire occurrence, but how they interact to amplify or deamplify human influences on fire occurrence patterns, and how those interactions vary spatially is less understood.

Our goal was to identify the drivers that influence fire occurrence and how their influence varies across the conterminous United States. To achieve this goal, we examined patterns of fire occurrence across the United States and asked the following questions: What drivers had the most influence on fire occurrence for all fires? What drivers had the greatest influence on the occurrence of only large fires? Did the influence of human variables on fire occurrence vary spatially across the country? Was the influence of human variables the same for large fires as it was for all fires? We developed statistical models that examined the influence of human variables on fire occurrence, while controlling for climate, vegetation, and topography. Finally, we estimated the probability of fire occurrence, assuming that places similar to those that burned in the past are most likely to burn again.

Methods

Overview

To address our research questions, we developed a series of logistic regression models that determined the probability of fire occurrence as a function of the predictor variables. We evaluated the performance of our models using area under the curve (AUC) of receiver operating characteristic plots (Hanley and McNeil 1982). Then, we estimated the relative importance of different predictor variables using hierarchical partitioning (Chevan and Sutherland 1991, Mac Nally 2000). Large fires present unique ecological consequences, socioeconomic risks, and management challenges and large-fire occurrence may be driven by a different suite of processes than other fires (Strauss et al. 1989, Turner and Dale 1998, Kasischke et al. 2002, Lynch 2004, Keane et al. 2009). Therefore, we built two sets of models to compare the relative importance of drivers for large fires and all fires.

We selected a number of data sets as sources of response and predictor variables in our models. As our response variable, we used fire data collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensors onboard NASA's Earth Observing System Aqua and Terra satellites (Justice et al. 2002*b*, Giglio et al. 2003). Satellite data offer consistent observation of fire occurrence with more consistent spatial and temporal accuracy (Flannigan and Vonder Haar 1986, Giglio et al. 1999, Justice et al. 2002*a*, Hawbaker et al. 2008). We selected MODIS fire data because they include fires across all land ownerships, have consistent spatial detail across the globe, and often provide more accurate locations than other fire records, such as the federal fire occurrence database (Brown et al. 2002).

Our predictors included variables representing human, vegetation, climate, and topography drivers. We used housing density and distance from roads to represent human effects; land cover and the normalized difference vegetation index to represent vegetation type and productivity (a proxy for fuel load production); annual precipitation and temperature summaries to represent climate effects; and elevation, slope, and southwestness to represent topographic effects.

We constructed fire occurrence models for all fires and for large fires for Omernik level II ecoregions (Omernik 1987). These ecoregions capture broad-scale differences in weather, climate, soils, vegetation, and land-use patterns. The ecoregion-level approach also provided localized estimates of the driving variables of fire occurrence, facilitating analysis of how those drivers vary spatially across the United States (Loveland et al. 2002). Additionally, subdividing the large volume of input data by ecoregions made our modeling approach more computationally efficient.

Modeling approach

We constructed two generalized linear models to identify the variables influencing fire occurrence for each ecoregion (Fig. 1b). The first modeled the occurrence of all fires and the second only modeled the occurrence of large fires. In both models, we used a logit link to represent fire occurrence as a binary response. We made no a priori assumptions about which variables influenced fire occurrence and used step-wise forward selection (Chatterjee et al. 2000). We selected predictor variables based on Akaike's information criteria (AIC) and removed variables if they did not generate an AIC difference greater than two. When step-wise selection included quadratic variables, the linear form of the variables was also retained.

To avoid spatial autocorrelation and to reduce our data volume, we generated a sample, using a spatially stratified sampling scheme, where observations cannot be closer than the range of spatial autocorrelation observed in the model residuals (Fortin et al. 1989). Our sampling scheme subdivided each ecoregion into blocks of (initially) 3×3 pixels. Within each block, we randomly selected one fire and one non-fire observation. If there were no fire observations within a block, then we retained only the non-fire observation and vice versa. Using the sampled observations, we fit fire models and then fit spherical variograms to a random sample of 2500 of the model residuals. If the spherical variogram explained more variability in model errors than did a constant variance model, we increased block sizes (5×5, 7×7, etc.), generated a new sample of observations and refit our fire model, until there was no significant evidence of spatial autocorrelation in model residuals. Successively increasing block sizes increases the distance between observation, which avoids spatial autocorrelation and ensures that our sampled observations were widely distributed across each ecoregion.

This sampling strategy produced a different proportion of fire and non-fire observations in the sample than exists in the population. These differences can bias model results, so we applied a correction factor (Manly et al. 2002, Keating and Cherry 2004) that weighted the sampled proportion of fires (P_f) and non-fires (P_n) relative to their prevalence in the population of fires and non-fires:

$$\text{Correction} = \ln(P_n/P_f). \quad (1)$$

The number of fires relative to non-fire observations was small (1.2% of all observations were fires), potentially complicating modeling (Dixon et al. 2005).

When events are rare, the precision of predicted event occurrence may be low (Dixon et al. 2005) and the risk of over-fitting models increases (Freedman and Pee 1989). The precision of predictions may be increased by increasing sample size (Dixon et al. 2005). While total sample size was never a limiting factor, the number of fire events in some ecoregions was low and over-fitting may occur when the number of events (fires) per predictor variable is less than 10 (Freedman and Pee 1989, Peduzzi et al. 1996, Dixon et al. 2005). In a few ecoregions this was the case, especially in the large-fires-only samples, and we set a limit on the number of predictor variables to less than or equal to 1/10th the number of fires observed. If this limit was exceeded during step-wise forward selection, then we incrementally removed the least significant variables until the variable limit was met. No large-fire model could be fit for the Atlantic Highlands ecoregion due to the lack of any large fires from 2000 to 2006, and intercept-only models were fit for the mixed wood plains and central plains because only 22 and 16 large-fire pixels were observed in these ecoregions respectively.

Data sources

Fire observations.—The Aqua MODIS sensor captures actively flaming fires at 01:30 and 13:30 and the Terra sensor does so at 10:30 and 22:30 (Justice et al. 2002*a*). In our analysis, we included Terra active fire observations for 2000–2002 and both Terra and Aqua fire observations for 2003–2006 (Fig. 1a). Individual images were mosaicked, reprojected, and converted with the MODIS reprojection tool (U.S. Geological Survey 2009*a*) resulting in 926-m resolution pixels. We removed low-confidence MODIS active fire detections to avoid false detections, limiting our analysis to the more intense fires.

Large fires occur as distinctive clusters of connected MODIS active fire pixels. We developed an algorithm that identified fire clusters by tracking the spatial and temporal spread of active fires (Chuvieco and Martin 1994, Loboda and Csiszar 2007). Our algorithm grouped MODIS active fire pixels into clusters if their spatial and temporal distance or overlap was less than user specified minimums. Based on our visual comparison of MODIS fire pixels with known fire perimeters, we found that one pixel spatial and one-day temporal overlap produced MODIS fire clusters that closely matched fire perimeters measured from Landsat imagery (Eidenshink et al. 2007). After MODIS active fire pixel clusters were identified, we calculated the size or number of pixels included in each cluster. We then selected a cluster size threshold to define large fires. The threshold we used was 13 contiguous MODIS active fire pixels, which corresponded to the top 5% fire size quantile.

Throughout this paper, we refer to MODIS active fire pixels as "fires" and the clusters of MODIS fires at least 13 pixels in size as "large fires." However, MODIS active fire detections only indicate that fire activity was detected somewhere within the 926-m pixel, not that the entire pixel burned. Additionally, some small and low intensity fires may have been missed by MODIS (Hawbaker et al. 2008). Thus, the MODIS active fire data used here provided a conservative estimate of fire occurrence.

Human variables.—We included housing density and median distance to roads as proxies for human activities in our models. Housing density data were derived from the U.S. Census and converted to a 1-km grid (Radeloff et al. 2005*b*). We assumed housing units were uniformly distributed within census block polygons and calculated the pixel-level values as polygon-level housing unit counts multiplied by the proportion of each polygon covering a pixel.

We included Euclidian distance-to-road data at 30-m resolution from the National Overview Road Metrics database (Watts et al. 2007). We aggregated these data to 1-km resolution using a median rule. Both housing density and median distance to road data were $\log(x + 1)$-transformed prior to analysis. Since housing density may best predict fire occurrence at intermediate density (Syphard et al. 2007*b*), we included quadratic terms for both housing density and median distance to roads.

Land cover.—Fire occurrence varies among vegetation types. We accounted for that variability using the 2001 Multiple Resolution National Land Cover Database (NLCD), derived from 30-m resolution Landsat imagery (NLCD; Homer et al. 2004). Since we were primarily interested in wildland fires, we limited our analysis to fire observations in the grassland, shrubland, wetland, and deciduous, coniferous, and mixed forest NLCD classes. Therefore, we combined several of the NLCD classes to simplify the number of categories used in our models (Table 1). After combining classes, the modified land cover data set included eight unique land cover categories: developed, agriculture, wetland, grassland, shrubland, evergreen forest, deciduous forest, and mixed forest. We aggregated these land cover categories to 1-km resolution using a majority rule.

Vegetation index.—Land cover types alone might not capture spatial variability in the amount or the productivity of vegetation, which influence fuel loads. We therefore included the maximum normalized difference vegetation index (NDVI) in our models to represent spatial variability in fuel loads. The maximum NDVI value can be interpreted as a measure of the peak level of photosynthetic activity (Tucker 1979, Reed et al. 1994). We used maximum NDVI measured from the Advanced Very High-Resolution Radiometers for 1999 (U.S. Geological Survey 2009*b*). We selected the maximum NDVI value for 1999. NDVI values from the years over which MODIS fires were observed (2000–2006) were not included to avoid potential changes in NDVI that occurred as a result of fires.

Climate.—To represent the spatial variability in climate, we calculated long-term averages of temperature and precipitation. We acquired monthly tempera-

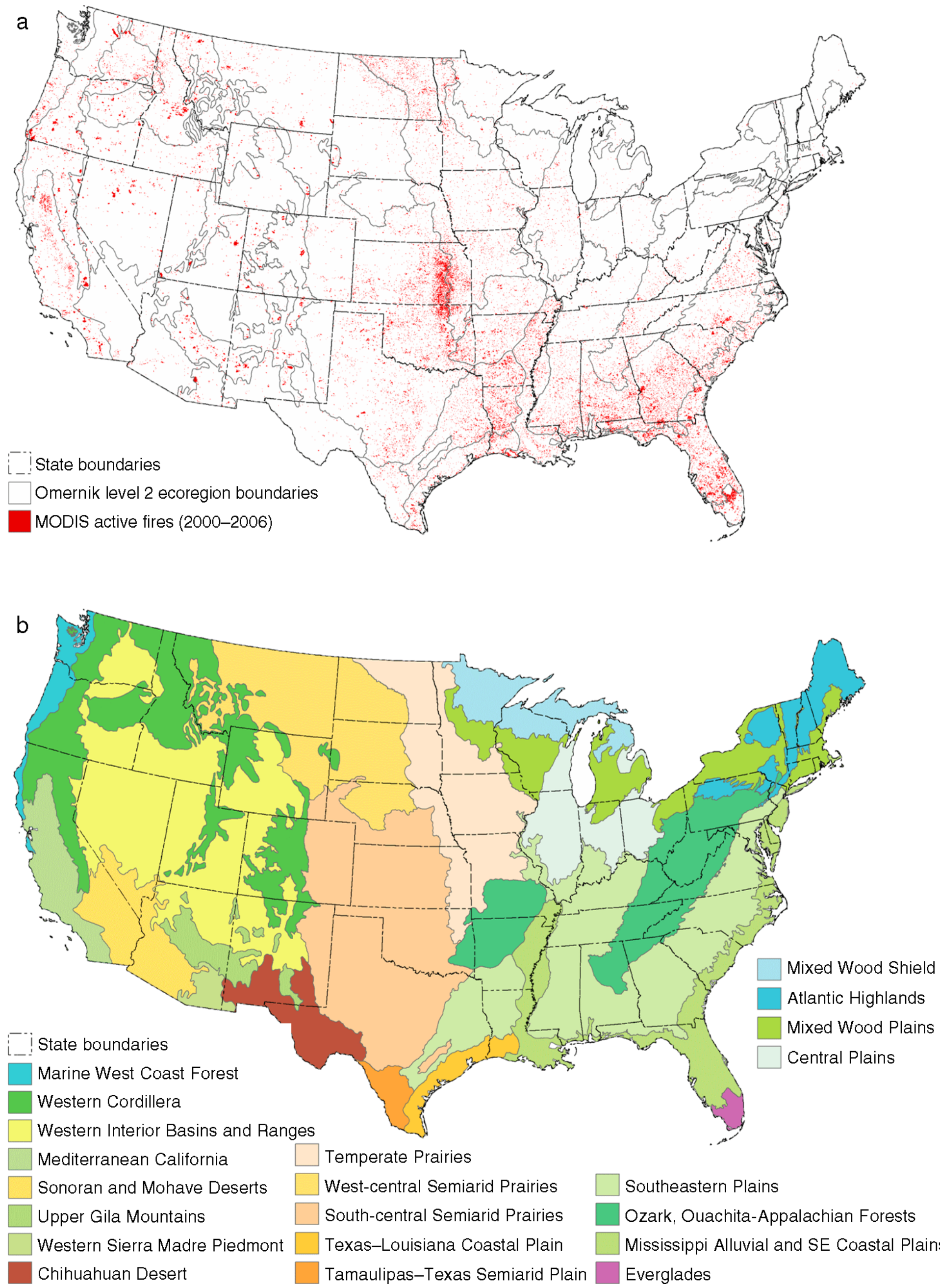

FIG. 1. (a) MODIS active fires from both the Terra and Aqua sensors (2000–2006), and (b) Omernik level II ecoregions.

ture and precipitation data with 4-km resolution from the PRISM Group at Oregon State University (data *available online*).[7] We calculated the long-term average of the monthly mean maximum temperature and the total annual precipitation from 1971 to 2000. We expected that fire occurrence would be greatest at intermediate temperature and precipitation levels because these conditions allow for high primary production. In contrast, in those places where conditions are at the extreme ends of the temperature and precipitation gradients, fuel production is either too low to support fire spread, or moisture is typically so high that fires only occur during extreme drought.

Topography.—We expected that fire occurrence would be more likely on south-facing slopes, on steeper slopes, and at lower elevations. We measured aspect, percent

[7] http://www.prismclimate.org

TABLE 1. Original national land cover database classes (Homer et al. 2004) and merged classes that were used in our analysis.

NLCD land cover category	Merged category
Developed (four classes)	developed
Pasture/hay	agriculture
Cultivated agriculture	agriculture
Woody wetlands (four classes)	wetland
Emergent herbaceous wetlands (four classes)	wetland
Open water	water, etc.
Permanent snow and ice	water, etc.
Barren	water, etc.
Grassland	grassland
Shrubland	shrubland
Evergreen forest	evergreen forest
Deciduous forest	deciduous forest
Mixed forest	mixed forest

slope, and elevation using the GTOPO 30 global elevation data set (U.S. Geological Survey 2009*c*). These data have approximately 1-km spatial resolution. Southerly or southwesterly facing slopes receive greater incident solar radiation and hence have less available moisture, limiting vegetation productivity but also drying fuels that do exist. We converted aspect, measured as degrees clockwise from north, to a southwesterly index increasing from −1 (northeast) to 1 (southwest) (Beers et al. 1966):

$$\text{southwestness} = \cos(\text{aspect} + 135) \times \frac{\pi}{180}. \tag{2}$$

Model validation and evaluation

We assessed the predictive power of our models using two data sets spanning two different time periods. The first data set included the MODIS fires for the years our models were constructed (2000–2006), which we refer to in the following as the training period. The second data set was independent and included MODIS fires from the years 2007–2009, which we refer to as the validation period. For both data sets, we assessed model performance using the area under a receiver operating characteristic curve (AUC). The AUC measures the probability of correctly classifying a random pair of fire and non-fire observations (Hanley and McNeil 1982). An AUC value of 0.5 indicates that model predictions are equivalent to a random guess and AUC value of 1.0 indicates perfect predictions.

AUC evaluates the entire model's predictive power, but provides no information about the relative importance of predictor variables. Hence, we used hierarchical partitioning (Chevan and Sutherland 1991, Mac Nally 2000), which calculates the independent contribution of a predictor as the average difference in model fit between models with and without the predictor. The independent contribution of a predictor is always positive and can be interpreted as the unique contribution of that predictor variable to model fit when other variables are also in the model. If there is no correlation among predictors, then the predictor's independent contribution equals the fit of a bivariate model containing only the response and predictor. However, this rarely occurs in practice. The difference between the bivariate model fit and the independent contribution is the joint contribution. The joint contribution is positive when the bivariate model fit is larger than the independent contribution, indicating collinearity among predictors. When the joint contribution is negative then the predictor increases the proportion of variation explained by other variables (Hamilton 1987).

After variable selection, we performed hierarchical partitioning for all models of fire occurrence and summarized the results according to four variable groups: human (housing density and median distance to roads), vegetation (land cover and maximum NDVI), climate (temperature and precipitation), and topography (elevation, slope, and southwestness; Table 2). We calculated the total proportional contribution of each variable group to the total model fit as the sum of individual and joint contributions for each variable group divided by the sum of the individual and joint contributions of all variable groups.

RESULTS

We found considerable variability in the estimated probability of fire occurrence among and within ecoregions (Fig. 2). Models of all fires predicted high probability of fire occurrence in the Southeast, the Flint Hills of Kansas, Upper Gila Mountains of Arizona and New Mexico, northern and western parts of the Western Cordillera, and in mediterranean California (Fig. 2a). The probability for large fires was generally lower than the probability for all fires (Fig. 2b); however, some clear hot spots remained, mostly in the West, and especially in the Upper Gila Mountains, mediterranean California, and northern parts of the Western Cordillera. Other areas with high large-fire probability included the Flint Hills of Kansas and parts of Oklahoma, Arkansas, Louisiana, and Florida. Areas with low fire probabilities, irrespective of fire size, included the Northeast and arid areas of the West.

We assessed model performance using AUC values, which ranged from 0.60 to 0.82 for the all-fire models, and from 0.50 to 0.88 for the large-fire models for the training period (2000–2006; Table 3). Performance of the all-fire models tended to be lowest in ecoregions with extensive fire activity, such as mediterranean California. However, performance measured by AUC, usually increased when only large fires were considered. AUC values calculated using an independent fire data set for the years in the validation period (2007–2009) varied from year to year. The AUC values from the validation period tended to be centered around the AUC value calculated from the training period, and ranged from 0.60 to 0.82 for the all-fire models, and from 0.50 to 0.88 for the large-fire models (Table 3).

TABLE 2. Input variables and units for logistic regression models.

Variable group and name	Units	Source
Vegetation		
Land cover	Four categories: grassland, shrubland, evergreen forest, deciduous forest	Homer et al. (2004)
max(NDVI)		USGS (2009*b*)
Climate		
Precipitation	mm	PRISM Group 2004 data, see footnote 7
Temperature	°C	PRISM Group 2004 data, see footnote 7
Topography		
Elevation	km	U.S. Geological Survey (2009*c*)
Slope	%	U.S. Geological Survey (2009*c*)
Southwestness		U.S. Geological Survey (2009*c*)
Human		
Housing unit density†	housing units/km^2	Radeloff et al. (2005*b*)
Median distance to road†	m	Watts et al. (2007)

Notes: Max(NDVI) was the maximum NDVI measurement obtained by the Advanced Very High-Resolution Radiometers for 1999. Southwestness is a conversion of the aspect, measured as degrees clockwise from north, and resulting in a index increasing from −1 (northeast) to 1 (southwest).

† Natural-log transformed.

Drivers of all-fire occurrence

Models of all-fire occurrence were fit for all 21 ecoregions in the coterminous United States. The predictor variables most commonly selected in the all-fire models included maximum NDVI, precipitation, temperature, housing unit density, distance from roads, and elevation (Table 4). Every model included a predictor from three of the four variable groups (human, vegetation, climate, and topography) and most models included predictors from all four variable groups (see Appendix).

We ranked the predictor variable groups according to their relative contribution to model fit. The climate variables had the greatest contribution to model fits most frequently, ranking first in nine and second in six of the 21 ecoregions (Table 5; Fig. 3a). The vegetation variables were also important contributors and were ranked first in eight ecoregions and second in seven ecoregions. Climate variables tended to have the highest relative contribution in the East and Great Plains while vegetation variables had the highest relative contribution in the West.

Human variables were present in models for 19 out of 21 ecoregions, but their contribution to model fit had lower rankings than the climate and vegetation variables. Human variables were ranked highest in the Central Plains, the Mixed Wood Plains, and the Ozark-Ouachita-Appalachian Forests ecoregions in the East and in these ecoregions, the human variable, housing unit density had a consistent negative relationship with the probability of fire (see Appendix). Human variables were also important in the West, especially in the Marine West Coast Forests, the Chihuahuan Desert, and Mediterranean California ecoregions. Similar to the patterns observed in eastern ecoregions, the probability of fire was negatively related to housing unit density in the Marine West Coast Forest ecoregion. However, the pattern was different in the Chihuahuan Desert and Mediterranean California ecoregions, and fire probability increased with housing unit density but decreased with distance from roads.

Topography variables were generally ranked low in terms of their contribution to model fits even though they were selected in 18 of the 21 ecoregion models (Table 5, Fig. 3a). However, topography variables were ranked highest in terms of their contribution to model fit for a couple of ecoregions, including the Western Cordillera and the Everglades. In the Western Cordillera, the probability of fire generally decreased as elevation increased. In the Everglades ecoregion, probability of fire also had a decreasing relationship with elevation, which is consistent with observations of fire activity being more prevalent in wetland areas and less prevalent in the surrounding uplands.

Drivers of large-fire occurrence

Models of large-fire occurrence were fit for 18 of the 21 ecoregions that we examined. Most models included predictor variables from three of the four variable groups (human, vegetation, climate, and topography) and half the models included predictor variables from all four groups. The predictor variables most often selected for the large-fire models included precipitation, temperature, elevation, vegetation type, maximum NDVI, and housing unit density (Table 4). Data limitations prevented us from fitting fire models for the remaining 3 ecoregions. Large fires were observed in the Central Plains and Mixed Wood Plains ecoregions; however, we were only able to construct intercept-only models because the number of fire observations in each ecoregion was small ($N < 30$). No large fires were observed in the Atlantic Highlands ecoregion.

The climate variable group had the greatest contribution to model first most frequently and was ranked first in 11 of the 18 models (Table 5, Fig. 3b). Similar to the all-fire models, the climate variable group tended to be ranked first in the East (five of five models) and Great Plains (four of five models). Vegetation variables were also important and ranked first in six of the models, and similar to the all-fire models, the vegetation variable group was frequently ranked first in the West (five of eight models).

Human variables were included in 15 out of 18 models and were typically ranked second to fourth in terms of their importance to model fit (Table 5, Fig. 3b). Human variables were import contributors in all of the eastern ecoregions, except the Everglades. In the Great Plains and the West, the human variable group was not the most important contributor to model fit, except for the Temperate Prairies, the Western Cordillera, and the Marine West Coast Forests. Both housing unit density and distance from roads tended to have negative relationships with large-fire occurrence in the eastern ecoregion models that included human variables (see Appendix). Similarly, in ecoregions in the Great Plains and in the West, human variables tended to be negatively related to large-fire occurrence. There were a few exceptions though. In the Sonoran and Mohave Deserts and the Western Interior Basins and Ranges ecoregions, large-fire occurrence was positively related to distance from roads. And in Mediterranean California, both housing unit density and distance from roads had a positive relationship with large-fire occurrence.

Topography variables were included in 15 out of 18 large-fire models and tended to be ranked second and third for contribution to model fit; this was generally higher than in the all-fire models (Table 5, Fig. 3b). Only one ecoregion had topographic variables as the most important group, the Western Cordillera. Elevation was the topographic variable most frequently included in the large-fire models, followed by slope and then southwestness (see Appendix). The relationship between elevation and large-fire occurrence was generally positive, except for southeastern coastal ecoregions and southwestern deserts, where the relationship was negative. Large-fire occurrence tended to be positively related to slope. The relationship between large-fire occurrence with southwestness was negative in the West but positive in the Great Plains and the East.

Differences in variable importance between all-fire and large-fire models

The contribution of variables differed between models of all-fire occurrence and large-fire occurrence (Fig. 3a and b). Climate variables were important in both models, but tended to have a greater contribution to model fits in the large-fire models. Variables in the vegetation group were also important for both fire models, but they tended to have a reduced contribution to model fit in the large-fire models compared to the all-fire models. The exceptions were the Chihuahuan Desert and Mediterranean California where the contribution of vegetation variables was greater in the large-fire models. The influence of topography variables was lower in the large-fire models than in the all-fire models for eastern ecoregions. However, in the Great Plains and West, the differences varied with topography increasing in importance in some ecoregions and decreasing in others. The importance of human variables was also mixed: the contribution to model fit of human variables increased in most eastern ecoregions in the large-fire models, but tended to decrease in the Great Plains and in the West. The exceptions were the Temperate Prairies in the Western Cordillera.

Discussion

We quantified drivers of fire occurrence using satellite fire observations for the coterminous United States collected between 2000 and 2006. We sought to identify which drivers (human, climate, vegetation, and topography) had the most influence on fire occurrence patterns, how their influence varied across the country for all fires and for large fires. Our results showed that climate and vegetation were the primary drivers of fire occurrence for both all fires and large fires in the United States. This finding is in agreement with the extensive body of fire-science literature that highlights the interactions among weather, climate and vegetation in determining fire patterns (Swetnam and Betancourt 1990, Flannigan et al. 2000, Schoenagel et al. 2004, Bond and Keeley 2005, and Westerling et al. 2006). Our results also demonstrated that climate and vegetation drivers are only part of the story though, and that human drivers played a significant role in predicting fire occurrence in most ecoregions in the conterminous United States. These findings reinforced the strong influences of people on fire that had been documented in regional studies across various parts of the United States and elsewhere (Cardille et al. 2001, Prestemon et al. 2002, Syphard et al. 2007*b*).

Although human variables were important predictors of fire occurrence, their influence varied among different regions of the country. The influence of human variables was strong in the Great Plains and the East for both all fires and large fires. Natural fire ignitions are rare in this region and mostly limited to southern Florida (Prestemon et al. 2002, Stephens 2005) and the importance of human variables was not surprising. There is a long history and tradition of using prescribed fire to reduce understory brush in managed forests in the Southeast (Cleaves et al. 2000, Haines et al. 2001, Lafon et al. 2005). There is also an extensive wildland–urban interface, and a large proportion of the population lives in close proximity to wildland fuels and this increases the likelihood of accidental ignitions. In spite of the strong relationship between humans and fires in the East, our models showed negative relationships between housing unit density and fire occurrence. Because the MODIS active fire data primarily capture larger fires (>1 acre [0.405 ha]), our results demonstrated that the areas

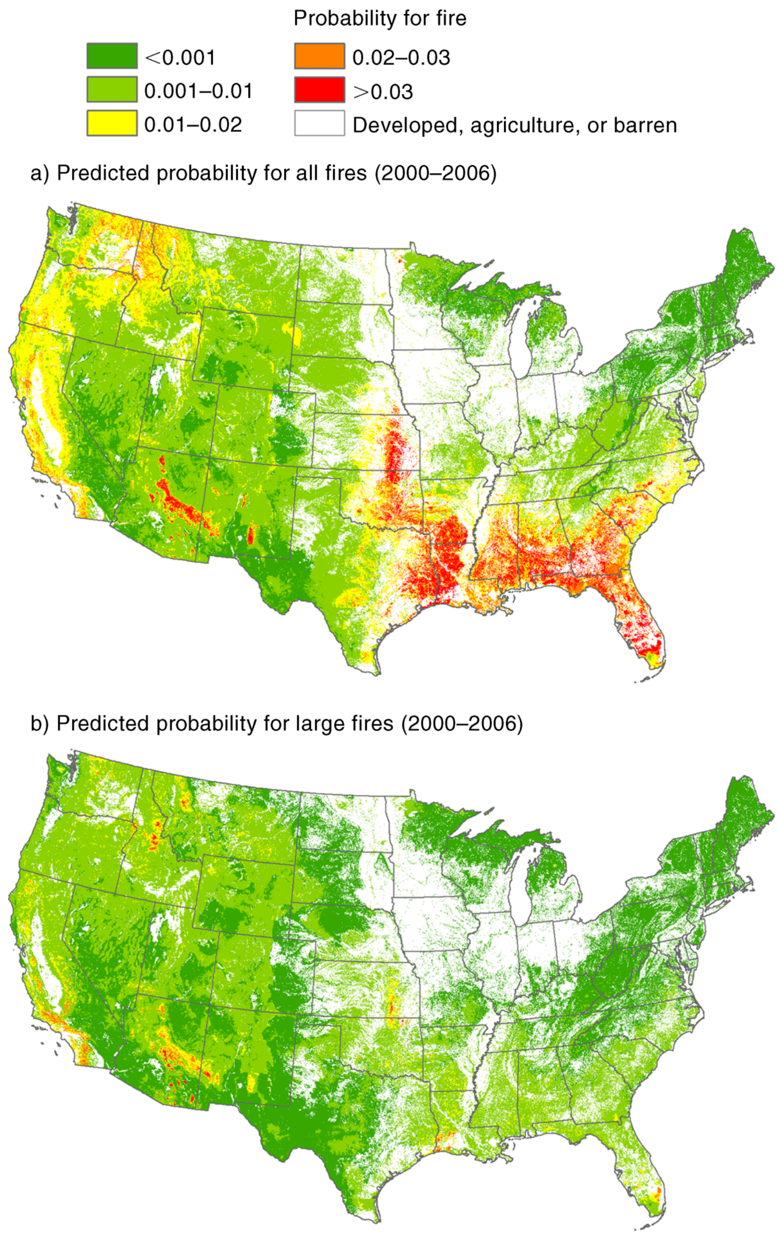

FIG. 2. Modeled probability for occurrence of (a) all fires and (b) large fires.

where fires did occur was largely limited to areas free of human development. This suggests that fires were and will be more or less limited to public lands and large tracts of private lands in the Great Plains and the East.

In the West, the influence of human variables was less important than in the Great Plains and in the East, but the relationships were largely similar to that in the Great Plains and the East, highlighting higher fire suppression in areas that are more developed. For example, in the Western Cordillera, probability of fire was negatively related to distance from roads and housing density. This indicated that fires were more likely in areas with limited development and this may reflect fire suppression efforts near development and policies allowing fires to burn when there is little risk, e.g., appropriate management response policies on public lands (Miller 2006).

There were a couple of ecoregions in the West where the relationship between people and fire differed though. In the Desert Southwest, fires were more likely to occur distant from roads. This strong human influence may be related to invasive species. Historically, vegetation productivity has been low in these ecoregions and vegetation was often too spares to carry fires. Invasive species, such as cheatgrass (*Bromus tectorum*) and buffelgrass (*Pennisetum ciliare*) introduced as cattle forage, produce continuous fuels capable of supporting

TABLE 3. Area under curve (AUC) of the receiver operating characteristics (ROC) curve using for all-fire and large-fire models by ecoregion.

Ecoregion and model	Training period 2000–2006	Validation years		
		2007	2008	2009
Everglades				
All fires	0.65	0.71	0.56	0.74
Large fires	0.72	0.71	0.53	0.61
Mississippi alluvial and SE coastal plains				
All fires	0.65	0.66	0.64	0.68
Large fires	0.73	0.81	0.59	0.73
Ozark, Ouachita-Appalachian forests				
All fires	0.78	0.75	0.74	0.74
Large fires	0.83	0.85	0.74	0.78
Southeastern plains				
All fires	0.71	0.70	0.69	0.71
Large fires	0.76	0.75	0.76	0.77
Central plains				
All fires	0.78	0.70	0.66	0.82
Large fires	0.50	0.50	0.50	NA
Mixed wood plains				
All fires	0.82	0.79	0.83	0.86
Large fires	0.50	NA	0.50	NA
Atlantic highlands				
All fires	0.77	0.79	0.81	0.71
Large fires	NA	NA	NA	NA
Mixed wood shield				
All fires	0.77	0.75	0.73	0.78
Large fires	0.88	0.74	0.91	0.73
Tamaulipas–Texas semiarid plain				
All fires	0.72	0.63	0.64	0.63
Large fires	0.75	0.25	0.69	0.69
Texas–Louisiana coastal plain				
All fires	0.71	0.70	0.60	0.58
Large fires	0.72	0.72	0.56	0.58
South-central semiarid prairies				
All fires	0.78	0.73	0.74	0.78
Large fires	0.79	0.78	0.69	0.74
West-central semiarid prairies				
All fires	0.66	0.66	0.56	0.67
Large fires	0.77	0.69	0.71	0.60
Temperate prairies				
All fires	0.77	0.69	0.77	0.76
Large fires	0.88	0.84	0.59	0.90
Chihuahuan Desert				
All fires	0.74	0.66	0.67	0.67
Large fires	0.78	0.58	0.67	0.74
Sonoran and Mohave Deserts				
All fires	0.76	0.92	0.85	0.92
Large fires	0.79	0.94	0.63	0.88
Western interior basins and ranges				
All fires	0.74	0.72	0.77	0.76
Large fires	0.75	0.73	0.76	0.78
Mediterranean California				
All fires	0.60	0.60	0.55	0.59
Large fires	0.72	0.77	0.55	0.74
Western Sierra Madre piedmont				
All fires	0.79	0.65	0.69	0.70
Large fires	0.83	0.74	0.79	0.71

TABLE 3. Continued.

Ecoregion and model	Training period 2000–2006	Validation years 2007	2008	2009
Upper Gila Mountains				
All fires	0.73	0.78	0.76	0.74
Large fires	0.73	0.72	0.66	0.69
Western cordillera				
All fires	0.65	0.64	0.65	0.67
Large fires	0.65	0.70	0.68	0.64
Marine west coast forest				
All fires	0.70	0.73	0.66	0.68
Large fires	0.75	0.75	0.60	0.53

Notes: AUC values for the training period were based on fire data from the years used to parameterize the models. AUC values for the validation period were based on fire data from years after and are independent from the training period. NA stands for "not applicable"; i.e., in that ecoregion and year, there were no fires that could be modeled.

fires. The presence of invasive species is correlated with human development (Gavier-Pizarro et al. 2010, 2011, Rogers et al. 2010) and may make fires more likely in invaded areas near homes and roads (Brooks et al. 2004, Keeley 2006). In Mediterranean California, the probability of fire increased with housing unit density in both the all-fire and large-fire models. However, the relationship between fire and distance from roads varied, being negative in the all-fire models, but positive in the large-fire models. In California, many fires are ignited directly by humans or inadvertently caused by human presence (Syphard et al. 2007*b*). Small fires were common and scattered throughout this ecoregion and the negative relationship with roads is most likely capturing small fire activity in less developed areas. Large fires were less common and tended to be concentrated in southern California, where there is extensive urban and suburban development. The relationships between people and fire in all these ecoregions thus show a pattern where human development has altered fire regimes either directly through increased ignitions in some areas and suppression in other areas, or indirectly through invasive species.

Model validation

The predicted patterns of fire probability shown in our maps (Fig. 1) generally matched our expectations; however, some results were surprising. We did not expect the isolated hot spots of large-fire probabilities in the south-central United States (i.e., the Flint Hills in Kansas and parts of Oklahoma, Arkansas, and Louisiana). Continuous grassland expanses allow fires to spread quickly when fire weather conditions are extreme. We were also surprised that the Upper Midwest and Northeast had notably low probabilities for fire in our predictive maps given that large fires do occur in places like the Boundary Waters Canoe Area Wilderness in northern Minnesota (Heinselman 1973). The low fire probabilities in these areas may be a combination of the short time-span over which MODIS fire observations were collected and the generally low fire frequencies in these regions (Cleland et al. 2004).

We first assessed model performance using AUC, calculated using MODIS fire observations from the model training period (2000–2006). An AUC value of 0.5 would indicate that model performance was essentially random and an AUC value of 1.0 indicates perfect model performance. Model performance for the all-fire models was better than random and ranged between 0.6 and 0.82 (Table 3). Model performance for the large-fire models were more variable and ranged from 0.5 to 0.88, but tended to be greater than all-fire model performance. In the Mixed Wood Plains and Central Plains ecoregions, large-fire model performance was random, most likely because the limited number of large-fire observations precluded development of any valid model. Excluding these ecoregions, large-fire model performance was somewhat better than the all-fire models and ranged between 0.65 and 0.88.

TABLE 4. Predictor variables and number of times they occurred in ecoregion models ($N = 21$ ecoregions).

Variable group and name	All fires	Large fires
Human		
Housing unit density	16	11
Median distance from roads	16	9
Vegetation		
Grassland	7	7
Shrubland	6	5
Evergreen forest	10	5
Deciduous forest	3	1
max(NDVI)	20	12
Climate		
Precipitation	19	15
Temperature	19	15
Topography		
Elevation	15	14
Slope	9	7
Southwestness	8	5

TABLE 5. Predictor variable groups ranked according to their contribution to total model fit.

Region and ecoregion	All fires: First	All fires: Second	All fires: Third	All fires: Fourth	Large fires: First	Large fires: Second	Large fires: Third	Large fires: Fourth
East								
Everglades	topo.	climate	veg.	human	climate	topo.	veg.	human
Mississippi alluvial and coastal plains	climate	veg.	human	topo.	climate	human	veg.	
Ozark, Ouachita-Appalachian forests	climate	human	topo.	veg.	climate	human	topo.	veg.
Southeastern plains	climate	topo.	human	veg.	climate	human	topo.	veg.
Central plains	human	climate	topo.					
Mixed wood plains	human	veg.	topo.	climate				
Atlantic highlands	climate	veg.	human					
Mixed wood shield	climate	veg.	human		climate	human	topo.	
Great Plains								
Tamaulipas–Texas semiarid plain	veg.	topo.	climate		climate	topo.	veg.	
Texas–Louisiana coastal plain	climate	veg.	human	topo.	climate	veg.	human	
South-central semiarid prairies	climate	veg.	topo.	human	climate	veg.	topo.	human
West-central semiarid prairies	veg.	topo.	human	climate	veg.	topo.	climate	
Temperate prairies	climate	topo.	veg.	human	climate	human	topo.	veg.
West								
Chihuahuan Desert	veg.	human	climate	topo.	veg.	topo.		
Sonoran and Mohave Deserts	veg.	climate	human	topo.	veg.	topo.	climate	human
Western interior basins and ranges	veg.	climate	topo.		veg.	climate	topo.	human
Mediterranean California	veg.	human	climate	topo.	veg.	topo.	human	
Western Sierra Madre Piedmont	veg.	climate	human	topo.	climate	veg.	human	topo.
Upper Gila Mountains	veg.	climate	human	topo.	veg.	climate	human	
Western Cordillera	topo.	veg.	climate	human	topo.	human	veg.	climate
Marine west coast forest	climate	human	veg.		climate	human	topo.	

Note: Abbreviations are: veg., vegetation; topo., topography. Empty cells indicate that no other predictor variable groups were significant in the models; the number of predictor variable groups that were significant differed among the ecoregions.

The performance differences between the all-fire and large-fire models may be related to differences in the drivers behind fire occurrence. Small fires are more likely to be human-caused, and the lower predictive success for these fires might reflect the variety and spatial variability of different human activities that contribute to small fire occurrence. These results may indicate that commonly used human predictor variables of housing unit density and distance from roads are not entirely capable of capturing those patterns. Large fires on the other hand, are more restricted to areas with large contiguous patches of fuels or wildland vegetation and the locations of these areas are well defined by the suite of predictor variables we used, especially in the East and the Great Plains.

Across the ecoregions that we analyzed, the predictive power of both the all-fire and large-fire models tended to be greatest in the East and Great Plains and lowest in the West (Table 3). The processes of fire spread plays a critical role in determining where large fires burn and this is a difficult process to capture with statistical models. None of our predictor variables quantified the potential for fire spread. However, the sampling design that we implemented to avoid spatial autocorrelation required greater spacing among samples in the West than in the East (see Appendix). This greater spacing may be an indication of the uncertainty introduced into model predictions because of potential fire spread and these uncertainties are larger in the West where fires tended to be much larger than in the East.

In addition to validating our models using fire observation from the training period, we performed an additional validation using fire observations from an independent time period (2007–2009). For each year in the independent period, we calculated AUC for each ecoregion using the predicted fire probabilities from our models and observed MODIS active fires. AUC values reached up to 0.92 for the all-fire models and 0.9 for the large-fire models, exceeding AUC values during the training period. The results did show variability in model performance among years, but single-year AUC values for the validation period generally were centered on AUC values calculated for the training period. This variability was most likely a reflection of inter-annual climate variability that was not represented in our models. This analysis assumed that climate conditions during the training period (2000–2006) and independent validation period did not change substantially. However, the results do show that our models were capable of predicting near-term fire occurrence well.

There are few comparable national-level studies examining fire occurrence. One recent study by Preisler et al. (2009) used daily weather and satellite imagery to calculate fire danger indices and related those indices to fire occurrence. Unfortunately, they did not generate model performance metrics comparable to ours. Another recent study by Parisien and Moritz (2009) used a habitat distribution model approach using Maxent and boosted regression tree algorithms. They trained their national-level model using fires greater than 121 ha (300

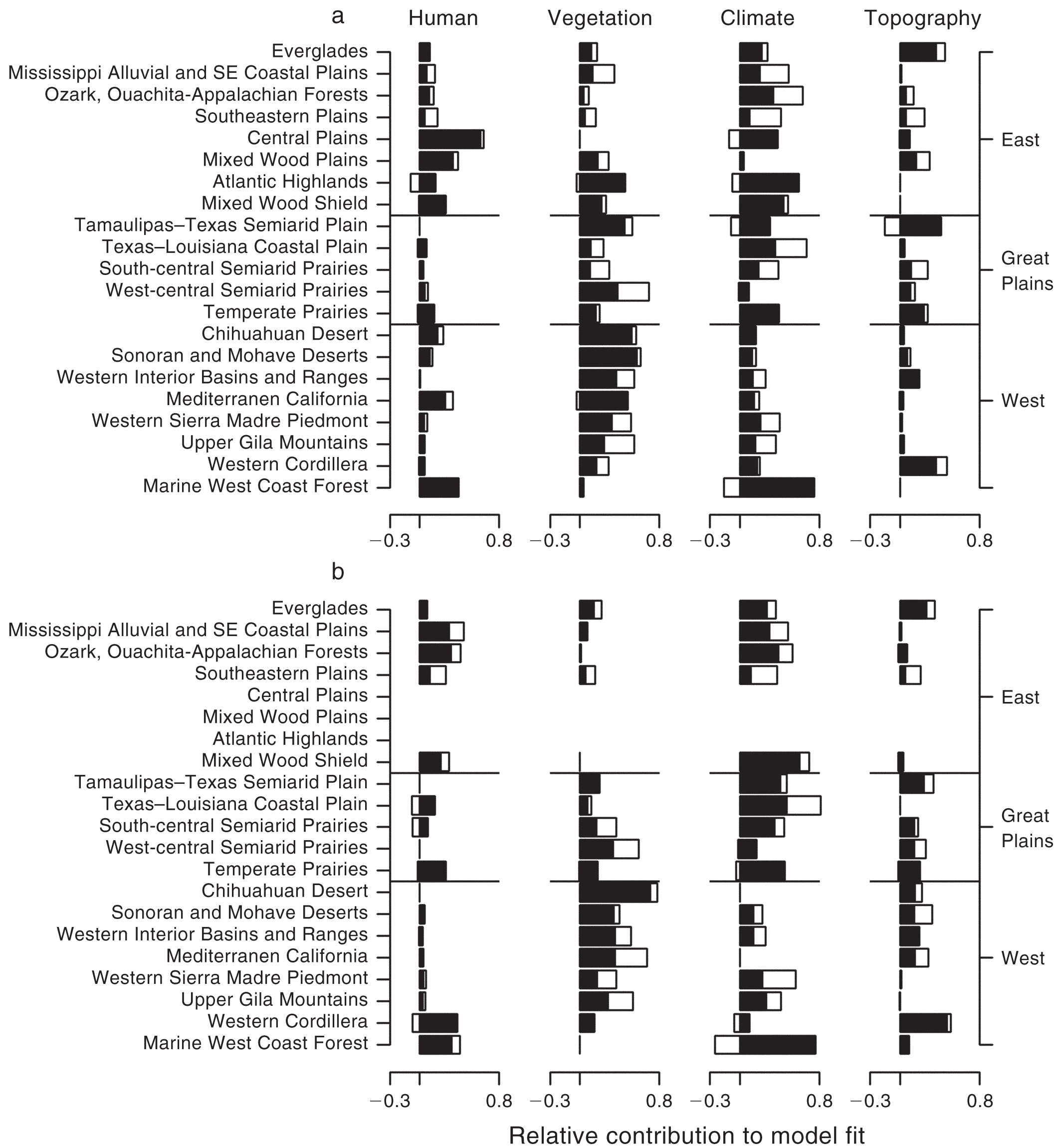

FIG. 3. Hierarchical partitioning results showing contributions of variable groups to model fit for models of (a) all fire occurrence and (b) large fire occurrence.

acres) in size from the federal fire occurrence database from 1980 to 2003. In addition to potential vegetation type and elevation, their predictors included a large suite of climate summary variables than we used. Their reported AUC values ranged up to 0.85 and 0.88 for the Maxent and boosted regression tree algorithms respectively, and thus, the performance of their models was similar to ours. However, their models did not capture fires on private lands well, because these are not included in the federal fire occurrence database.

Limitations and uncertainties

Our models of fire occurrence successfully described observed fire patterns and demonstrated the relative importance of climate, vegetation, topography, and human variables. However, there were a few limitations to our approach and these limitations may have affected the applicability of our models to address important questions about fire occurrence and management in the United States.

The MODIS active fire data present challenges to monitoring and modeling fire occurrence. One important limitation of these data is the lack of information about the cause of fires, which is not easily determined from satellite observations. Human-caused and natural-caused fires may have different groups of driving variables. For instance, there is large body of literature documenting the influence of roads and development on human ignition locations (Cardille et al. 2001, Syphard et al. 2007*b*). Some inferences about ignition sources can be made at the regional level (Stephens 2005) or using ancillary data to predict the likelihood of different ignitions sources (Bar Massada et al., *in press a*). Additionally, our modeling approach did not examine ignitions locations from where fires eventually spread, and that may have limited the explanatory power of our models, because ignition and spread are affected by different factors (Calef et al. 2008, Syphard et al. 2012; Bar Massada et al. 2011, *in press b*). Our ability to understand the differences in the patterns and driving forces behind human and natural-caused fires from satellite fire observations could be improved by better data sets of ignition locations and ignition types, which are lacking at a national scale for the United States for all types of land ownership.

Another limitation of our approach was the climate data that we used. Inter- and intra-annual variability in climate and weather play a large role in determining when and where fires occur, influencing both ignition and spread probabilities (Rothermel 1972, Bessie and Johnson 1995, Rollins et al. 2002, Westerling et al. 2006, Balshi et al. 2009, Cary et al. 2009). Our analysis used short-term (6-year) climate averages of precipitation and temperature. At this temporal resolution, our approach may not fully account for the temporal variability in climate and the potential influence on fire occurrence. Consequently, our study may be underestimating the importance of climate variability. However, similar approaches have been used in previous studies (Parisien and Moritz 2009) and, in spite of the lack of climate variability, we still found climate variables to be among the most important predictors of fire occurrence. Our models could thus be used to project how fire occurrence patterns may change under future climates but ideally such models should consider incorporating inter- and intra-annual climate or weather variables as predictors.

Implications

Humans have a significant influence on fire occurrence across most of the United States. Although the relative contribution of humans was often low in our models compared to vegetation, climate, and topography, human impacts have implications for both ecosystem conservation and fire management. The cumulative impacts of human influence on fire regimes have both increased fire frequency (Veblen et al. 2000, Cleland et al. 2004, Grissino-Mayer et al. 2004) and decreased fire frequency (Keeley 2006, Syphard et al. 2006). In both cases, this pushes disturbance regimes outside their historic range of variability and that affects biodiversity and ecosystem function. Consequences include changes in plant community types (Lorimer 1977, Franklin et al. 2005, Scheller et al. 2005), exotic species invasions (Brooks et al. 2004, Keeley 2006), landscape structure (Baker 1992, Radeloff et al. 1999), and ecosystem processes (Reed et al. 1999, Turner et al. 2004, Smithwick et al. 2005). Our results also reiterated the importance of climate and vegetation in determining fire occurrence patterns. We used short-term climate summaries as predictors of fire occurrence. Even though year-to-year climate variability was not included in our models, our results can help to project how patterns of fire occurrence may shift with concurrent changes in short-term climate averages. As future development occurs (Hammer et al. 2007, Syphard et al. 2007*a*) and as its impacts interact with climate changes (Flannigan et al. 2000, Lenihan et al. 2003, Westerling et al. 2006, Fried et al. 2008) to alter patterns of fire occurrence, we can expect the challenges of managing fire to increase.

Fire management policies generally aim to reduce fire risk. Fire risk is a function of both the probability of a fire, and the amount of damage that a fire could cause. Homes and other structures make up a major component of the values at risk from fire. Our models predicted fire occurrence, not fire risk, but it is interesting to interpret them in the context of settlement patterns. In the East, both development and fire occurrence were widespread and, in these places, fire risk can be high where vegetation types with potential for extreme fire behavior exist. Relative to the East, fires in the West tended to be larger, more variable, and more localized. However, development is constrained by topography and land ownership (Miller et al. 1996, Turner et al. 1996), and the localized nature of western development is both good and bad from a fire management perspective. On one hand, the limited footprint of human development limits fire risk to houses, and thus the area needing direct fire suppression. However, on the other hand, large fires are by far the most challenging to suppress, and when large fires do occur in or near development, houses are also concentrated and losses can be great.

In addition to the insight our results provide about the relative influence of climate, vegetation, topography, and human development on fire occurrence across the coterminous United States, our models fill a critical gap by providing a framework to compare the relative probability of fire across the country. The probability maps generate by our models could be combined with housing locations and other social value maps to help prioritize fuel treatment and fire management resources across the country.

Humans influence fire occurrence differently in different ecoregions. Culture, settlement pattern, public lands, policy, and invasive species all interact with climate, vegetation, and topography to determine where fires do and do not occur. This leaves us with a complex problem in a changing world. Topography is about the only variable likely to remain constant. There is much uncertainty in how our climate will change and where future road and housing development will occur (Radeloff et al. 2005*a*, Hawbaker et al. 2006, Gonzalez-Abraham et al. 2007, Hammer et al. 2007). Fire occurrence will change concurrently, but the uncertainty in climate change and development may challenge efforts to predict where fires will most often occur, and limit the success of preventive policies.

ACKNOWLEDGMENTS

We gratefully acknowledge funding for this research by the National Fire Plan through the U.S. Department of Agriculture Forest Service Northern Research Station. We are also grateful for comments and suggestions by D. Mladenoff, P. Townsend, M. Turner, J. Diffendorfer, X. Chen, and two anonymous reviewers. Their suggestions helped greatly to improve our manuscript.

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Supplemental Material

Appendix

Detailed model results by ecoregion (*Ecological Archives* A023-027-A1).